Ferdowsi University of Mashhad

Journal of Agricultural Machinery

Iranian Society of Mechanical Engineers (ISME)

Vol. 15 No. 3

2025

ISSN: 2228-6829

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Journal of Agricultural Machinery

Vol. 15 **No. 3** **2025**

Published by: Ferdowsi University of Mashhad, (College of Agriculture), Iran

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P.O. BOX: 91775-1163

Fax: +98-05138787430

E-Mail: jame@um.ac.ir

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Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 275-289

Investigating the Potential of the Innovative YOLOv8s Model for Detecting Bloomed Damask Roses in Open Fields

F. Fatehi [1], H. Bagherpour [1*], J. Amiri Parian [1]

1- Department of Biosystems Engineering, Faculty of Agriculture, Bu-Ali Sina University, Hamedan, Iran
(*- Corresponding Author Email: h.bagherpour@basu.ac.ir)

Received: 14 May 2024
Revised: 25 July 2024
Accepted: 27 July 2024
Available Online: 31 May 2025

How to cite this article:
Fatehi, F., Bagherpour, H., & Amiri Parian, J. (2025). Investigating the Potential of the Innovative YOLOv8s Model for Detecting Bloomed Damask Roses in Open Fields. *Journal of Agricultural Machinery*, *15*(3), 275-289. https://doi.org/10.22067/jam.2024.88066.1249

Abstract

Manually picking the flowers of the Damask rose is significantly challenging due to the numerous thorns on its stems. Consequently, the accurate detection of bloomed Damask roses in open fields is crucial for designing a robot capable of automating the harvesting process. Considering the high speed and precise capabilities of deep convolutional neural networks (DCNN), the objective of this study is to investigate the effectiveness of the optimized YOLOv8s model in detecting bloomed Damask roses. To assess the impact of the YOLO model size on network performance, the precision and detection speed of other YOLO network versions, including v5s and v6s, were also examined. Images of Damask roses were taken under two lighting conditions: normal light conditions (from civil twilight to sunrise) and intense light conditions (from sunrise to 10 AM). The outcomes demonstrated that YOLOv8s exhibited the highest performance, with a mean average precision (mAP50) of 98% and a detection speed of 243.9 fps. This outperformed the mAP50 and detection speed of YOLOv5s and YOLOv6s networks by margins of 0.3%, 6.1%, 169.3 fps and 198.6 fps, respectively. Experimental results show that YOLOv8s performs better on images taken in normal lighting than on those taken in intense lighting. A decline of 5.2% in mAP50 and 2.4% in detection speed signifies the adverse influence of intense ambient light on the model's effectiveness. This research indicates that the real-time detector YOLOv8s provides a feasible solution for the identification of Damask rose and provides guidance for the detection of other similar plants.

Keywords: Ambient light, Deep learning, Object detection, Rose flower, YOLO

Introduction

Damask rose (*Rosa damascena* mill.) is a precious species of rose and has been extensively used in various cosmetic, health, and pharmaceutical industries. Bulgaria, Turkey, India, and Iran are ranked first through fourth in the cultivation area dedicated to this crop. Furthermore, Bulgaria, Turkey, and Iran hold this plant's top three positions in oil and essential oil production. (Ucar, Kazaz, Eraslan, & Baydar, 2017; Yousefi & Jaimand, 2018).

Harvesting Damask rose is the most labor-intensive aspect of this flower's production. This is due to the rapid emergence of rose blooms, which occur only once a year for a short period of 15 to 20 days. These plants produce numerous bloomed and fully-opened flowers each day, necessitating harvesting from 4:00 AM to 7:00 AM to obtain the highest-quality Damask rose oil in quantity and quality. Most Damask rose buds fully bloom early in the morning and should be harvested on the same day, as withered flowers

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https://doi.org/10.22067/jam.2024.88066.1249

that had fully bloomed the previous day are not harvested (Rusanov, Kovacheva, Rusanova, & Atanassov, 2011). In addition to the requirement to harvest fully-bloomed flowers in a narrow window, the harvesting of this crop is inherently difficult and has not yet been fully mastered technologically, so manual harvesting remains the traditional approach. While harvesting the buds, workers may sustain injuries from the thorns on the stems. As such, it is imperative to provide adequate training for these workers. The challenges related to labor, along with the costs and time required for worker training, significantly contribute to the total expense of harvesting this crop (Manikanta, Rao, & Venkatesh, 2017). Consequently, the real-time identification of bloomed Damask rose in open fields is crucial for developing a machine or robot capable of autonomously harvesting Damask roses. One approach to achieving high efficiency in this field involves the utilization of machine vision techniques.

In recent years, convolutional neural networks (CNN) have emerged as novel machine learning methods garnering substantial attention from researchers for flower classification and qualitative evaluations. (Guru, Kumar, & Manjunath, 2011; Wang, Underwood, & Walsh, 2018; Sun, Wang, Liu, & Liu, 2021; Zhang, Su, & Wen, 2021; Bataduwaarachchi *et al.*, 2023). CNN model was designed to detect apple blossoms, which was able to identify apple tree blossoms with an accuracy of over 79%. This model, without the need for retraining, could identify apple, peach, and pear blossoms on the trees with an accuracy of over 67%, 86%, and 94%, respectively (Dias, Tabb, & Medeiros, 2018). Wu, Lv, Jiang, and Song (2020) developed a channel pruning-based YOLOv4 that facilitates the acquisition of apple blossom thinning robots. This model can identify apple blossoms with a mean average precision (mAP) of 97.31% and a detection speed of 72.33 fps, which compared to the base model YOLOv4, reduces the mAP, detection speed, and size by 0.24%, 39.47%, and 231.51 MB, respectively. By pruning low-load weights of model in apple blossom detection using the channel pruning method, they achieved a lighter model. Wang *et al.* (2022) used the developed YOLOv4, called YOLO-PEFL, to estimate the performance of pear orchards through detecting and counting flowers. ShuffleNetv2, embedded by the SENet (Squeeze-and-Excitation Networks) module replacing the original backbone network of the YOLOv4 model, formed the backbone of the YOLO-PEFL model. The empirical findings indicated that the mean accuracy of the YOLO-PEFL framework was 96.71%, the framework's dimensions were decreased by approximately 80%, and the mean recognition velocity was 0.027 s. In comparison to the YOLOv4 framework and the YOLOv4-tiny framework, the YOLO-PEFL framework exhibited superior performance in framework dimensions, recognition precision, and recognition speed, thereby effectively decreasing framework deployment expenditure and enhancing framework effectiveness. YOLO network training using drone-captured images was employed to create a map depicting pumpkin flower distribution in the field. In this research, the mAP50 was 91% (Mithra & Nagamalleswari, 2023). To aid the marketing of roses, Anjani, Pratiwi, and Nurhuda (2021) developed a Convolutional Neural Network (CNN) model capable of categorizing the variety of roses without manual categorization. In this study, the accuracy achieved on the evaluation dataset was 96.33%. Shinoda *et al.* (2023) recognized that strategic planning for cut flower production is pivotal, as demand varies throughout the year. Nevertheless, manual enumeration of all rose blossoms in the greenhouse is time-intensive and arduous. They used YOLOv5 to identify small rose blossoms from various angles during camera motion, diminishing detection inaccuracies and attaining an F1 score of 0.950.

By reviewing the research literature, it has become apparent that there is a gap in the existing literature regarding a thorough examination of the precise and real-time identification of bloomed Damask rose flowers

in agricultural fields for the purpose of automating the harvesting process. As a result, the present study aims to address this deficiency by leveraging the potential of deep learning models, specifically focusing on the compact YOLO models, known for their adeptness in accurately and swiftly identifying various types of flowers. In this investigation, upon completion of training the models and fine-tuning their weights, the performance of each individual model was assessed using a collection of images captured during harvest time. To carefully examine the effect of ambient lighting on the detection proficiency of the chosen model, the model underwent training and evaluation using images captured under two distinct lighting conditions: normal light and intense light.

Materials and Methods

Data collection and preparation

In order to extract the optimal essence from high-quality Damask rose petals, it is imperative to harvest these blooms during the early hours of the morning (Kumar, Sharma, Sood, Agnihotri, & Singh, 2013; Thakur, Sharma, & Kumar, 2019). To train models, two distinct sets of videos were acquired from Damascus rose fields situated in the village of Sarab, Dehgolan, Kurdistan Province, Iran. These videos were obtained using a Samsung Galaxy Note 9 smartphone camera during May–June 2022. The first collection of videos, which were labeled "Normal Light Condition," was obtained in the morning from twilight until sunrise. Conversely, the second set, labeled "Intense Light Condition," was acquired from sunrise to 10 AM to assess the impact of intense illumination on the efficacy of the chosen model trained using the aforementioned images (Fig. 1).

In the study conducted by Sharma and Kumar (2018), the six distinct flowering stages of Damask rose were explored. These stages that affect the yield and quality of the essence are: 1) Sepals intact with dark immature petals, 2) Sepals separated from petals, petals whorl closed, 3) Petals whorl loosened, 4) Petal whorl opened, 5) Fully opened flower, and 6) Flower opened the previous day. The outcomes of their study indicated that the early harvest stages of flowers (1, 2, and 3) exhibited variations in scent characteristics when compared to fully bloomed flowers. Moreover, the maximum essential oil content exhibited notable differences across various harvest stages and the duration of hydrodistillation. Notably, at the fourth stage of flowering (fully open petal whorl), along with a hydrodistillation duration of 5 hours, yielded the highest quality of essential oil. Additionally, immature or overly mature flowers not only diminish essential oil yield but also compromise oil quality. Consequently, stages 4 and 5 were identified as the target harvesting stages for rose flowers, classified as bloomed flowers in this study. Fig. 2 depicts different flower opening stages from 1 to 6, as described earlier.

Labeling

The LabelImg v1.8.0 software was utilized for the purpose of annotating images of damask roses. Utilizing this software resulted in the generation of output files saved in the TXT format specifically tailored for YOLO networks. As depicted in Fig. 3, a visual representation is provided, illustrating the contents of the output file pertaining to two individual flowers. Within this illustration, various symbols such as NO, Nc, Xc, Yc, W, and H are utilized to represent specific parameters including the number of objects in the image, the object class, longitudinal and transverse coordinates of the frame's center, width, and height of bounding boxes, respectively. All these values are normalized within a range of zero to one. Given that the main focus of the present study was the identification of bloomed Damask roses, a single class was considered, denoted as "Ripe=0".

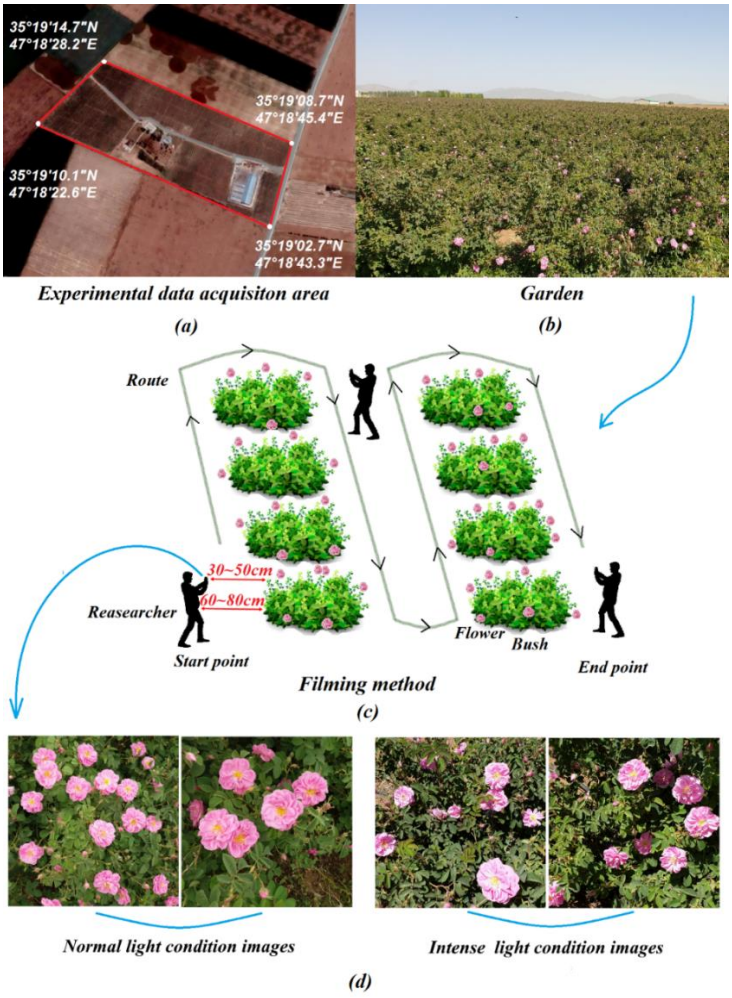


Fig.1. Schematic diagram of the image acquisition process: (a) Geographical coordinates of the garden, (b) The garden, (c) Video capture method, and (d) Example images

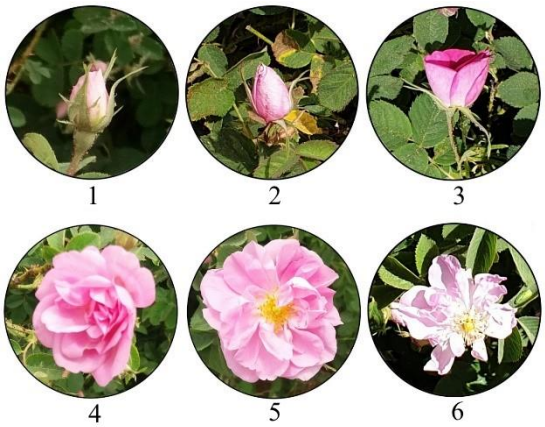


Fig.2. Different stages of development of damask rose: (1) sepals intact with dark immature petals, (2) sepals separated from petals, petals whorl closed, (3) petals whorl loosened, (4) petal whorl opened, (5) fully opened flower, and (6) flower opened the day before

In this study, five hundred images were extracted from collected videos. Extracting consecutive frames from the video is essential for the stability of YOLO detection (Tung *et al.*, 2019). To reduce the computational cost and increase the image processing speed and speed up the model training, all images were 512 x 512 pixels. To check the robustness of the model and issues like overfitting and underfitting, a technique called K-fold cross validation was used. We created 10 folds of the dataset, and each fold was executed 5 times. In this study, 10% of images were allocated for testing purposes**.**

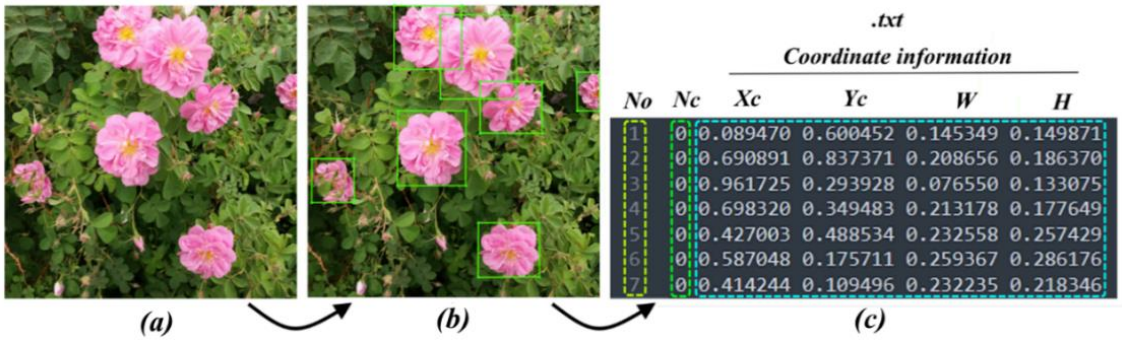


Fig.3. The process of creating the annotation: (a) original Damask rose, (b) labeled desired flowers, and (c) annotation results in .txt format

YOLO Model

The YOLO model has had a notable development in the field of real-time object detection. By employing a convolutional network that evaluates images in a single step, YOLO can detect objects directly and calculate the precise object coordinates. The utilization of this methodological approach has resulted in a substantial enhancement in detection speed (Redmon, Divvala, Girshick, & Farhadi, 2016; Silva, Monteiro, Ferreira, Carvalho, & Corte-Real, 2019).

In January 2023, Ultralytics unveiled the YOLOv8 model, building upon their prior launch of the YOLOv5 model. This latest version represents the pinnacle of advancements in comparison to its predecessors. The YOLOv8 model, which underwent training on ImageNet, demonstrated heightened accuracy and speed of detection in contrast to the YOLOv5 and YOLOv6 models that had undergone similar training (Jocher, Chaurasia, & Qiu, 2023). A comprehensive schematic depiction of the YOLOv8 model can be observed in Fig. 4. This model retains the primary network of YOLOv5, but features a notable modification in its CSP layer, now referred to as the C2f module. The C2f module improves detection accuracy by combining high-level features with contextual information. YOLOv8 is an anchor-free model that employs a distinct head for the autonomous processing of object detection, classification, and regression tasks. This design facilitates each branch's concentration on its respective task, thus enhancing the overall precision of the model. In the output layer of YOLOv8, the sigmoid function serves as the activation function for abjectness, while the softmax function is employed for class probabilities (Terven & Cordova-Esparza, 2023).

Among the different scales of each architecture in the YOLO family, only those meeting the following criteria were chosen: 1- Having a parameter count below 2 million, and 2- Achieving a detection speed of less than 1.5 ms per image on the COCO dataset using a GPU A100. Ultimately, the scale with the highest mAP50-95 value was selected for each architecture, in the YOLO family, only YOLOv8s, YOLOv6s, and YOLOv5s met these criteria (Ultralytics, n.d.).

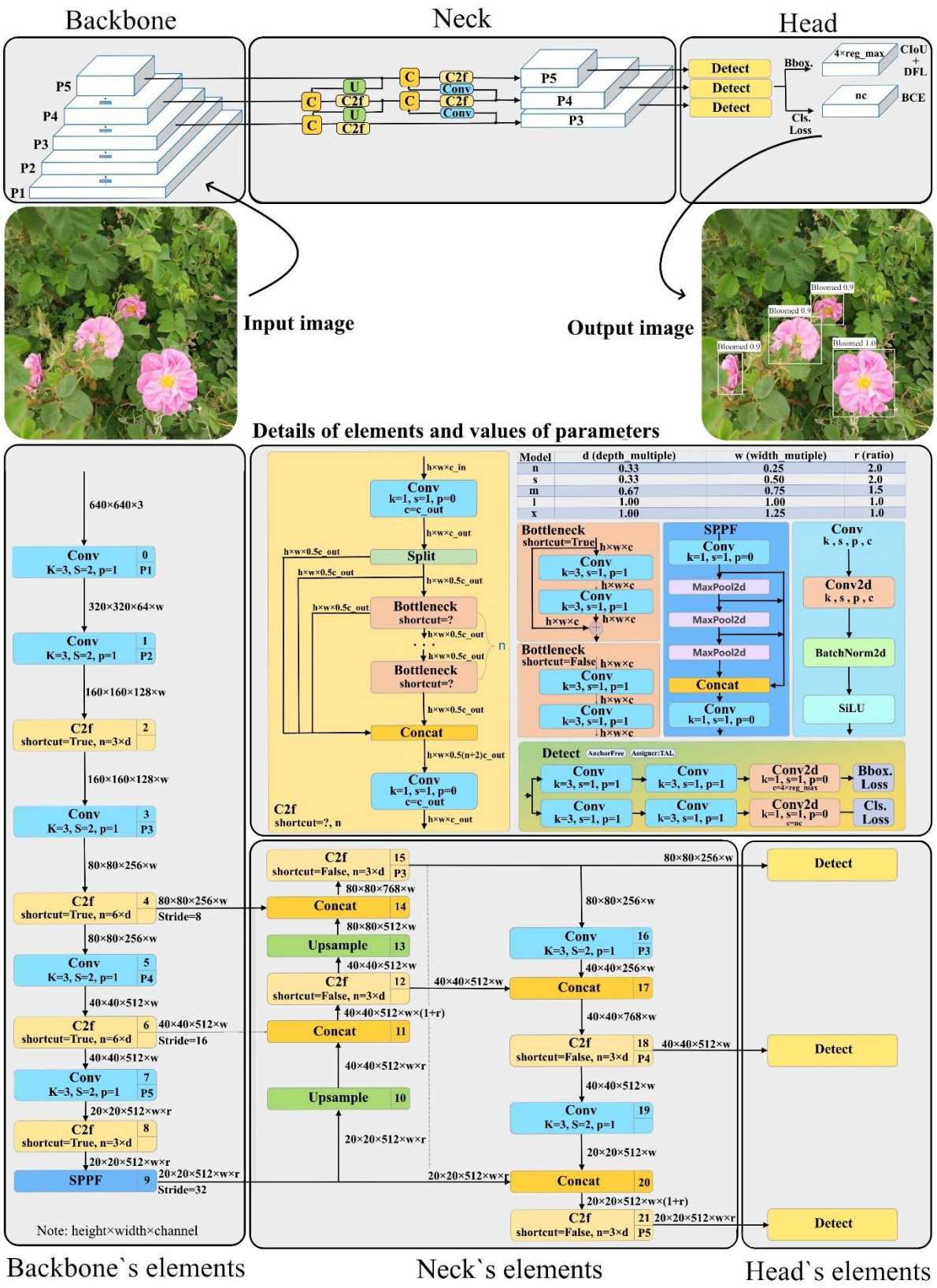


Fig.4. The architecture of YOLOv8 used in the detection of Damask rose

Evaluation Parameters of YOLOv8s

Adjustable parameters of the YOLOv8s model, pre-trained on the COCO val2017 dataset, primarily include changes in input size, batch size, number of classes, learning rate, and number of iterations (Table 1). Additionally, to generalize the model's detection to other farm-like conditions close to the flower harvest timeframe, data augmentation techniques were utilized during training. By adjusting hyperparameters related to these techniques, changes were made in the color values (HSV color space), image brightness, clarity, and images were rotated and flipped in different directions.

Table 1- Parameters of YOLOv8s for *Rosa damascena mill* flower detection

Parameter	Value
Input size	512×512
Learning rate	1×10^{-3}
Batch size	32
Classes	1
Epochs	75

A loss function is a mathematical function that quantifies the difference between predicted and actual values in a machine learning model. According to Equations 1 to 8, the loss function in the training of YOLO models mainly comprised three sections: the bounding box location loss (L_{CIoU}), the confidence loss ($L_{confidence}$), and the class loss (L_{class}) (Wu *et al.*, 2020):

$$Loss = L_{CIoU} + L_{confidence} + L_{class} \quad (1)$$

$$Loss_{CIoU} = 1 - IoU + \frac{d^2}{c^2} + \alpha v \quad (2)$$

$$L_{confidence} = \sum_{i=0}^{S^2}\sum_{j=0}^{B} K[-\log(p) + BCE(\hat{n}, n)] \quad (3)$$

$$L_{class} = \sum_{i=0}^{S^2}\sum_{j=0}^{B} 1_{i,j}^{noobi}[-\log(1 - p_C)] \quad (4)$$

$$BCE(\hat{n}, n) = -\hat{n}\log(n) - (1-\hat{n})\log(1-n) \quad (5)$$

$$\alpha = \frac{v}{(1-IoU)+v} \quad (6)$$

$$v = \frac{4}{\pi^2}(\tan^{-1}\frac{w^{gt}}{h^{gt}} - \tan^{-1}\frac{w}{h})^2 \quad (7)$$

$$K = 1_{i,j}^{obj} \quad (8)$$

IoU is defined as the ratio of the intersection and union of the predicted bounding box and the ground truth bounding box, with *c* and *d* denoting the distances between the centers of the two bounding boxes and the diagonal distance of their union, respectively. The parameters w^{gt} and h^{gt} represent the width and height of the ground truth bounding box, while w and h correspond to the width and height of the predicted bounding box. The variable *S* stands for the number of grids, while *B* signifies the anchor number associated with each grid. *K* is a symbol for weight, taking the value of 1 in case there is an object in the j-th anchor of the i-th grid; otherwise, it is 0. Moreover, $\hat{\boldsymbol{n}}$ and *n* indicate the actual and predicted classes of the j-th anchor in the i-th grid, and *p* represents the probability of the object being a Damask rose flower. The mean average precision (mAP), precision, recall, F1 score, F2 score, and detection speed were employed to assess the efficacy of the models:

$$mAP = \frac{\sum_{c=1}^{c} AP(C)}{C} \quad (9)$$

$$Precision = \frac{TP}{TP+FP}\times100\% \quad (10)$$

$$Recall = \frac{TP}{TP+FN}\times100\% \quad (11)$$

$$F1 = 2\times\frac{Precision\times Recall}{Precision+Recall}\times100\% \quad (12)$$

$$F2 = 5\times\frac{Precision\times Recall}{4\times Precision+Recall}\times100\% \quad (13)$$

where *c* refers to the number of classes (here, *c* = 1), and TP, FP, FN, and TN are true positive (the bloomed flowers that are correctly classified as bloomed flower), false positive (a region of background that is classified as a bloomed flower), false negative (the bloomed flowers that are considered as background), and true negative (defined as all background areas in the image except for regions where bloomed flowers are present), respectively.

Results and Discussion

Comparison of different detection algorithms

Fig. 5 depicts the training mAP50 of four models on images captured under normal light conditions. The training curve for the four models indicated that the YOLOv8s model reached saturation faster than the other models, exhibited lower fluctuations, and maintained a more uniform curve. Table 2 presents the performance results of the YOLOv8s model compared with the YOLOv5s and YOLOv6s models regarding detecting bloomed Damask roses. Based on the results, the mAP50 scores for the three object detection models were as follows: 0.98%, 93.9%, and 97.7%, respectively. According to these results, YOLOv8s demonstrated the highest mAP50 among the three models. A preliminary analysis suggested that the CSPDarknet53 feature extractor, as a backbone of the YOLOv8-Seg model, which is followed by a novel C2f module instead of the traditional YOLO neck architecture, is more competent in extracting diverse and complex features of targets, playing a fundamental role in the detection accuracy improvement of YOLOv8.

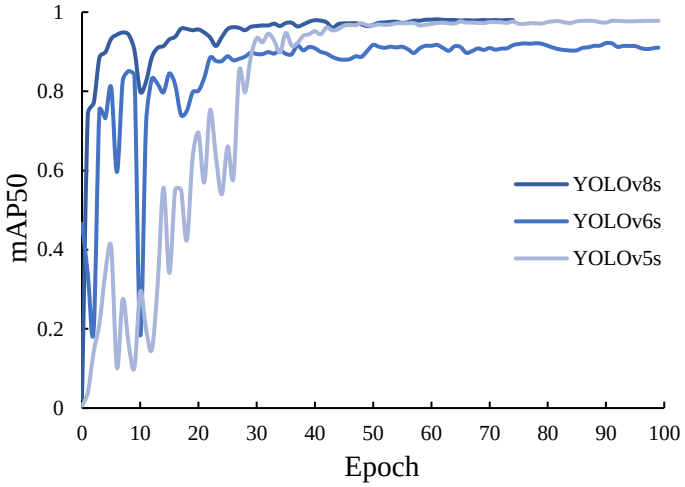


Fig.5. Comparing mAP50 of different YOLO models obtained from the training dataset

Table 2- Performance results of various models in the detection of Damask roses

Algorithm	Recall (%)	Precision (%)	mAP50 (%)	Detection speed (fps)	F1 (%)	F2 (%)	Model size (MB)
YOLOv8s	93.7	97.3	98.0	243.9	95.5	94.4	21.5
YOLOv6s	84.7	88.2	93.9	45.3	86.4	85.4	41.3
YOLOv5s	94.1	95.1	97.7	74.6	94.6	94.3	14.1

The analysis of the results indicates that all models demonstrated high precision in detecting the bloomed Damask roses. Notably, the YOLOv8s model exhibited superior precision at 98% and a remarkable detection speed of 243.9 fps, outperforming the other models. In contrast, the YOLOv5s model, while achieving a close precision rate of 97.7% compared to the YOLOv8s model and having a smaller size of 14.1 MB, exhibited a significantly lower detection speed, being 3.27 times slower. This underscores the YOLOv8s model's exceptional suitability for real-time detection tasks. Worth noting is that the YOLOv6s model achieved a detection precision of 88.2%. Nevertheless, its applicability for real-time and robotic tasks was limited due to its low detection speed of 45.3 fps and a substantial size of 41.3 MB (Wu *et al.*, 2020). This limitation is especially significant considering that the frame rate of most videos is 30 fps, and economic robot controllers typically possess limited memory capacity. The YOLOv5s model was explicitly designed for real-time detection tasks like apple thinning and crop yield estimation

before thinning. Its parameters and size were optimized through channel pruning and weight adjustments. Consequently, boasting a size of 1.4 MB and a detection speed of 125 fps, this model performed well (Wang & He, 2021).

Furthermore, the YOLOv8s model, with its enhanced attributes of precision, speed (198.6 fps), and smaller size (19.8 MB), surpassed the YOLOv6s model in all aspects. This positions the proposed model as an ideal choice for real-time detection of bloomed Damask rose, effectively addressing the challenges associated with precision, size, and speed. Consequently, it can be seamlessly integrated into mobile phone applications or employed in Damask rose harvesting robots.

The efficacy of various versions of the YOLO model is impacted by their scale (quantified by the number of parameters), as well as the dataset employed for both training and evaluation. Hence, it is essential to assess the performance of the intended models. Apeinans *et al.* (2024) created a cherry dataset (CherryBBCH81) for training neural networks. They aimed to find the best YOLO model for fruit detection. YOLOv5m performed better with the CherryBBCH81, achieving a mAP50 of 0.886, compared to YOLOv8m with 0.870. However, YOLOv8m showed better results with the Pear640 dataset, reaching 0.951 compared to 0.943 for YOLOv5m. Estrada, Vasconez, Fu, and Cheein (2024) tested YOLO models 5, 7, and 8 of various sizes (n, s, m, l, and x) for peach fruit detection. The findings indicated that YOLO version 7 X model exhibited the highest performance.

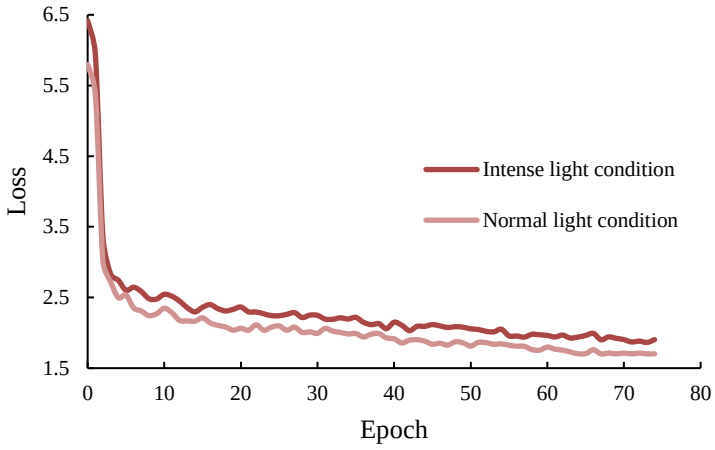


Fig.6. Loss of training YOLOv8s

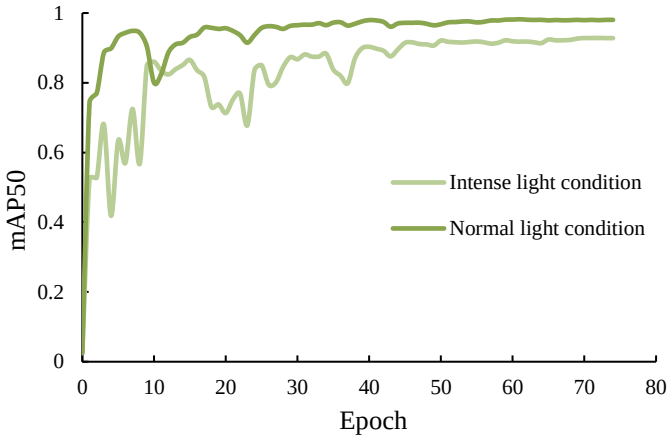


Fig.7. mAP50 of training YOLOv8s

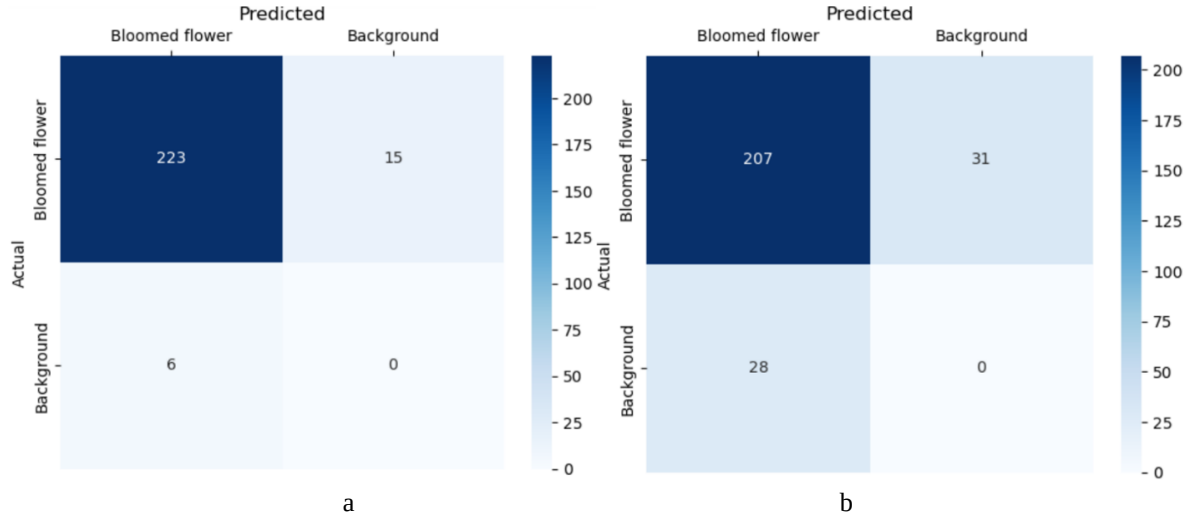
Ambient light effect on YOLOv8s performance

Figs. 6 and 7 display the model's loss

curves and mAP50 during training, based on two images taken under normal and intense light conditions. The visual data from these figures reveals that when Damask rose bushes were blooming, the model showed increased learning efficiency and faster convergence in the early stages of object detection training. However, as time passed, the learning curve gradually flattened, indicating a slower rate of improvement until the model's learning efficiency reached a saturation point through deep learning processes. It is also important to note that the loss function stabilized at a constant value after the 64th epoch for normal light and the 71st training epoch for intense light. This indicates that the training process has been completed, resulting in a stable and well-optimized detection model.

The Fig. 8 illustrates the confusion matrix obtained from the YOLOv8s results related to the data of normal and intense light conditions. The confusion matrix of this model highlights the potential of this method in the detection of bloomed flowers under normal light conditions. As this confusion matrix shows, just fifteen flowers (6.6%) were classified incorrectly as background, whereas under intense light conditions, 31 (13%) samples were incorrectly classified as background. The results of these matrices indicated the negative impact of intense lighting conditions on model performance.

To analyze and compare the performance of DCNN models, four important metrics, such as precision, recall, F1, and F2, were extracted from these figures based on equations 10 to 13, respectively.



a b

Fig.8. Confusion matrix of YOLOv8s for: (a) normal, and (b) intense light conditions

Table 3 presents the YOLOv8s model training results on two images on normal and intense light conditions. In this table, the performance metrics for images captured under normal light conditions were as follows: mAP50 at 98%, precision at 97.3%, recall at 93.7%, F1 at 95.5%, and F2 at 94.4%. For images taken under intense light conditions, the corresponding metrics were mAP50 at 92.8%, precision at 88.1%, recall at 86.8%, F1 at 93%, and F2 at 87.1%. Additionally, the detection speed reached 243.9 and 238.1 fps, respectively The data presented in this table suggests that the model performed significantly better under normal lighting conditions, indicating that sunlight adversely impacts its effectiveness. In general, the results of this research can be used in the open field. However, we cannot infer that other object detection tasks will exhibit similar mAP to the present study.

Tung *et al.* (2019) have pinpointed that Ultralytics utilizes images sourced from COCO, ImageNet, and various datasets, with a primary focus on solitary objects positioned at the center of the image, for the purpose of

training and assessing YOLO models. These images have been acquired through the utilization of diverse cameras featuring distinct configurations, positioned at varying distances and under different lighting conditions. The findings presented by this company are unable to comprehensively capture the potential influence of environmental variables, such as lighting conditions, on the efficacy of the models. Consequently, they have demonstrated the impact of ambient light on the performance of YOLO models.

Table 3- Detection results of Damask roses by YOLOv8s

Light condition	Evaluation index					
	Recall (%)	Precision (%)	mAP50 (%)	Detection speed (fps)	F1 (%)	F2 (%)
Normal (twilight to sunrise)	93.7	97.3	98.0	243.9	95.5	94.4
Intense (sunrise to 10 AM)	86.8	88.1	92.8	238.1	93	87.1



Fig.9. (a, b) Original images, and (c, d) the results of YOLOv8s in detecting desired Damask rose flowers

Fig. 9 visually illustrates the output of the YOLOv8s for two input images. In addition to ambient lighting conditions, which can impact the precision and speed of bloomed Damask rose detection, various other factors must also be considered. These factors include the meticulous care of flowers, variations in background, deployment, orientation, flower size, distance from the camera, potential obstructions by factors like foliage and other flowers, and the presence of only a few flowers in specific frames. These complexities can sometimes confuse researchers and experts when labeling the flowers, as depicted in Fig. 10. In this figure, flower number 2 was wrongly detected as fully bloomed, whereas

flower number 1 was not identified due to being blocked by leaves.



Fig.10. (a) Original image, and (b) result of target detection by YOLOv8s; a flower that (1) could not be detected or (2) was wrongly detected

Conclusion

In this study, the YOLOv8s detection model was introduced for the real-time identification of bloomed Damask rose plants in natural field settings. The principal findings of the investigation were highlighted, revealing the model's remarkable capabilities in achieving high precision and real-time detection of bloomed Damask rose plants. Specifically, when data collected under normal light conditions were applied, an impressive precision rate of 98% was exhibited by the model, underscoring the influence of ambient lighting conditions, which can introduce noise during the detection process. The YOLOv8s model was found to outperform YOLOv5s and YOLOv6s models in terms of both size and detection performance, presenting a more compact footprint while superior detection speed and precision were maintained. Consequently, the YOLOv8s model is well-suited for integration into mobile applications, such as crop yield estimation and the operation of Damask rose harvesting robots, by which it can be utilized. This study highlights the efficacy and practicality of the YOLOv8s detection model for real-time detection tasks in agriculture, particularly for the precise identification of bloomed Damask rose flowers, and it is positioned as a valuable tool for enhancing the efficiency of crop management and automation tasks in Damask rose harvesting.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

F. Fatehi: Conceptualization, Methodology, Software services, Validation, Data acquisition, Writing original draft preparation.

H. Bagherpour: Supervision, Conceptualization, methodology, Technical advice, Validation, Text mining, Review and editing.

J. Amiri Parian: Review and editing.

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۲۸۹-۲۷۵

بررسی پتانسیل مدل نوآورانه YOLOv8s در شناسایی گل‌های محمدی شکفته در مزرعه روباز

فرهاد فاتحی [۱]، حسین باقرپور [۱*]، جعفر امیری پریان [۱]

تاریخ دریافت: ۱۴۰۳/۰۲/۲۵
تاریخ پذیرش: ۱۴۰۳/۰۵/۰۶

چکیده

چیدن دستی گل‌های محمدی به دلیل وجود خارهای زیاد روی ساقه‌های آن بسیار دشوار است. بنابراین تشخیص بی‌درنگ گل محمدی شکفته در مزارع روباز برای طراحی یک ربات به‌منظور برداشت خودکار این گل ضروری است. با توجه به سرعت بالا و دقت مناسب شبکه‌های عصبی کانولوشن عمیق (DCNN)، هدف از این مطالعه بررسی پتانسیل مدل بهینه‌شده YOLOv8s در تشخیص گل‌های محمدی شکفته است. به‌منظور ارزیابی اندازه مدل YOLO بر عملکرد مدل، دقت و سرعت تشخیص نسخه‌های دیگر مدل YOLO ازجمله v5s و v6s نیز مورد بررسی قرار گرفت. برای رسیدن به این هدف، تصاویر گل‌های محمدی تحت شرایط نور عادی (از سپیده‌دم تا طلوع آفتاب) و شرایط نور شدید (از طلوع آفتاب تا ۱۰ صبح) تهیه شدند. نتایج ارزیابی نشان داد که مدل YOLOv8s با میانگین متوسط دقت (mAP50) و سرعت شناسایی به‌ترتیب ۹۸٪ و ۲۴۳/۹ فریم در ثانیه (fps) بهترین عملکرد را به نمایش گذاشت و در مقایسه با مدل‌های YOLOv5s و YOLOv6s مقدار mAP50 آن به‌ترتیب ۰/۳ ٪ و ۶/۱ ٪، و مقدار سرعت تشخیص آن به‌ترتیب ۱۶۹/۳ fps و ۱۹۸/۶ fps بیشتر بود. نتایج تجربی نشان می‌دهد که YOLOv8s در تصاویر گرفته‌شده در نور عادی عملکرد بهتری نسبت به تصاویر گرفته‌شده در نور شدید دارد. کاهش ۵/۲ ٪ در مقدار mAP50 و ۲/۴ ٪ در سرعت تشخیص نشان‌دهنده تأثیر منفی نور شدید محیطی بر اثر بخشی مدل است. این تحقیق نشان می‌دهد که مدل YOLOv8s یک راه‌حل قابل‌قبول برای تشخیص بی‌درنگ گل محمدی فراهم می‌کند و راهنمای خوبی برای تشخیص سایر گیاهان مشابه است.

واژه‌های کلیدی: تشخیص اشیا، گل رز، نور محیطی، یادگیری عمیق، YOLO

۱- گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه بوعلی سینا، همدان، ایران
(*- نویسنده مسئول: Email: h.bagherpour@basu.ac.ir)

https://doi.org/10.22067/jam.2024.88066.1249

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 291-304

Impact of Field Characteristics on Pneumatic Seed Drill Performance: A Case Study in Eritrea

T. A. Medhn [1, 2*], A. G. Levshin [2], S. G. Teklay [1, 3]

1- Department of Agricultural Engineering, Mai-Nefhi College of Engineering and Technology, Eritrea
2- Russian State Agrarian University, Timiryazev Moscow Agricultural Academy, Moscow
3- Water Science and Management Program, College of Agriculture, Consumer and Environmental Sciences, New Mexico State University, Las Cruces, NM 88003-8001, USA
(*- Corresponding Author Email: noahtesas@gmail.com)

Received: 27 September 2024
Revised: 14 October 2024
Accepted: 05 November 2024
Available Online: 30 December 2024

How to cite this article:
Medhn, T. A., Levshin, A. G., & Teklay, S. G. (2025). Impact of Field Characteristics on Pneumatic Seed Drill Performance: A Case Study in Eritrea. *Journal of Agricultural Machinery*,*15*(3), 291-304. https://doi.org/10.22067/jam.2024.89995.1286

Abstract

The efficient use of agricultural machinery significantly improves both the quantity and quality of field operations; therefore, it is essential to optimize operational speed and field time. Factors such as field shape complexities and soil surface roughness (SSR) significantly impact seeding performance. The objective of this research was thus to evaluate how these key factors affect seeder performance: (1) field size and shape, and (2) the interaction of seeder speed and SSR. The performance metrics, effective field capacity (F_{eff}), efficiency (η), and average working speed (v_a), were analyzed using SAS software. The convexity (I_{con}) and rectangularity (I_R) indices for each plot were calculated using the ArcGIS minimal bounding geometry Data Management tool, while the elevation standard deviation (σ_e) was computed using Python. The resulting values for F_{eff}, η, and v_a varied widely, with values ranging from 10.2 to 3.1 ha h^{-1}, 30% to 65.7%, and 5.2 to 17 km h^{-1}, respectively. A v_a process capability index (C_{pk}) of 0.22 indicates a significant challenge in meeting the established limits. As the plot run-length increased, the F_{eff} also increased (R^2 = 42%), while it decreased with a rising perimeter to area ratio (P/A) (R^2 = 51%). Additionally, F_{eff} exhibited an upward trend as the I_{con} and I_R indices rose, while it experienced a decline with greater compactness (I_{com}) and square perimeter (I_{sp}) indices; albeit these relationships were not statistically significant. Higher roughness levels generally resulted in a decline in η. Furthermore, operating the planter at higher speed on uneven terrain led to a significant decrease in efficiency. Hence, redesigning the plots to minimize border complexities, eliminating topographic abnormalities, and implementing tailored plot-specific pre-sowing procedures, will significantly enhance planter performance.

Keywords: Effective field capacity, Plots, Shape and size index, Soil surface roughness

Introduction

Mechanizing agricultural systems through the efficient use of machinery unit (MU) (Diao, Takeshima, & Zhang, 2020; Shinde *et al.*, 2023), is a key factor in increasing agricultural production through improving productivity, optimizing operation timing (such as planting and harvesting), lowering peak labor needs, and minimizing human work drudgery (Srivastava, Goering, & Rohrbach, 2006). MU productivity is measured by the amount of work performed per unit time, which could be the area (ha) processed or the mass of agricultural (crop) product (tonnes) per unit time (Griffel, Vazhnik, Hartley, Hansen, & Richard, 2018; Janulevičius, Šarauskis, Čiplienė, & Juostas, 2019). The

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https://doi.org/10.22067/jam.2024.89995.1286

area processed per unit time refers to the product of the operational speed (v) and the effective width (w) (Biocca *et al.*, 2022; Khater, 2017; Zangiev & Skorokhodov, 2018). The MU operational speed is crucial for field operations, particularly for sowing machines, as it affects both the quantity and quality of the output. Research, on sowing quality associated with high speeds, reports operational speed limits due to issues such as excessive lateral soil throws, reduced furrow backfill, and interactions between adjacent furrows (Toscano *et al.*, 2022). Uniform plant stand is achieved by consistent 3D placement of seeds, which necessitates a careful selection of ground speeds (Ale, Manuwa, & Olukunle, 2023; Badua, Sharda, Strasser, & Ciampitti, 2021; Ivančan, Sito, & Fabijanić, 2004; Kirkegaard Nielsen *et al.*, 2018). Variation in sowing depth affects seeds' exposure to moisture and temperature, influencing their germination and survival, which ultimately impacts plant population. Operational speeds higher than optimal limits can result in seeds being planted too shallowly or left uncovered by soil (Brandelero, Adami, Modolo, Baesso, & Fabian, 2015). Operational speed ranges are specific for specific types of planting machines and vary according to the level of technology used. Different literatures claim the minimum, ideal, and maximum limits as 6.5, 8, and 11 km h^{-1}, respectively (Griffel *et al.*, 2018; Janulevičius *et al.*, 2019). It is also reported that pneumatic seeder operating at 10–12 km h^{-1} provided better uniformity of seed distribution (Toscano *et al.*, 2022), although these parameters are influenced by the physical characteristics of arable soil layer and the texture of the soil surface.

Fields' soil surface texture results from tillage operations could be influenced by various factors, such as moisture content, stoniness of the arable layer, and soil texture. In highly rough fields, planters ought to be operated slower; otherwise, mechanical vibration could be high enough to cause vertical variability (Badua *et al.*, 2021; Wang *et al.*, 2024) in seed placement and exert an influence on seed germination (Kirkegaard Nielsen *et al.*, 2018). Moreover, mechanical vibration causes disassembly of the planter components and increases the risk of minor and/or major damage; and are also known as significant contributors to musculoskeletal disorders among operators, primarily as a result of whole-body and hand-arm vibrations (Benos, Tsaopoulos, & Bochtis, 2020). Research finding indicated that the shape and size of fields, obstacles, or contour farming usually call for increased maneuverability complications during different field operations (Zangiev & Skorokhodov, 2018). Shape in this study refers to the plot's boundary configurations, including the length and curvature of the perimeters, the presence of obstacles that hinder the navigation of the farm machinery, compactness, convexity of the boundary, and rectangularity. Size, on the other hand, indicates the length of the run and the area of the plot, which usually reduce efficiency by affecting operational speed and productive time moves. The unevenness of the soil surface, subjected to factors such as soil texture, aggregate size, and stoniness, plays a crucial part in planter performances by affecting elements such as lateral and vertical seed placement, operational speed and quality of operation, planter traction, planter stability and maneuverability, and time utilization efficiency. Comprehending the association between soil surface roughness (SSR) and farm machinery performance is indispensable for farm operations' optimization, improving productivity, curtailing in-field operational trials, and helping in decision-making by selecting the type and frequency of operations for specific fields or plots.

Despite the research carried out regarding the influence of field shape and size factors and SSR on the performance of different farm machines, these types of studies have been lacking for Eritrean contexts, particularly for the active wheat sowing implement, the Dora Air Drill. The machinery unit has been operated as per the company's specifications and the operators' experiences. Even though minor changes in field setup and operations can significantly affect machinery

productivity, detailed and extensive evaluation of these impacts has been overlooked since the machinery was imported; specifically, the effects of the field and operational conditions were given little emphasis. Therefore, this research focused on examining how field configuration, soil surface, and topographic conditions interact with operational speed to impact planter performance. It also proposed potential solutions to enhance efficiency.

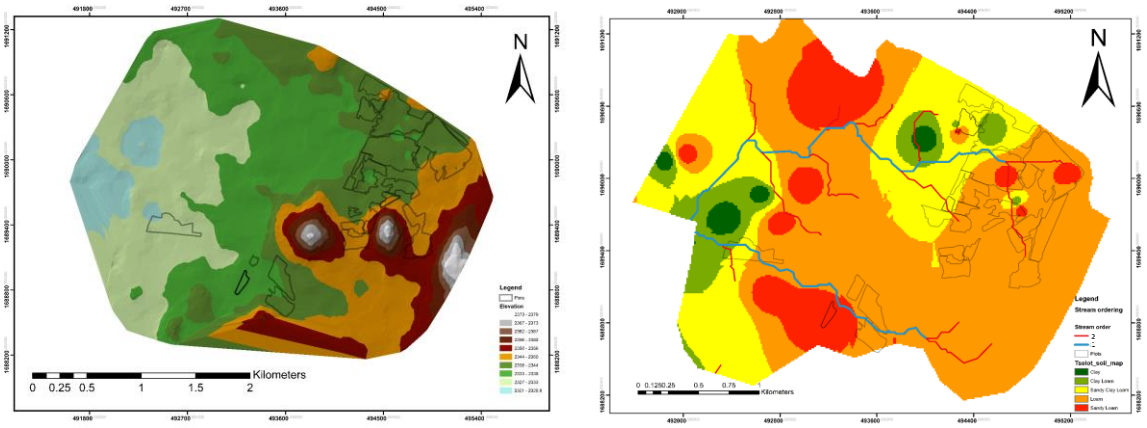
Materials and Methods

Study Site and MU Description

The research took place at Tselot Farm in Asmara, Eritrea, situated at a Latitude of 15°17'6.4" and a Longitude of 38°56'59", at an altitude of 2341 meters. During the field experiment, the grain drill carried out the usual wheat sowing operations, which covered an area of 107 hectares. The pneumatic and tractor-mounted Nardi Dora Air Drill (DORA 600) with a working width of 6 meters and equipped with 40 coulters was used in this study. For convenient transportation, it can be folded to 2.5 m. The drill was powered by a New Holland T6090 tractor with 152 horsepower. It had Suffolk-style coulters, a standard PTO-driven fan, mechanical bout markers, and an 800-liter hopper, which is standard for all models. The interrow spacing of the drill is 15.3 cm, and it weighs 1090 kg (AMIA, 2021). Figure 1 shows the elevation map of the site with the plots' polygons (a) and the soil textural class map (b).

A soil texture map of the study area was generated (Fig. 1), showing clay infestation or dominance on one side of the field and loam dominance on the other side. Several plots fell into multiple soil classes, while others fell solely into a single class. Soil texture and composition greatly impact MU performance, with seed drills having different requirements for clayey compared to silty or loamy soils. In clayey soil, the MU requires frequent maintenance due to clogging, leading to prolonged downtime. Additionally, soil texture affects compaction, highlighting the importance of selecting appropriate planters for subsequent operations. Data on soil textural classes were obtained from the national ministry of agriculture for this study.

Despite the variations in soil texture, stoniness, and moisture retention capacity, the type and frequency of tillage operations performed prior to sowing remained consistent. The plots were assumed to be uniform, and tillage frequency, along with the tillage equipment and tractors employed for pre-sowing operations, were similar.



a b

Fig. 1. Study site map showing (a) elevation and the boundaries of the plots, and (b) soil type and stream order

Small drainage channels or sunken areas slow down farm machinery, cause more wear, increase the risk of damaging planter components and requiring more inspections

and adjustments, ultimately increasing downtime. The ModelBuilder tool in ArcGIS—a visual programming language designed for crafting geoprocessing workflows—was used to automate and detail geographic analysis and data management processes. This tool was utilized for generating the stream orders illustrated in Fig.1b.

Analysis of Planter Performance Parameters

An 8-day experiment was conducted across 23 plots, measuring various metrics, including the time taken for each move by the planter from garage to the field, in the field, and from the field back to the garage. The recorded on-farm operations include the main working time, idle travel time, and periods of downtime, along with spatial details that contribute to the study.

To assess the performance of the planter, the parameters considered were the effective field capacity (F_{eff}), efficiency (η), and average working speed (v_a), which were determined by expressions 1, 2, and 3, respectively (Janulevičius *et al.*, 2019; Srivastava *et al.*, 2006; Toba, Griffel, & Hartley, 2020; Zangiev & Skorokhodov, 2018).

$$F_{eff} = \frac{A}{T_{total}} \quad (1)$$

$$\eta = \frac{T_1}{T_k} = \frac{\sum_{i=1}^{n} t_n}{\sum_{i=1}^{k} t_k} \quad (2)$$

$$v_a = \frac{A}{T_1} \times \frac{10}{w} \quad (3)$$

where $A = \sum_1^k a_k \Rightarrow a_k = l_n \times w$; a_k–the actual processed area in pass '*k*', *ha;* T_{total} – the total time taken to complete the plot, s; l_n– length of the working pass '*n*', *m*; t_n–working pass time, *s*; t_k – time taken to complete pass '*k*', *s* (time taken from the start of pass *'k'* to the start of pass *k* +1). The t_k includes the working pass time and overhead time (time taken for turning, technical adjustment, seed hopper checking, etc.); and *w* – working pass width (*w* = 6.15 m for the specified planter) (Oksanen, 2013; Vereshchagin *et al.*, 2018).

The v_a was assessed for its capability to remain within predefined operating limits as documented in literature, which can be done via process capability test. Process capability is used to quantify the ability of a manufacturing process to meet standard or user-defined specifications. In other words, it assesses a process's capability to operate within predefined limits and levels of precision, thereby verifying its ability to meet the specified requirements. Process capability indices are often used in the domains of statistical quality control and process control, serving as vital tools to assess the efficiency and effectiveness of manufacturing processes. This approach, using SAS software, was adopted to ensure compliance of v_a with the specified limits. In this study, the planter's operational speed was tested to determine its capability to meet specified requirements and to evaluate the quality of its performance in relation to the ability test.

The following four categories are widely recognized as fundamental measures of process capability indicators (Matsuura, 2023; Montgomery, 2013; Wu, Pearn, & Kotz, 2009).

$$C_p = \frac{USL - LSL}{6\sigma} \quad (4)$$

$$C_{pL} = \frac{\mu - LSL}{3\sigma} \quad (5)$$

$$C_{pU} = \frac{USL - \mu}{3\sigma} \quad (6)$$

$$C_{pk} = \text{mini}\ \{C_{pU}:C_{pL}\} \quad (7)$$

where C_p is the process capability index; C_{pL} and C_{pU} are the lower and upper process capability indices, respectively; μ is the process mean; σ is the process standard deviation; LSL is the lower specification limit; and USL is the upper specification limit. C_p <1 indicates that speed of operation is not well centered (process incapable), meaning that the speed of operation often exceeds the specification limits; C_p = 1 indicates the variability of the speed of operation is the same as the specification, but there is no margin for errors; and C_p > 1 ensures better performance, denoting the speed of operation does not exceed the USL or fall below the LSL, with a higher value demonstrating higher capability.

Equation 4 indicates the degree to which speed variation fits within the specification

limits. A higher value reflects a narrower speed spread in relation to these limits, signifying enhanced capability. Whereas Equations 5 and 6 evaluate the speed capability by comparing the mean speed to the lower and upper specification limits (LSL and USL), considering the speed variability. C_{pk} (Equation 7) compares both the LSL and USL to assess overall capability. A C_{pk} value greater than 1 indicates that the process speed meets or exceeds the specified requirements.

Factors that Influence the Performance of a Planter

Field conditions: layout and dimension of field polygons, soil texture, terrain slope, soil moisture, obstacles, and rough surfaces; and *operational parameters:* consistent maintenance to diminish downtime and the skill level of the operator are vital factors for planter performance. A thorough investigation of the interplay between field conditions and operational factors is essential for enhancing planter performance, as it reveals adaptable solutions that can be implemented effectively.

Shape and Size Indices

A plot in this article describes a two-dimensional area that might contain natural and man-made obstacles like holes, stone piles, and electric poles as subsets. This article presents metrics for 23 plots, focusing on the following indices: average plot run length, convexity (I_{con}), perimeter to area ratio (P/A), compactness index (I_{com}), square-perimeter index (I_{sp}), and rectangularity (I_r) (Demetriou, See, & Stillwell, 2013; Griffel *et al.*, 2018; Oksanen, 2013). The brief descriptions of these indices are as follows:

The smallest convex polygon encompassing all the vertices of a given polygon is known as a convex hull. A_{coh} being the convex hull area (Fig. 2b), I_{con} can be determined by Equation 8. Similarly, shape complexity can be quantified by the relationship between the perimeter (P) and the area of the shape, and it provides important information on the complexity and irregularity of a polygon employing the length of the boundary relative to the enclosed area (Equation 9). When calculating the perimeter of plots, those with highly broken and jagged boundaries are referred to as irregular or complex boundary plots.

$$I_{con} = \frac{A}{A_{coh}} \quad (8)$$

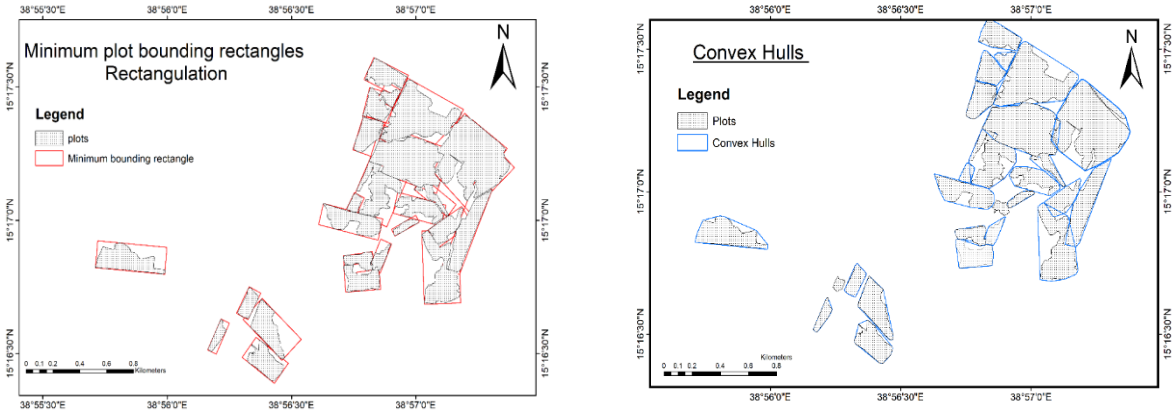
$$P - A_{ratio} = \frac{P}{A} \quad (9)$$

Compactness measures how circular a polygon is and is given by Equation 10, while the square perimeter index represents the relationship between the square root of the area and the polygon's perimeter (Equation 11).

$$I_{com} = 4\pi \frac{A}{P^2} \quad (10)$$

$$I_{sp} = \frac{4\sqrt{A}}{P} \quad (11)$$

Rectangular fields are preferred in agriculture because they allow for straight, parallel swaths, making them more convenient to manage unless specific needs arise.



a b

Fig. 2. (a) Minimum bounding rectangles and (b) convex hulls results of ArcGIS

The area of a minimum bounding rectangle (A_{mbr}) (Fig. 2a) is considered to define the rectangularity index, Equation 12.

$$I_r = \frac{A}{A_{mbr}} \quad (12)$$

The areas of the convex hull and minimum bounding rectangle for each plot were computed with the assistance of the ArcGIS tool. The Locus GIS offline land survey—offline data collector, mapper, area calculator, and SHP editor version 1.17.0—was used to calculate the area of individual plots, determine field boundaries, and track the routes for specific plots. Google Earth Pro and ArcGIS tools were utilized for further processing. The areas calculated by the mobile application were verified with the areas calculated by Garmin GPS, and the areas obtained by digitizing the margins of individual plots in Google Earth Pro; and were found to be reliable for use.

Soil Surface Roughness Analysis

The elevation standard deviation was employed in determining the SSR index in this research, which comprises determination of the standard deviation of elevations (σ_e) (Equation 13) (Herodowicz-Mleczak, Piekarczyk, Kaźmierowski, Nowosad, & Mleczak, 2022) across the surface of the plots. A higher σ_e implies substantial variability and intricacy in soil surface elevation.

$$\sigma_e = \left(\frac{\sum_{i=1}^{n}(Z_i - Z_{ref})^2}{n-1}\right)^{\frac{1}{2}} \quad (13)$$

where Z_i–elevation (m) reading above mean sea level at location i; Z_{ref}–reference elevation; and n–number of elevation readings.

Data was analyzed using the Python programming language within the Anaconda distribution environment, utilizing Pandas for data manipulation, NumPy for numerical operations, and SciPy's ndimage module for image processing functions.

Results and Discussion

Analysis of Planter Performance Parameters

Field efficiency, effective field capacity, and average operational speed appear to be the top measures for assessing a planter's performance. Typically, planters' η ranges between 55 and 80%, with 70% being ideal (Srivastava *et al.*, 2006). The v_a limits are 5, 8, and 12 km h^{-1} (Srivastava *et al.*, 2006; Toscano *et al.*, 2022). The η (%) and v_a (km h^{-1}) lie in the range of 30–65.7% and 5.2–17 km h^{-1}, respectively. Generally, η is much lower than the typical ranges; 70% fall below the lower limit of the range, 30% between the lower and typical values, and there are no values exceeding the typical value.

The v_a capability test assessed v_a's ability to adhere to acceptable speed limits. For this test, the acceptable speed limits are defined by the LPS, target, and USL. As illustrated in Fig. 3, the speed data was tested for distribution and capability, and a lognormal distribution model found the best model with AIC, AIC Weight, and BIC values of 121.3, 0.4, and 123, respectively. The test results showed a mean of 10.32, a standard deviation of 3.37, and a coefficient of variation (CV) of 32.64%. This signifies higher variability of v_a, which could have contributed to the reduction and variation in η and F_{eff}. According to Equation 7, C_{pk} was 0.22, indicating that the planter v_a was not good enough to optimally adhere to the specified limits, as a lower value indicates a weakness in the process (Matsuura, 2023). The v_a had 28% off-range values, with 2% below the LSL and 26% above the USL. Additionally, 83% of the v_a exceed the USL, corresponding to efficiencies less than 45%; 10% less than the lower efficiency limit indicated. This suggested that the increased v_a in the region higher than the USL was accompanied by a severe reduction in η.

The specified planter has a constant constructional width of 6 m, which means F_{eff} and v_a are directly related (Fig. 4). This relationship shows that both are negatively correlated with η (R^2 = -0.48), indicating that as the v_a increases, η tends to decrease. This suggests that an increase in v_a leads to a reduction of η and the planter's performance.

Intricate the maneuverability, leading operators to favor slower driving speeds and operate at variable speeds for greater control.

Consequently, increased complexity in plot boundary is accompanied by lower planter performance.

Furthermore, the correlation coefficient of 0.41 illustrates that F_{eff} responded moderately to the length variability of the plots (run length). The association is statistically significant, signifying a moderate association, although only 41% of the change in the F_{eff} can be explained by the average length of the plots, suggesting the relationship is not robust enough to promise a perfect connection. As the average plot length increased, the F_{eff} also increased at a decreasing rate.

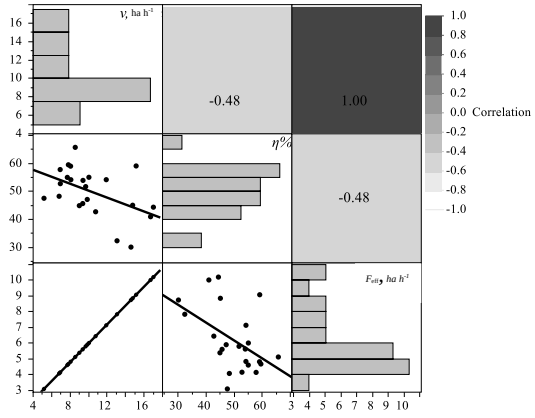


Fig.3. Correlation matrix of the length of the plots, efficiency, effective filed capacity, and operational speed

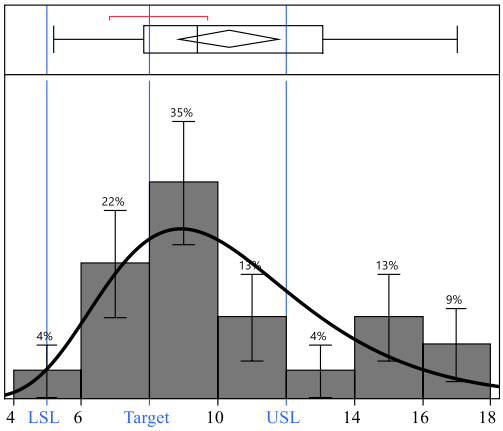


Fig.4. Speed distribution and specification limits

The negative correlation serves as a warning alert for planter operators and farm managers, emphasizing the importance of balancing the increase in v_a while ensuring the retention of optimal η levels. Because, as indicated in Fig. 3, higher v_a can improve planter productivity, but it may also lead to a reduced η due to issues such as equipment wear, decreased precision, and increased energy consumption. Comprehending the relationship could help operators make informed decisions and adjust operational parameters to maximize productivity while optimizing efficiency. Increased fuel consumption could result in higher emissions, impacting environmental sustainability.

Effect of Shape and Size Indices on the Effective Field Capacity

This section discusses the correlation between size and shape indices and the effective field capacity, with results presented in Fig. 5. The P/A showed a moderately strong correlation with F_{eff}, indicating that 51% of the variability in F_{eff} can be accounted for by the changes in P/A. F_{eff} decreased as the P/A rose at a decreasing rate. A higher P/A signifies a more intricate and irregular boundary, resulting in an increase in the P/A value. As depicted in Fig. 5, the P/A has the highest correlation, implying that this shape index has the greatest impact on the F_{eff}. Because the more complicated the boundary, the more

Analytically, the F_{eff} can be explained as the product of η, v_a, and w, with v_a being directly proportional to the run-length of the plot. Based on this relationship, the maximum length would be expected to result in maximum F_{eff}; however, due to the variation in downtimes, longer plots did not necessarily correspond to higher F_{eff}. In practice, longer plots need a smaller number of turnings than shorter plots with the same area, which ideally, is expected to have a higher η. However, the η appeared to be uncorrelated with the run-length. This could be due to the increased time required for repair and inspection at the headlands as a result of repeated disassembling of the functional components of the planter caused by the v_a exceeding the USL. The situation led to higher mechanical vibrations, especially in relatively rough areas. This part is detailed in Section 3.3, as it could have a relationship with mechanical vibration in relation to higher speeds.

F_{eff} also tended to increase with the increase in I_{con} and I_R and decrease with I_{com} and I_{sp}, although the correlations were not significant. I_R, I_{con}, I_{com}, and I_{sp} evinced feebler relationships with the F_{eff} (Fig. 5), implying weaker influence on the performance of the machine. Furthermore, the 26% exceedances of the v_a. beyond the USL is an indication that the planter was frequently operated outside the permissible v_a limits, which could lead to suboptimal performance and potential quality reduction.

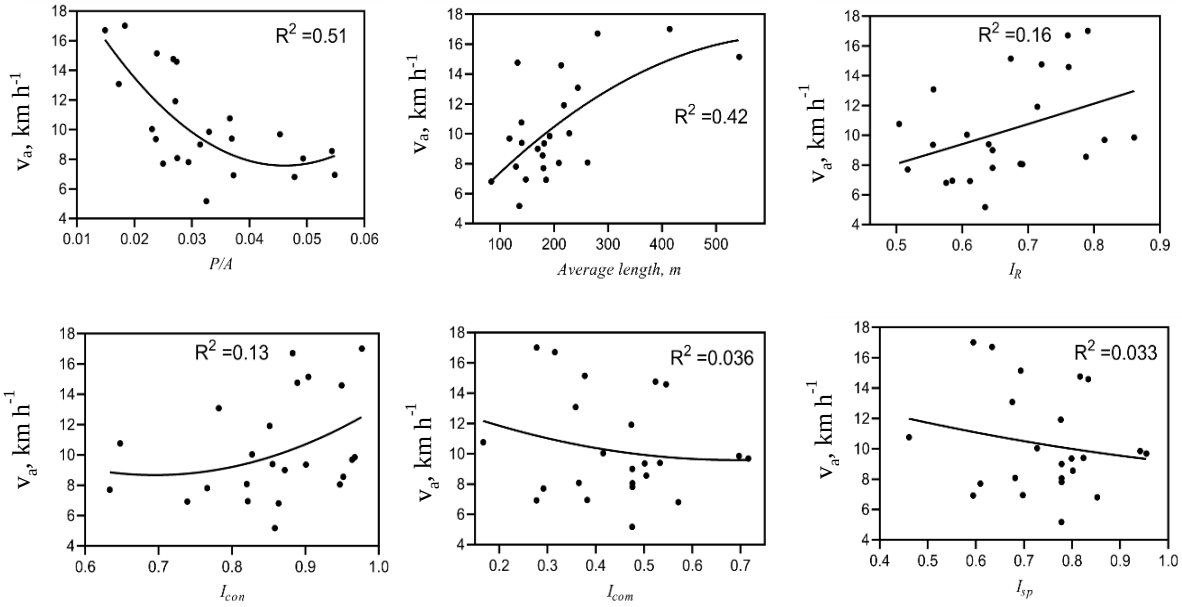


Fig. 5. Correlation between effective average speed and shape and size indices

This might lead to the variability of seed placement in three dimensions: vertically below the soil surface, horizontally along the rows, and across the swath. Variability in seed exposure to moisture and temperature can cause differences in germination, leading to variations in plant population density. Similar research has also reported that higher speeds cause issues with quality of operation and productivity (Brandelero *et al.*, 2015).

Soil Surface Roughness Analysis

The difference in soil moisture content and texture exhibited varying responses to tillage, resulting in inconsistency in surface. This led to cloddy or fine tillage outputs depending on specific conditions. Figure 6 (a and b) were taken from proximity of the same field but exhibit differences in surface textures, while those in Fig. 6 (c and d) – a few hundred meters apart, exhibited different soil classes and different surface finishes.

For better visualization of the plots' topographic variation and irregularity, the difference of the surface elevations and the mean plot elevations were 3D-plotted in Fig. 7 using Python programming. This figure represents the peaks and nadirs of the plots which the planter had passed over in performing the operations. As illustrated, the plots are uneven, requiring the planter to frequently ascent and descend over short distances in some areas. Other plots are sloping, which could complicate maneuverability and impose lateral instability issues on the planter functional components. These inconveniences slowed down the operational speed, impacted F_{eff}, and contributed to the variation in the performance of the planter. Moreover, the drainage channels of varying stream orders illustrated in Fig. 1 were also an addition to the roughness complications. Plots 4, 6, 9, 10.1, and 11 are crossed by shallow natural drainage channels of 2nd-order streams, while 2 and 13 are crossed by 1st-order streams. These drainage

channels added complications to the topography and intricate field operation (Fig. 7), making maneuverability difficult and affecting the speed of operation. The drainage channels are naturally oriented in such a manner that the planters must cross them over considerably larger areas of the plot. This required the operator to frequently change gears to regulate the speed when approaching and receding the channels. Therefore, the planter had to decelerate when approaching the drainage channels and nadirs or peaks and then accelerate, which contributed to the speed variability and, therefore, to the performance.

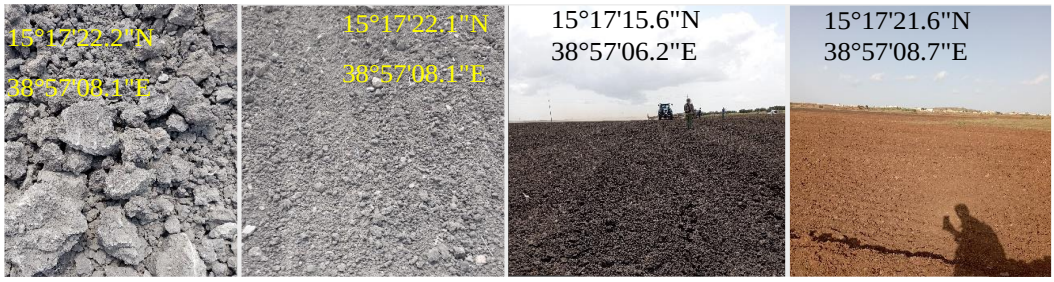


Fig. 6. Variations in Surface Textures and Soil Classes: (a) and (b) showing differing surface textures observed within the same plot; (c) and (d), taken a few hundred meters apart, highlight distinct soil classes and surface finishes.

The impact of SSR on the planter performance parameters was analyzed employing the elevation standard deviation (σ_e) as a measure of roughness index. Based on this, the plots were classified into 3 categories shown in Table 1: high (highest 25%), moderate (middle 50%), and low roughness (lowest 25%).

In this section, the analysis was conducted in two stages: initially, the trend of the η was analyzed against the overall patterns of the SSR. Then individual category analysis took place to compare the η among the SSR categories and examine the trend within each category in relation to the SSR and v_a, analytically. This part considered extreme values of v_a, i.e., above the USL, in relation to the σ value in general and the higher values of σ_e in particular.

The overall trend of the η in relation to the holistic SSR indices is depicted in Fig. 8a. As plot10.5 is small (0.8 ha) and the η of the planter is exclusively higher than the second highest η by around 7%, it is excluded from the analysis given in Fig. 8a for better visualization. The η has shown a decreasing trend as σ_e increased, with correlation coefficients of 0.24. This indicates that η responded relatively mildly to the overall SSR.

Table 1- Elevation (above mean sea level) standard deviation as a measure of SSR index

Low roughness index					Medium roughness index					High roughness index				
Plot name*	**σ_e**	**v_a**	**η%**	**F_{eff}**	**Plot name***	**σ_e**	**v_a**	**η%**	**F_{eff}**	**Plot name***	**σ_e**	**v_a**	**η%**	**F_{eff}**
12.4	0.20	8.1	59.0	4.8	10.1	0.99	8.1	54.2	4.8	12.3	1.56	11.9	54.2	7.1
8A'	0.49	6.8	48.3	4.1	13	0.99	10.0	55.0	6.0	2	1.56	17	44.4	10.2
6	0.50	9.0	44.9	5.4	7A	1.03	6.9	57.8	4.2	11	1.65	9.4	53.9	5.6
9	0.57	9.7	51.7	5.8	10.3	1.14	7.8	59.5	4.7	1	1.79	14.6	30.1	8.8
10.7	0.83	7.7	55.0	4.6	5	1.25	15.1	59.1	9.1	10.5	2.44	8.6	65.7	5.1
10.4	0.96	6.9	52.8	4.2	8A	1.29	5.2	47.5	3.1	4	2.65	16.7	41	10
					12.2	1.30	9.4	45.7	5.6					
					12.1	1.35	9.9	47.1	5.9					
					7(B+C)	1.41	10.8	42.7	6.5					
					8B	1.49	14.8	45.1	8.9					
					3	1.54	13.1	32.4	7.8					
Average η% = 51.9					Average η% = 49.6					Average η% = 48.2				

*Plot name column should be read as plotx, for example, a plot name indicating 12.4 is the same as plot12.4.

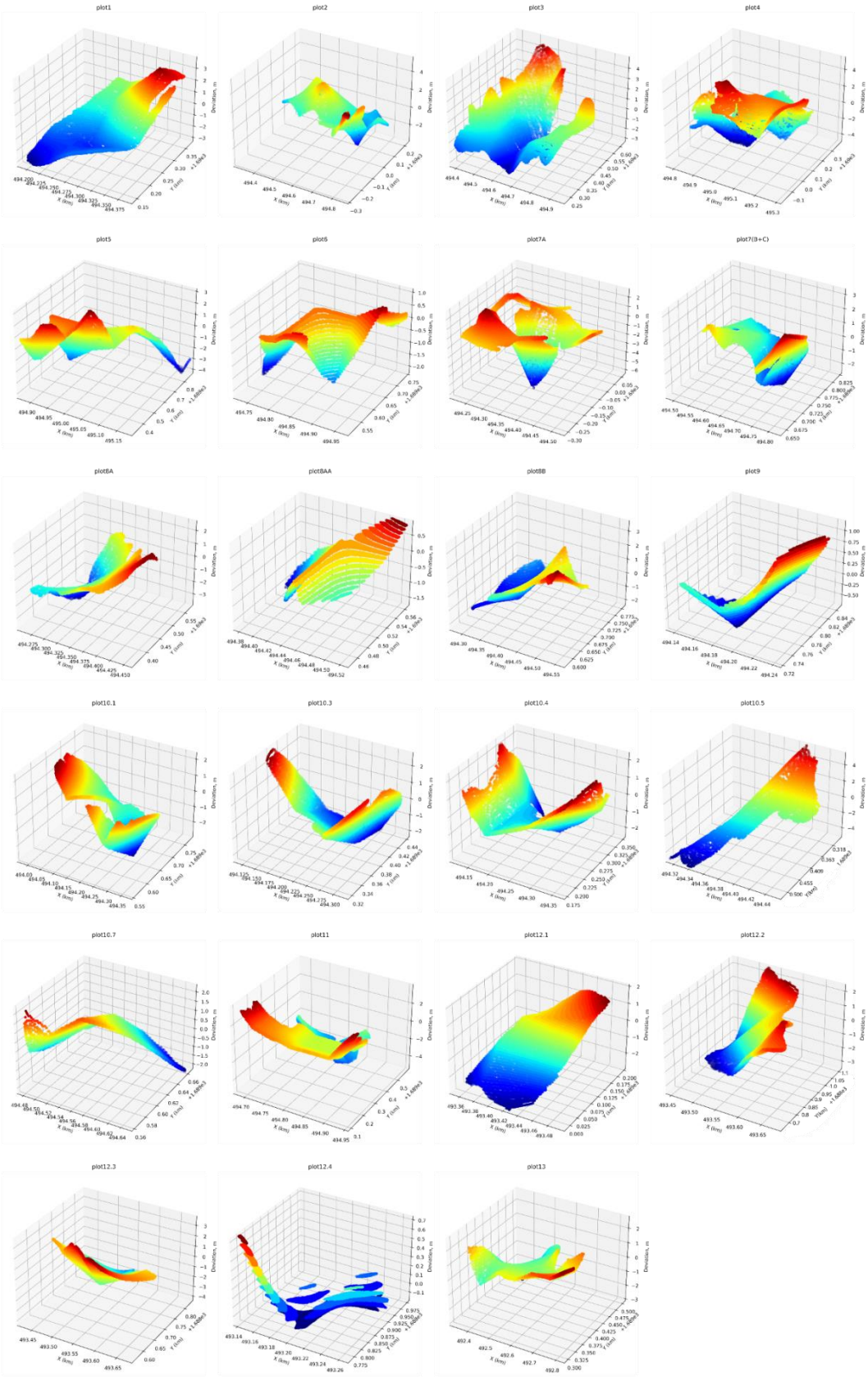


Fig. 7. Plots' topographic variation and irregularity, generated from the deviation of the surface elevation from the mean plot elevation

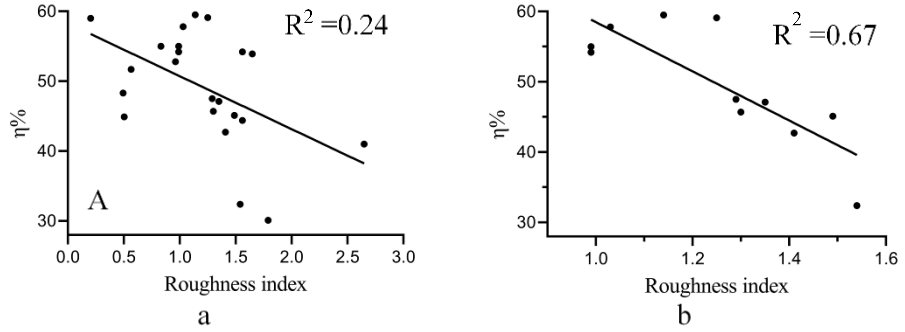


Fig. 8. Relationship between η and σ_e for (a) the 22 plots and (b) the plots with moderate roughness

As shown in Table 1, the average η% decreased as the roughness category increased, i.e., the average η for the lower, moderate, and high roughness categories were 51.9%, 49.6%, and 48.2%, respectively.

Low roughness category: The v_a was within the allowable limit in all the plots; the shorter length of the plots seems to have hindered the operator from accelerating as fast as they could have on longer plots. The η showed a mild trend with the increase in roughness index (Table 1).

Moderate roughness category: This data represents 50% of the total plots, and a correlation graph was created to visualize the relationship between η and the roughness index (Fig. 8b). As the SSR increased, the η decreased, with a correlation coefficient of 0.67, indicating a strong and consistent relationship. This demonstrates that 67% of the variability in η can be characterized by SSR variability. In other words, the SSR did have a strong influence on machinery performance. As the roughness increased (for instance, due to roughened terrain and soil surface texture), the η decreased in at least half of the plots. Therefore, as the SSR increases, planters may experience a decrease in performance.

High roughness category: Generally, in this category, as the planter v_a exceeded the USL, the η was diminished (plot names: plot1, plot2, and plot4). Additionally, operations at high SSR and higher speed are characterized by reduced η (plot1 and plot4 in Table 1). Thus, when the planter was operated at v_a higher than the USL and the soil surface was rougher, the η values were among the lowest.

Therefore, based on the complex interaction between SSR and η, planters operated in smoother soils complying with the operational constraints can effectively be exploited without being influenced by the soil roughness conditions. However, as soil roughness increased to a moderate level, the planter performance became more sensitive to the soil roughness variability, impacting the planter performance explicitly. This could be due to the increase in mechanical vibrations that lead to temporary dismantling of the planter components or damage to parts sensitive to mechanical vibrations, ultimately increasing downtime. At the highest SSR category, however, the combined effect of the interplay between high SSR and exceedance of the average operational speed from the USL excessively challenged the machinery performance, resulting in low efficiency. Thus, farm managers and machinery operators could comprehend these dynamics and develop focused techniques to maximize machinery performance in different soil conditions to pursue improved productivity and longevity in farm operations.

Conclusion

This study found that the performance of a seeder is significantly influenced by plot length, boundary complications, and soil roughness. Longer, rectangular plots generally enhance seeder performance by minimizing idle travels and reducing variability in operational parameters. As plot area to

perimeter ratio (P/A) increases, the effective field capacity decreases.

Soil roughness also plays a crucial role, with efficiency decreasing as roughness increases. Operating machinery at high speeds on rough terrain notably reduces efficiency. Therefore, field levelling to remove irregularities is a prime requirement. Pre-sowing tillage operations should be tailored to specific fields for better output.

The study concludes that the combined effect of field boundary layouts and soil surface roughness significantly reduces machinery performance. Hence, these factors need careful consideration in optimizing farm machinery operations. Other plot-specific factors, such as impediments, soil moisture content, and operator conditions, which were not extensively covered in this study, also need to be considered for maximizing productivity. Understanding the impact of off-range speeds can help farm managers and operators optimize efficiency and minimize downtime.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

Tesfit A. Medhn: Responsible for conceptualization, Study design, Data collection, Methodology, Analysis, and Writing the manuscript

Alexander G. Levshin: Provided technical advice and guidance throughout the research process

Simon G. Teklay: Offered review and editing services for the manuscript, Enhancing clarity

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۳۰٤-۲۹۱

تأثیر ویژگی‌های مزرعه بر عملکرد بذرکار پنوماتیک: مطالعه موردی در اریتره

تسفیت مدهن [۱، ۲*]، الکساندر لوشین [۲]، سایمون تکلای [۱، ۳]

تاریخ دریافت: ۱۴۰۳/۰۷/۰۶
تاریخ پذیرش: ۱۴۰۳/۰۸/۱۵

چکیده

استفاده کارآمد از ماشین‌های کشاورزی به‌طور قابل‌توجهی کمیت و کیفیت عملیات زراعی را بهبود می‌بخشد؛ بنابراین، بهینه‌سازی سرعت و زمان عملیات زراعی ضروری است. عواملی مانند شکل هندسی مزرعه و زبری (زمختی) سطح خاک (SSR) به‌طور قابل‌توجهی بر عملکرد بذرکار تأثیر می‌گذارند. هدف این تحقیق، ارزیابی چگونگی تأثیر این عوامل کلیدی بر عملکرد بذرکار بود: (۱) اندازه و شکل مزرعه و (۲) اثرات متقابل سرعت کارنده و زبری سطح خاک (SSR). شاخص‌های عملکردی، ظرفیت مزرعه‌ای مؤثر (F_{eff})، کارایی(η) و سرعت متوسط کارنده (v_a)، با استفاده از نرم‌افزار SAS تحلیل شدند. شاخص‌های تحدب (I_{con}) و درجه مستطیل‌شکل بودن (I_R) هر قطعه با استفاده از ابزار مدیریت داده حداقل هندسه محصور ArcGIS محاسبه شد، در حالی‌که انحراف استاندارد ارتفاع (σ_e) با استفاده از پایتون محاسبه شد. مقادیر به‌دست‌آمده برای F_{eff}، η و v_a به مقدار زیادی متغیر بودند و به‌ترتیب با مقادیر در محدوده ۱۰/۲ تا ۳/۱ هکتار در ساعت، ۳۰٪ تا ۶۵/۷٪ و ۵/۲ تا ۱۷ کیلومتر در ساعت به‌دست آمد. شاخص قابلیت پردازش v_a (Cpk) 0.22 نشان‌دهنده‌ی چالش قابل‌توجهی در تحقق محدودیت‌های تعیین‌شده است. با افزایش طول مسیر قطعه، ظرفیت مزرعه‌ای مؤثر نیز افزایش یافت (R^2=٪۴۲)، در حالی‌که با افزایش نسبت محیط به مساحت (P/A) کاهش یافت (R^2=٪۵۱). علاوه بر این، با افزایش شاخص‌های I_{con} و I_R ظرفیت مزرعه‌ای مؤثر روند افزایشی نشان داد، در حالی‌که با افزایش ضریب فشردگی (Icom) و شاخص مربعی (I_{sp}) کاهش یافت؛ اگرچه این روابط از نظر آماری معنادار نبودند. سطوح بالاتر زبری عموماً منجر به کاهش η می‌شدند. علاوه بر این، کارکرد بذرکار با سرعت بالاتر در زمین ناهموار منجر به کاهش قابل‌توجهی در کارایی شد. بنابراین، طراحی مجدد قطعات زمین برای به حداقل رساندن دشواری‌های مرزی آن‌ها، از بین بردن ناهنجاری‌های توپوگرافی و اجرای رویه‌های پیش‌کاشت ویژه هر قطعه، به‌طور قابل‌توجهی عملکرد بذرکار را بهبود خواهد بخشید.

واژه‌های کلیدی: زبری سطح خاک، شاخص شکل و اندازه، ظرفیت مزرعه‌ای مؤثر، قطعات زمین

۱- گروه مهندسی کشاورزی، دانشکده مهندسی و تکنولوژی، مای-نفی، اریتره
۲- دانشگاه دولتی کشاورزی روسیه، آکادمی کشاورزی تیمیریازف مسکو، مسکو
۳- برنامه علوم و مدیریت آب، دانشکده کشاورزی، علوم مصرف‌کننده و محیط زیست، دانشگاه ایالتی نیومکزیکو، لاس کروسس، نیومکزیکو ۸۰۰۱-۸۸۰۰۳، ایالات متحده آمریکا
(*- نویسنده مسئول: Email: noahtesas@gmail.com)

https://doi.org/10.22067/jam.2024.89995.1286

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 305-318

Effect of Magnetic Field on Seeds of Parsley (*Petroselinum crispum*): Modeling and Optimization by Response Surface Methodology

M. Rafiei[1], F. Khoshnam[1], M. Namjoo[1*]

1- Department of Mechanical Engineering of Biosystems, Faculty of Agriculture, University of Jiroft, Jiroft, Iran
(*- Corresponding Authors Email: m.namjoo@ujiroft.ac.ir)

Received: 10 June 2024
Revised: 05 July 2024
Accepted: 11 July 2024
Available Online: 31 May 2025

How to cite this article:
Rafiei, M., Khoshnam, F., & Namjoo, M. (2025). Effect of Magnetic Field on Seeds of Parsley (Petroselinum crispum): Modeling and Optimization by Response Surface Methodology. *Journal of Agricultural Machinery, 15*(3), 305-318. https://doi.org/10.22067/jam.2024.88417.1256

Abstract

In the current study, the modeling and optimization of various seedling growth and germination indices for parsley seeds were investigated. A lab-scale quadrupole magnetic field was developed, and experiments were conducted using a completely randomized factorial design with three replications. The factors considered were magnetic field intensity (150, 300, and 450 mT), exposure time (30, 60, and 90 minutes), and culture time (0, 7, and 14 days after applying the magnetic field). The results revealed that the magnetic field significantly affected shoot length, fresh root weight, and fresh shoot weight, while exposure time significantly impacted root length. Sowing day also significantly influenced root length and fresh root weight, along with other factors. Immediate sowings after magnetic field application enhanced root length, while sowing 14 days following the exposure increased shoot length, fresh root weight, and fresh shoot weight. A 30-minute exposure to magnetic field intensities of 150 to 300 mT did not significantly affect seedling growth parameters. However, higher field strengths of 450 mT for 60 to 90 minutes proved beneficial, leading to enhanced shoot length, fresh root weight, fresh shoot weight, germination rate, germination percentage, and reduced mean germination time. The analysis and optimization using Response Surface Methodology revealed that the optimal magnetization condition, with a desirability of 0.682, was achieved at a magnetic field of 450 mT, an exposure time of 60 minutes, and sown 14 days post-exposure. Higher magnetic fields appeared to enhance field durability and significantly impact seedling growth indices.

Keywords: Germination, Magnetic field, Modeling, Parsley, Stability

Introduction

Parsley seeds (*Petroselinum crispum*), a globally cultivated herb, present a challenge for growers among the myriad of vegetable crop seedlings in commercial nurseries. Growers in the southeastern United States have encountered obstacles in cultivating parsley under both greenhouse and field conditions, citing issues with poor germination and inconsistent seedling emergence (da Silva, de Barros, Foshee, Candian, & Diaz-Perez, 2022).

Magnetic treatments enhance seed vigor by influencing biochemical processes, thereby stimulating protein and enzyme activity. Additionally, some studies have reported that magnetic fields positively affect the number of flowers and yield, nutrient and water uptake, and increase seed germination and plant growth, demonstrating the benefits of stronger

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https://doi.org/10.22067/jam.2024.88417.1256

magnetic fields (Alarcon, Cuesta, Molejon, Paragsa, & Ypon, 2024).

Numerous experiments have demonstrated that magnetic fields can efficiently enhance the germination characteristics of different plant species. A study on the magnetoreception of *Arabidopsis thaliana* analyzed several developmental responses to weak static magnetic fields ranging from nearly zero up to 122 µT. A 50 µT field accelerated seed germination by approximately 20 hours compared to samples kept in a nearly null field (Dhiman, Wu, & Galland, 2023). Afzal *et al.* (2021) revealed how seed magnetization could enhance sunflower seed growth, germination, and yield. The seeds underwent direct exposure to MF intensities of 50, 100, and 150 mT for durations of 5, 10, and 15 minutes, followed by standard germination tests. The findings indicated that subjecting seeds to MF at 100 milliTesla for 10 minutes, along with seed priming using a 3% solution of moringa leaf extract in water subjected to magnetic treatment, markedly enhanced emergence, rate of crop growth, and yield of sunflowers (Afzal *et al.*, 2021). Sarı, Demir, Yıldırım, and Memiş (2023) documented that magneto-priming augments both seedling growth and germination characteristics of lettuce and onion seeds. They found pre-soaked seeds treated with MF showed a significant increase in germination, and seedling emergence percentages in each species. Their findings indicated that magneto-priming could serve as an effective pre-germination treatment before sowing (Sarı, Demir, Yıldırım, & Memiş, 2023). In another study, the impact of magnetization before planting (45 mT for 15 and 30 seconds) on common bean seeds has been reported to influence plant growth and development elements. The fresh weight of the initial and fifth leaves was favorably impacted by pre-sowing magnetic field stimulation of common bean seeds, but their dry weight was not affected. The bio-stimulation of the seeds with magnetic fields also enhanced the energy, germination capacity, and strength of the common bean seeds (Pszczółkowski *et al.*, 2023). Another experiment was conducted by Alarcon *et al.* (2024) on the effects of magnetic treatment on string bean (*Phaseolus vulgaris*) plants. They concluded that the plants subjected to magnetic treatment are more significant in size, height, and overall health (Alarcon *et al.*, 2024). Nagalakshmi and Dayal (2023) used pre-sowing magnetic field (MF) and electric current (AC) treatments on germination, seedling parameters, and yield attributes in buckwheat (*Fagopyrum esculentum* L.). Results showed that the seeds treated with the magnetic field demonstrated remarkable effects on growth and yield parameters of buckwheat. Germination percent (99%), seedling fresh and dry weight 0.177 g and 0.035 g, respectively, and chlorophyll (a & b) content was maximum in magnetic field 125 mT for 5 minutes, which performed better among the other treatments (Nagalakshmi & Dayal, 2023). The effects of different magnetic field strengths and durations on seed germination (tomato and wheat) and bacteria growth (*Bacillus* and *Staphylococcus*) were investigated in another study. The samples were exposed to a magnetic field of 0.2 and 1 Tesla for 4 days, with the effects of each day evaluated independently. Tomato seeds demonstrated the greatest susceptibility to the application of high magnetic fields, whereas wheat seeds exhibited the lowest level of impact (Atlı & Erez, 2023). The effect of magnetic fields on parameters of seedling growth and germination of parsley seeds has not yet been studied or researched. Therefore, the aim of this investigation was to study the possible effects of different intensities and durations of magnetic fields on some seedling growth indices of parsley seeds such as root length, shoot length, fresh root weight, fresh shoot weight, germination percentage (GP), germination rate (GR), mean germination time (MGT), and to model and optimize the characteristics using response surface method.

Materials and Methods

Sample preparation and experimental procedure

Parsley seeds sourced from the Pakan Bazr Company (Isfahan, Iran) were employed in the study. These seeds were untreated with

chemicals, ensuring consistent germination rates throughout the experiment. Selection criteria involved choosing seeds devoid of visible defects, deformities, or signs of insect infestation. Prior to exposure to the magnetic field device, the seeds underwent a three-minute disinfection process using a 1.5% sodium hypochlorite solution, immersed for three minutes and subsequently rinsed with distilled water. A quadrupole magnetic field (Fig. 1) was engineered at the University of Jiroft. The strength of the magnetic field generated within the pole gap was monitored using a digital tesla-meter (LB-828, Taiwan).

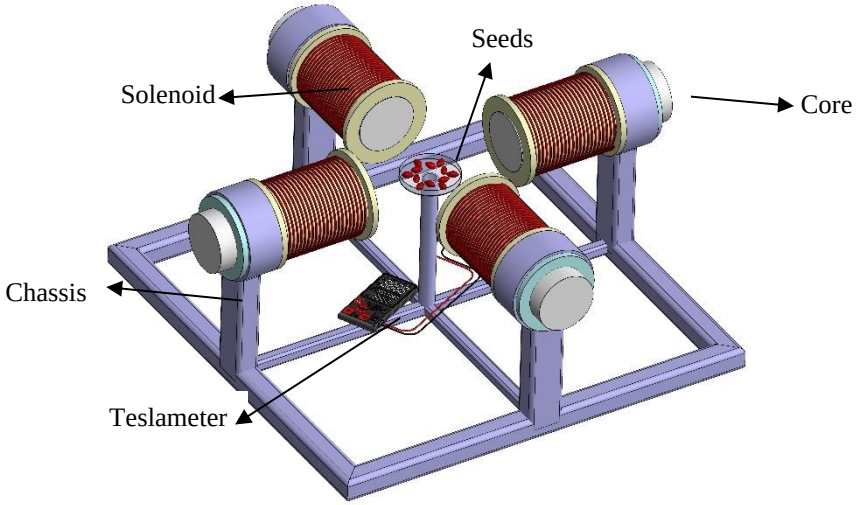


Fig. 1. Quadrupole magnetic field

Output Variables

Firstly, preliminary tests were conducted on parsley to determine appropriate exposure times. Seeds were placed in petri dishes measuring 100 millimeters in diameter, with each dish containing twenty-five seeds allocated for each treatment. The experimental factors comprised magnetic field intensities of 150, 300, and 450 mT, exposure durations of 30, 60, and 90 minutes, and sowing days of 0, 7, and 14 days after magnetic field exposure. After exposing the seeds to the magnetic field, the petri dishes were kept in the growth medium (type IK-RH 200) at 25 ± 1°C. The interval between magnetic field application and seeding aimed to assess the stability of the magnetic field within the seeds. Seeds were checked every day, and seeds with radicle length greater than two millimeters were counted as germinated seeds for calculating germination percentage (GP), germination rate (GR), and the mean germination time (MGT), calculated by the following expressions (Namjoo, Moradi, Dibagar, Taghvaei, & Niakousari, 2022):

$$GP = \sum_{i=1}^{k} n_i / N \quad (1)$$

$$GR = \sum_{i=1}^{k} n_i / \sum_{i=1}^{k} d_i \quad (2)$$

$$MGT = \sum_{i=1}^{k} n_i d_i / \sum_{i=1}^{k} n_i \quad (3)$$

where n_i is the number of seeds germinated at the i-th time, k being the last time of germination, d_i is the number of days from the commencement of the test to the i-th observation, and N is the aggregate seed count (Dehkourdi & Mosavi, 2013; Ranal, Santana, Ferreira, & Mendes-Rodrigues, 2009). The lengths of roots and shoots were assessed by a digital caliper with an accuracy of 0.01 mm, while their fresh weights were determined using an electronic balance (accuracy of 0.001 g). The tests took place at the Mechanical Engineering of Biosystems laboratory at the University of Jiroft, employing a factorial layout based on a completely randomized

design with three replications. Statistical analyses were conducted using SAS 9.4 software, with means compared using Duncan's multiple range test at the 5% significance level.

Response surface methodology

The present study employed Response Surface Methodology (RSM) to explore the relationship between independent variables such as magnetic field intensity, durations of field application (exposure time), and sowing day, each at three levels (Table 1), and dependent parameters including root length (RL), stem length (SL), fresh root weight (FRW), fresh shoot weight (FSW), germination percent (GP), germination rate (GR), and mean germination time (MGT). To conduct the statistical analysis and visualize the response surfaces of the experimental outcomes, the software "Design-Expert 13.0.0" was employed. The experimental design layout was established using RSM based on historical data. Moreover, each response variable was characterized by employing a second-degree polynomial equation (Eq. 4) via RSM (Namjoo, Golbakhshi, Kamandar, & Beigi, 2024).

where Y denotes the response function (dependent variable), while X_1, X_2, and X_3 represent the independent variables corresponding to magnetic field intensity, exposure time, and sowing day, respectively. The polynomial coefficients were defined as follows: B_0 represents the constant term of the equation, B_1, B_2, and B_3 signify the linear effects, B_{11}, B_{22}, and B_{33} represent the quadratic effects, and B_{12}, B_{13}, and B_{23} denote the interaction effects (Namjoo, Moradi, Niakousari, & Karparvarfard, 2022).

Table 1- Experimental range and levels of the three variables

Variable	Symbol	Unit	Level		
Magnetic Field	MF	mT	150	300	450
Exposure Time	ET	min	30	60	90
Sowing day	SD	day	0	7	14

Results and Discussion

Table 2 reveals the analysis of variance for some parsley seedling growth indices under different magnetic field intensities, exposure times, and sowing days. The effect of magnetic fields (MF) showed significant impacts on several characteristics, including shoot length, fresh root weight, and fresh shoot weight. Likewise, exposure time (ET) and the interaction ET × SD demonstrated significance only on root length and germination percentage. Sowing day (SD) displayed significance across all indicators, encompassing root and shoot length, fresh root weight, fresh shoot weight, and seed indices such as germination rate, germination percentage, and mean germination time. Furthermore, the interactions of MF × ET and MF × SD exhibited significant effects across a broader range of indices.

$$Y = B_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_{12}X_1X_2 + B_{13}X_1X_3 + B_{23}X_2X_3 + B_{11}{X_1}^2 + +B_{22}{X_2}^2 + B_{33}{X_3}^2 \quad (4)$$

Table 2- Analysis of variance for some parsley seedling growth indices under magnetic field intensities, exposure times, and sowing days

S.O.V	df	RL	SL	FRW	FSW	GR	GP	MGT
MF	2	4.226^{ns}	290.507^{**}	$1.4\times10^{-5**}$	$1.8\times10^{-4*}$	0.032^{ns}	16.382^{ns}	0.042^{ns}
ET	2	14.272^{**}	64.424^{ns}	1.8×10^{-6ns}	3.3×10^{-5ns}	0.280^{ns}	491.716^{*}	0.817^{ns}
SD	2	165.548^{**}	119.333^{*}	$1.0\times10^{-5*}$	$8.4\times10^{-4**}$	0.522^{*}	978.901^{**}	11.751^{**}
MF×ET	4	11.924^{**}	141.347^{**}	$1.6\times10^{-5**}$	$3.7\times10^{-4**}$	0.441^{**}	777.845^{**}	2.658^{ns}
MF×SD	4	35.510^{**}	79.556^{ns}	$8.9\times10^{-6*}$	2.3×10^{-4ns}	0.696^{**}	458.475^{**}	7.270^{**}
ET×SD	4	14.725^{**}	9.667^{ns}	6.8×10^{-6ns}	1.1×10^{-5ns}	0.067^{ns}	302.364^{*}	0.760^{ns}
MF×ET×SD	8	23.057^{**}	46.364^{ns}	$1.9\times10^{-5**}$	$1.7\times10^{-4**}$	0.134^{ns}	344.799^{**}	0.626^{ns}
Erorr	54	1.448	31.842	2.9×10^{-6}	6.2×10^{-5}	0.126	117.555	1.125
C.V (%)	-	21.032	15.032	20.484	15.441	27.655	19.150	8.646

ns: not significant, *: significant at/above the 5% level, **: significant at/above the 1% level, S.O.V: Source of variation, df: Degrees of Freedom, MF: Magnetic field, ET: Exposure Time, SD: Sowing day, and CV: Coefficient of variation.

Magnetic treatments at 800 mT for durations of 1, 2, 5, and 10 minutes significantly influenced the germination percentage and mean germination time ($P<0.01$), as well as the seedling emergence percentage ($P<0.05$) and seedling emergence time ($P<0.01$) of onion seeds. Furthermore, a statistically significant difference was noted between the impacts of hydro-priming and magneto-priming on germination percentage, mean germination time, seedling emergence percentage, and seedling emergence time ($P<0.01$) in lettuce seeds (Sarı *et al.*, 2023).

Root length

Using the findings from the depicted testing conditions with different magnetic fields and sowing days at a fixed exposure time level (Fig. 2), the highest root length was established for both factors at their minimum values, e.g., magnetic field 150 mT, sowing on day zero, and exposure time 60 min. The minimum root length was recorded for a magnetic field of 300 mT, planting after 7 days, and an exposure time of 90 minutes. The increase in days following the application of a 150 mT magnetic field intensity resulted in a more significant reduction in root length compared to the other sowing days. Conversely, excessively rapid water uptake can cause physical damage to seed tissues, potentially leading to lower viability in seeds exposed to higher magnetic fields (300 and 450 mT) for 30 and 60 minutes. Root length can be used as the most important parameter in the vegetative growth process. Because researchers believe that root length per unit volume of soil is the best feature for evaluating soil water and nutrient uptake by plants (Eshghizadeh, Kafi, Nezami, & Khoshgoftarmanesh, 2012).

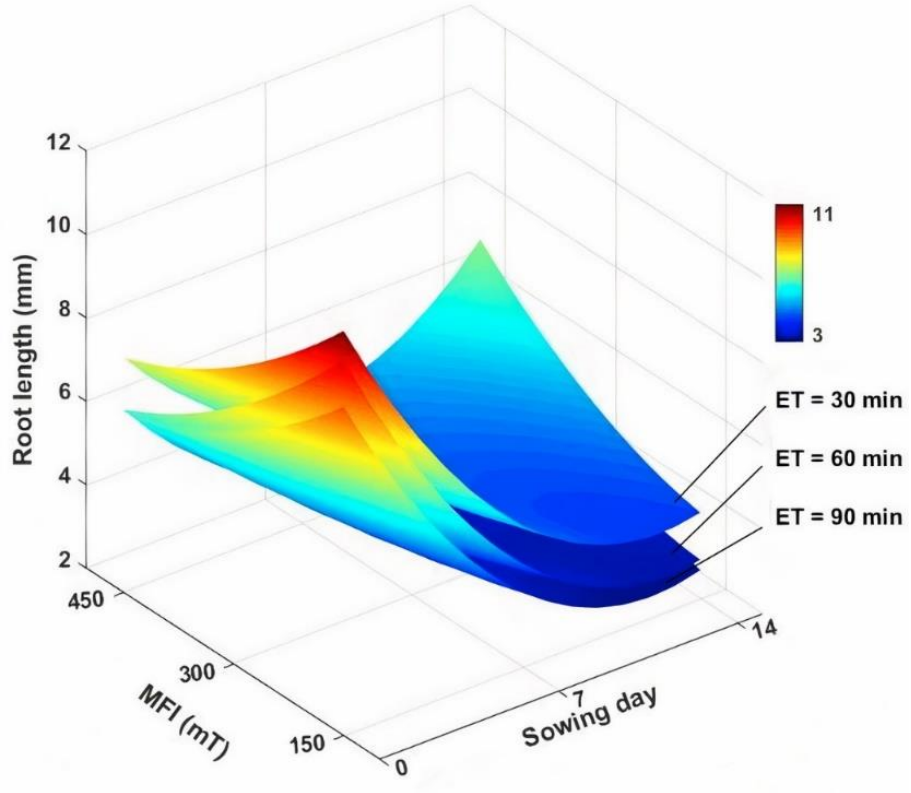


Fig. 2. 3D contour plots for root length against magnetic field, sowing day, and exposure time

Shoot length

Figure 3 depicts contour plots illustrating the relationship between shoot length and three variables: magnetic field, sowing day, and exposure time. The maximum shoot length was achieved with sowing after 14 days with an exposure time of 60 minutes. Conversely, the lowest shoot length was observed with sowing after 7 days, a magnetic field of 150 mT, and an exposure duration of 90 minutes. An increase in shoot length was observed following seed treatment with a magnetic field of 450 mT, potentially as a result of earlier initiation of emergence and a hastened rate of cell division in the root tips (Nagalakshmi & Dayal, 2023). Variations in magnetic field dosage impact root biomass, stem diameter, and leaf dimensions. Additionally, root expansion exhibits greater sensitivity to magnetic fields compared to shoot development. Magnetic fields govern the inherent behavior of iron (Fe) and cobalt (Co) atoms, harnessing their energies to facilitate the transportation of essential microelements within root meristems. Consequently, this process influences root growth by regulating nutrient intake and movement (Sarraf *et al.*, 2020). The plants exhibited enhancements in various morpho-physiological aspects derived from magneto-primed seeds, such as seedling biomass, seedling vigor, plant height, root development, leaf pigments and area, and plant dry weight (Bera, Dutta, & Sadhukhan, 2022).

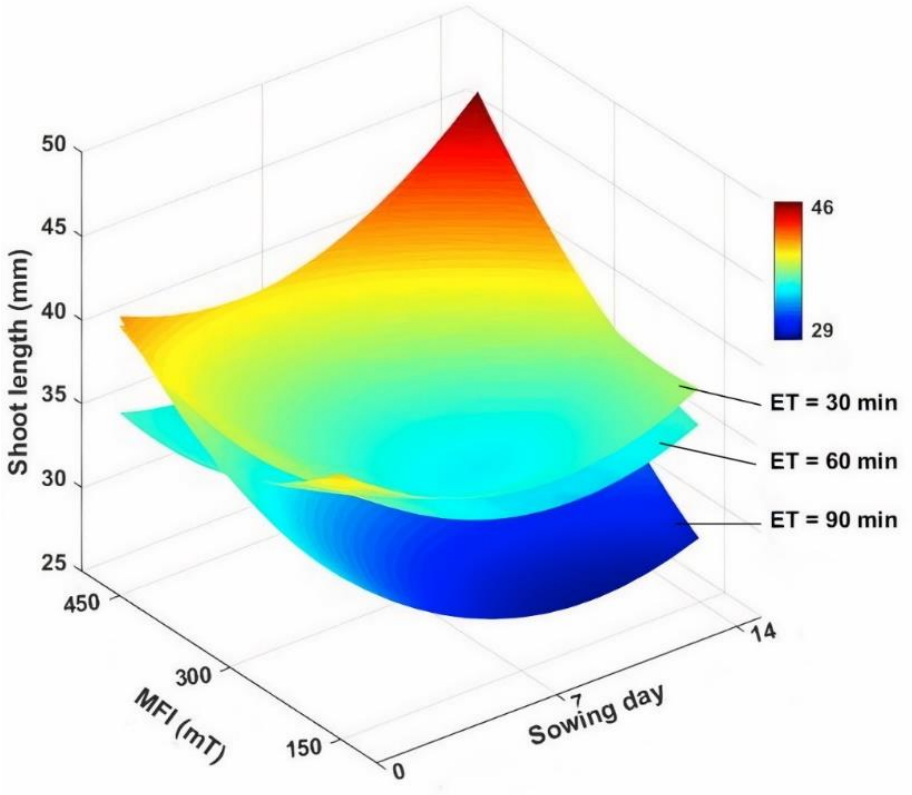


Fig. 3. 3D contour plots for shoot length against magnetic field, sowing day, and exposure time

Fresh root weight

Figure 4 illustrates the fluctuations in fresh root weight against the magnetic field, sowing day, and exposure time. While the impact of the magnetic field on fresh root weight is significant, it does not exhibit a consistent pattern. Consequently, interpreting and isolating potential factors stemming from variations in seed characteristics, such as shape and size, presents challenges. The peak

value was observed at high magnetic fields of 300 and 450 mT, occurring on various sowing days. In a study examining the effect of magnetic fields (MF) on *Salvia officinalis* seeds, it was documented that the treated seeds (exposed to 15 mT for 5 min) produced radicles that were heavier and longer in fresh weight compared to the control group. Specifically, the treated seeds achieved lengths of 50.46 mm and weights of 0.11 g (Abdani Nasiri, Mortazaeinezhad, & Taheri, 2018).

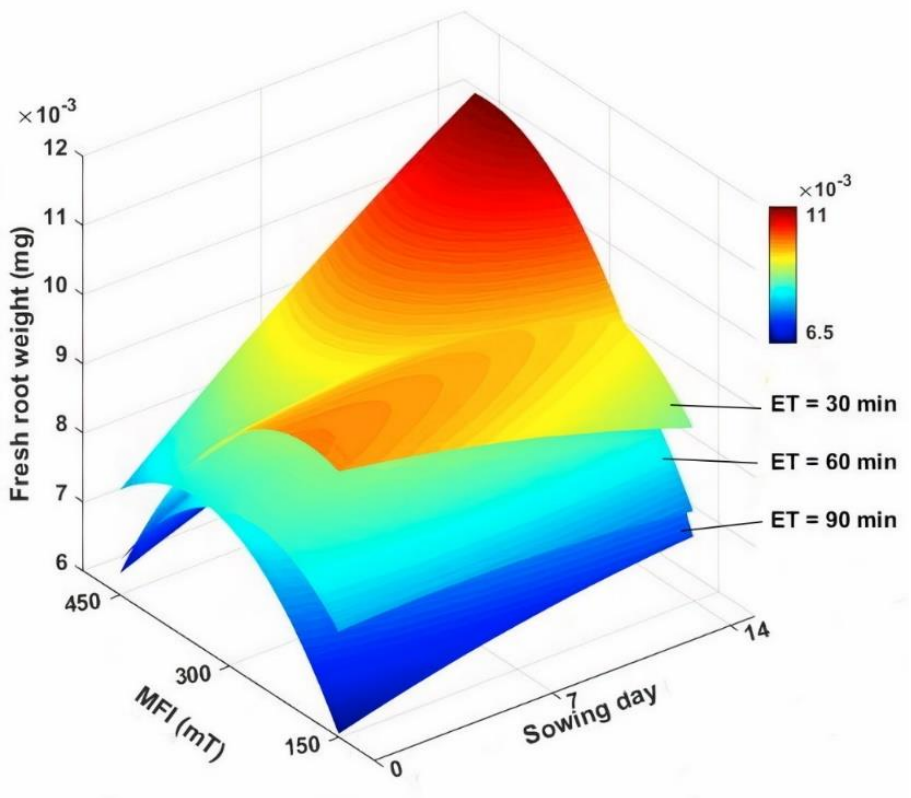


Fig. 4. 3D contour plots for fresh root weight against magnetic field, sowing day, and exposure time

Fresh shoot weight

Based on Fig. 5, the maximum fresh shoot weight correlates with a higher magnetic field, while the minimum fresh shoot weight corresponds to a lower magnetic field. It appears that the influence of the magnetic field on this parameter surpasses that on fresh root weight and exhibits consistent variability. Given that parsley's aerial components are typically in high demand, higher magnetic magnitudes seem to offer more advantageous effects. A comparison of Figs. 5 and 3 concluded that the fresh weight in the shoots increased gradually as the plant shoot duration extended. The precise mechanisms by which magnetic fields influence seeds and the stability of this effect remain unclear. The paramagnetic characteristics of atoms found in plant cells could potentially serve as one of the explanations for the beneficial effects of the magnetic field. Applying an external magnetic field has the ability to align atoms according to the direction of the magnetic field. The magnetic properties of molecules enable them to absorb energy, subsequently transferring this energy to other forms as well as other structures within plant cells, thereby activating them (Zeidali *et al.*, 2017).

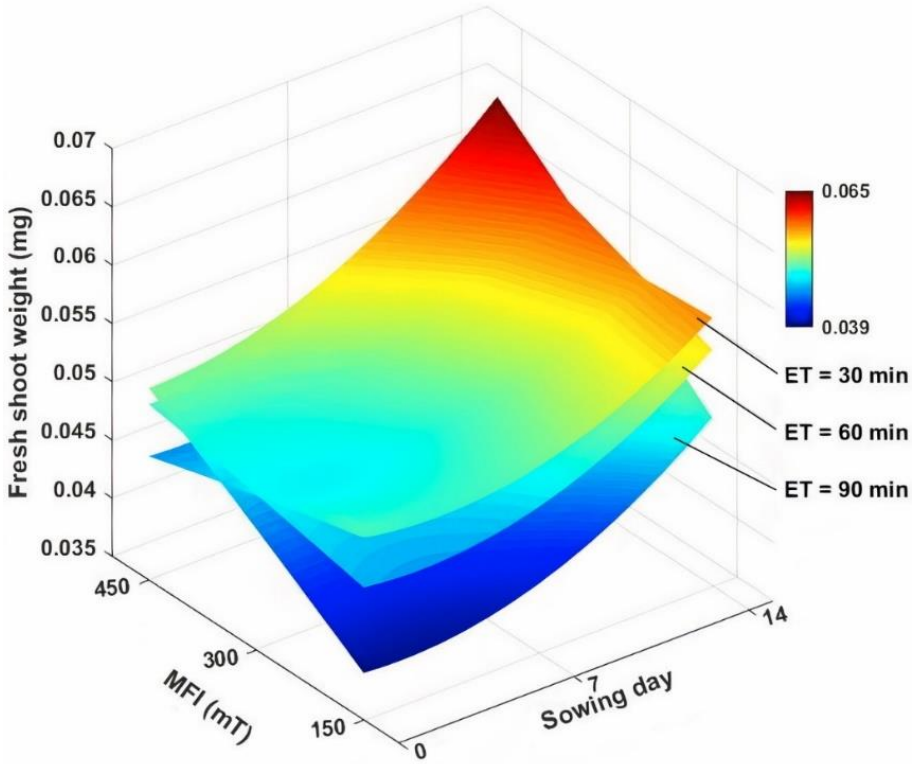


Fig. 5. 3D contour plots for fresh shoot weight against magnetic field, sowing day, and exposure time

Germination percentage

Based on Figure 6, the highest germination percentage was observed at 450 mT and sowing after 14 days, while the lowest was noted at 150 mT. Across all exposure times, a nearly parabolic trend indicated that the lowest germination percentage occurred with sowing after 7 days. Consequently, seeds treated on alternate sowing days (0 and 14 days post-magnetic field application) exhibited a significant increase in germination rate. The higher germination percentage in exposed seedlings may be attributed to their early sprouting, which results in prolonged exposure of growing meristems to electromagnetic fields. This increase could be due to the positive impact of magnetic field intensities on water uptake and the utilization of food reserves by the growing plantlets.

Germination rate

Based on Figure 7, it is generally observed that exposing seeds to low milliTesla magnetic fields tends to decrease the germination rate. However, longer sowing days and higher magnetic fields tend to increase the germination rate. This could be attributed to tiny microscopic perforations on the seed coat, which facilitate faster water uptake and consequently increase the germination rate. Moreover, the distinction between short and long sowing days turned out to be irrelevant. The process by which MF treatment promotes seed germination is linked to enhanced enzyme activity within seeds, accelerating seed water absorption, breaking seed dormancy, stimulating protein synthesis in seeds, and augmenting their respiration rate (Xia *et al.*, 2024).

Mean germination time

In Figure 8, contour plots depict the relation between mean germination time and magnetic field, sowing day, and exposure time. Similar to the previous figure, the highest and lowest values of this parameter correspond to the highest and lowest magnetic fields, respectively. The stimulation of seeds by the magnetic field, along with varying sowing days and exposure times, resulted in a notable

rise in this characteristic. In the study investigating the effects of magnetic fields (MF) on sunflower seeds, the most favorable outcome was observed with the application of 50 mT for 45 min. Compared to the control group, the treated seeds demonstrated significantly greater mean germination rates and antioxidant activity (Bukhari, Tanveer, Mustafa, & Zia-Ud-Den, 2021).

RSM optimization of the studied parameters

Design-expert software was used for fitting the response surfaces and optimizing the germination indices through solving a multiple regression equation (Eq. 4), using historical data, and RSM to evaluate the impact of the magnetization conditions on parsley seeds. The responses analyzed were root length (RL), stem length (SL), fresh root weight (FRW), fresh shoot weight (FSW), germination rate (GR), germination percent (GP), and mean germination time (MGT). The relationship between the input variables and the response surfaces was then determined through appropriate regression analysis. Table 3 shows the final second-order polynomial equations for each response variable in coded values, with neglected non-significant coefficients. The fitted equations correlated each response variable with the significant linear, interaction, and quadratic terms. Including the infinitesimal coefficients in the equations for fresh root weight (FRW), and fresh shoot weight (FSW) indicated minimal variations of these parameters and low affectability under the treatments. Each of the three treatments must be considered when measuring the studied parameters, as they contribute to the complex equations. However, the germination rate equation requires only the treatment of the sowing day.

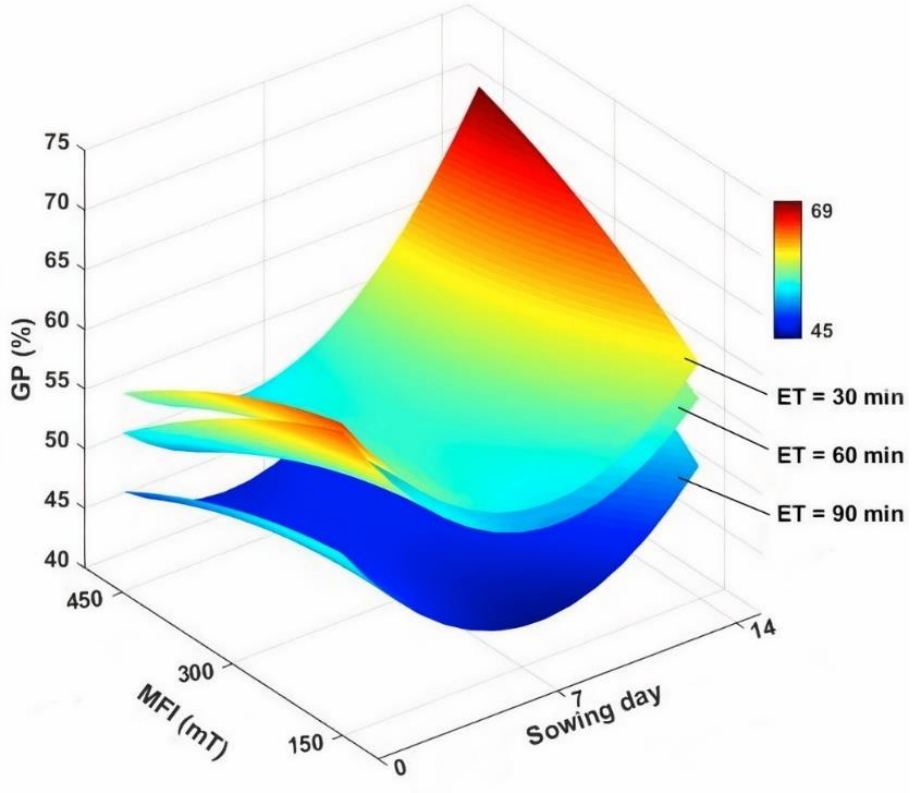


Fig. 6. 3D contour plots for germination percentage against magnetic field, sowing day, and exposure time

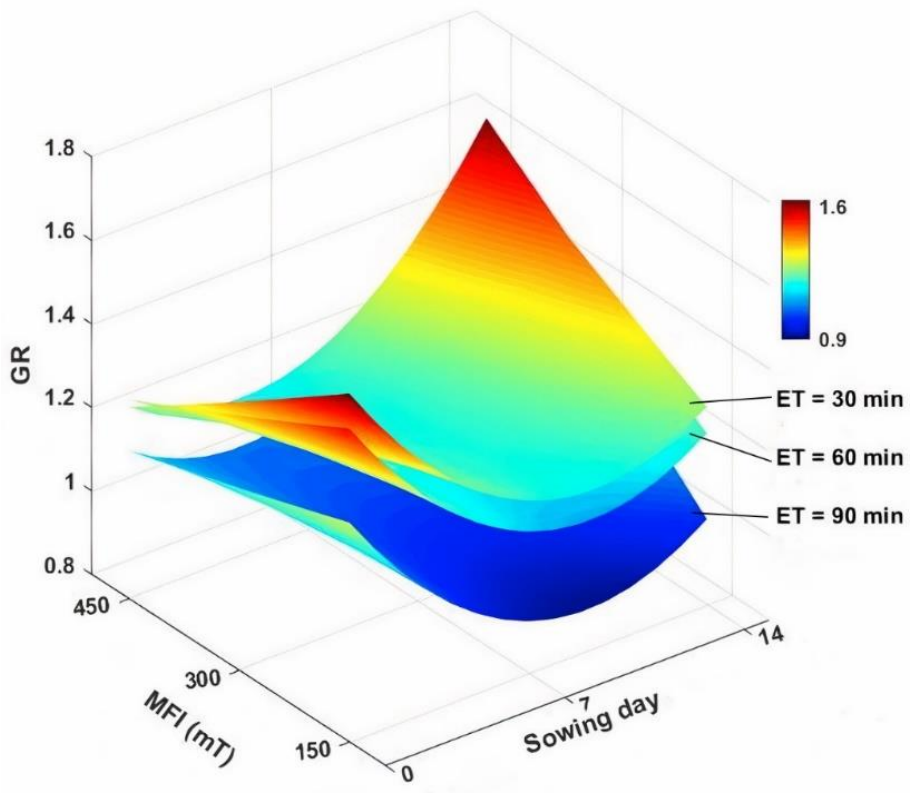


Fig. 7. 3D contour plots for germination rate against magnetic field, sowing day, and exposure time

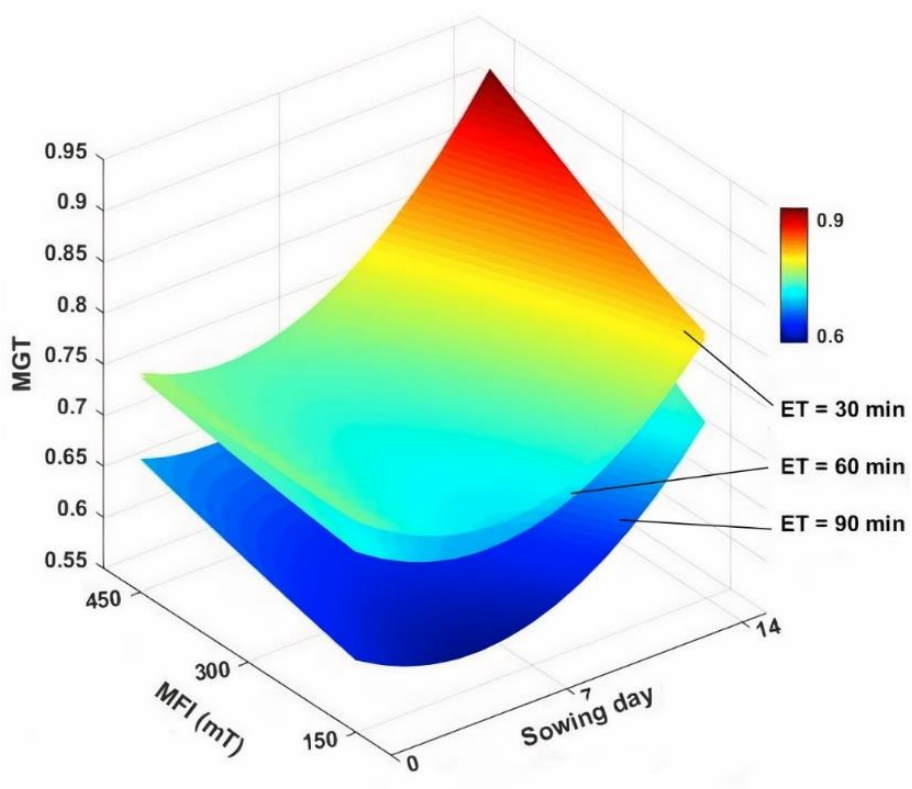


Fig. 8. 3D contour plots for mean germination time against magnetic field, sowing day, and exposure time

Table 3- Final second-order polynomial equations for each response variable in coded values, with neglected non-significant coefficients

Process variable	Second-order polynomial equations with neglected insignificant coefficients
RL	$RL=12.04-0.03\times MF+0.14\times ET-1.57\times SD+0.05\times SD^2$
SL	$SL=48.286-0.09\times MF+0.1\times ET-1.52\times SD+0.07\times SD^2$
FRW	$FRW=0.012+(2.78\times MF\times ET+6.88\times MF\times SD+26.4\times ET\times SD-0.55\times MF^2+4.69\times ET^2-27.2\times SD^2)\ e^{-7}$
FSW	$FSW=0.06+(-4.2\times MF+0.1\times MF\times ET+0.07\times MF\times SD+0.36\times ET\times SD-0.2\times ET^2+6.84\times SD^2)\ e^{-5}$
GR	$GR=1.83-0.12\times SD+0.005\times SD^2$
GP	$GP=57.27-0.02\times MF+0.56\times ET-4.34\times SD+0.2\times SD^2$
MGT	$MGT=0.73-0.024\times SD+(2.89\times MF\times ET+0.2\times MF\times SD+0.6\times ET\times SD+0.01\times MF^2-0.4\times ET^2)\ e^{-6}+0.002\times SD^2$

The primary challenge in the optimization process of the conducted research is selecting the appropriate magnetic parameters to achieve the desired response surfaces. In this study, the optimization process was conducted using an RSM-based approach, with the magnetic field, exposure time, and sowing day chosen as the key parameters. These input factors, along with their respective levels, were the critical variables in determining the criteria such as maximum root length (RL), stem length (SL), fresh root weight (FRW), fresh shoot weight (FSW), germination rate (GR), germination percent (GP), and mean germination time (MGT) (Table 4). Based on the optimization results, the first optimal working condition for seed magnetization of parsley was found to be a magnetic field of 450 mT, an exposure time of 66 min, and sowing after 14 days, with a desirability of 0.682. The responses for the total studied parameters under these conditions are detailed in Table 5.

Table 4- Criteria for simultaneous optimization of magnetic field effects on parsley seeds

Output	Criteria	Minimum value	Maximum value	Significance level
RL	Maximal	2	20	2
SL	Maximal	15.2	53.4	4
FRW	Maximal	0.001	0.014	2
FSW	Maximal	0.024	0.072	2
GR	Maximal	0.320	2.421	5
GP	Maximal	20	84	4
MGT	Maximal	0.307	1.117	5

Table 5- Optimal treatment conditions for parsley seeds: predicted responses and desirability

Number of points	MF	ET	SD	RL	SL	FRW	FSW	GR	GP	MGT	Desirability
1	450	66	14	7.219	47.099	0.01	0.063	1.614	70.674	0.926	0.682
2	450	66	14	7.219	47.096	0.01	0.063	1.614	70.688	0.927	0.682
3	450	67	14	7.216	47.113	0.01	0.063	1.612	70.606	0.926	0.682

Conclusion

The application of magnetic fields and planting time are found to affect some physiological and biochemical processes of parsley seeds, including their development. It is suggested that the pretreatment with magnetic fields (MF) has a significant impact on indices such as shoot length, fresh root weight ($p\geq0.01$), as well as fresh shoot weight ($p\geq0.05$). Additionally, the time exposure treatment is observed to significantly affect root length ($p\geq0.01$). The sowing day is noted to have a significant impact on root length, fresh root weight ($p\geq0.01$), and also a significant effect on other indices ($p\geq0.05$). The longest shoot length and the highest fresh shoot weight of parsley are observed when exposed to a magnetic field of 450 mT for 60 minutes, sown 14 days after exposure. It is indicated that exposure to stationary magnetic fields of 450 mT for 30 minutes, followed by planting after 7 days, enhances shoot length,

fresh root weight, fresh shoot weight, mean germination time (MGT), germination rate (GR), and germination percentage (GP) indices of parsley seeds under laboratory conditions. For instance, the fresh shoot weight is found to be highest with a magnetic field of 450 mT for 90 minutes, sown 14 days post-exposure. Additionally, the combination of a 300 mT magnetic field, a 30-minute exposure time, and planting on the 7th day after exposure significantly increases the fresh root weights. The seed magnetization strategy, followed by selecting the optimal points (magnetic field of 450 mT, exposure time of 66 minutes, sown after 14 days, with a desirability of 0.682), is found to enhance the performance of magnetic treatments, promoting various seedling growth and germination indices for parsley seeds.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

M. Rafiei: Data acquisition, Statistical analysis.

F. Khoshnam: Supervision, Writing-Original draft and editing.

M. Namjoo: Data pre and post processing, Software, Modeling and Optimization, Validation.

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۳۱۸-۳۰۵

مدل‌سازی و بهینه‌سازی تاثیر میدان مغناطیسی روی بذر جعفری (*Petroselinum crispum*) به روش پاسخ سطح

محمد رفیعی[۱]، فرهاد خوشنام[۱]، مسلم نامجو[۱*]

تاریخ دریافت: ۱۴۰۳/۰۳/۲۱
تاریخ پذیرش: ۱۴۰۳/۰۴/۲۱

چکیده

در این تحقیق، مدل‌سازی و بهینه‌سازی رشد گیاهچه‌های مختلف بذر جعفری و شاخص‌های جوانه‌زنی آن مورد بررسی قرار گرفت. بدین منظور میدان مغناطیسی چهار قطبی آزمایشگاهی ساخته و آزمایش‌ها به‌صورت فاکتوریل در قالب طرح کاملاً تصادفی با سه تکرار انجام شد. فاکتورهای شدت میدان مغناطیسی (۱۵۰، ۳۰۰ و ۴۵۰ میلی‌تسلا)، مدت زمان اعمال میدان بر روی بذرها (۳۰، ۶۰ و ۹۰ دقیقه)، و زمان کاشت (۰، ۷ و ۱۴ روز پس از اعمال میدان مغناطیسی) در نظر گرفته شد. نتایج نشان داد که میدان مغناطیسی بر طول ساقه‌چه، وزن تر ریشه‌چه و وزن تر ساقه‌چه، و مدت زمان اعمال میدان بر طول ریشه‌چه تاثیر معنی‌داری دارد. زمان کاشت و فاکتورهای دیگر تاثیر معنی‌داری بر طول ریشه‌چه و وزن تر ریشه‌چه داشت. زمان کاشت بلافاصله پس از اعمال میدان مغناطیسی طول ریشه را افزایش، ولی زمان کاشت پس از ۱۴ روز همراه با مدت زمان اعمال میدان باعث افزایش طول ساقه‌چه، وزن تر ریشه‌چه و وزن تر ساقه‌چه شد. مدت زمان اعمال میدان ۳۰ دقیقه و شدت میدان مغناطیسی بین ۱۵۰ و ۳۰۰ میلی‌تسلا تاثیر معنی‌داری بر پارامترهای گیاهچه نداشت. با این حال شدت میدان‌های بالاتر از ۴۵۰ میلی‌تسلا و مدت زمان ۶۰ و ۹۰ دقیقه موثرتر بوده و منجر به افزایش طول ساقه‌چه، وزن تر ریشه‌چه، وزن تر ساقه‌چه، سرعت جوانه‌زنی، درصد جوانه‌زنی و میانگین زمان جوانه‌زنی شد. تحلیل و بهینه‌سازی به کمک روش سطح پاسخ نشان داد که شرایط مغناطیسی بهینه، با مقبولیت ۰/۶۸۲، در میدان مغناطیسی ۴۵۰ میلی‌ثانیه، مدت زمان اعمال ۶۰ دقیقه و پس از ۱۴ روز کاشت به‌دست آمد. به نظر می‌رسد که میدان‌های مغناطیسی بالاتر ماندگاری میدان مغناطیسی را افزایش داده و تاثیر معنی‌داری بر شاخص‌های رشد گیاهچه دارد.

واژه‌های کلیدی: جعفری، جوانه‌زنی، ماندگاری، مدل‌سازی، میدان مغناطیسی

۱- گروه مهندسی مکانیک بیوسیستم، دانشکده کشاورزی، دانشگاه جیرفت، جیرفت، ایران
(*- نویسنده مسئول: Email: m.namjoo@ujiroft.ac.ir)

https://doi.org/10.22067/jam.2024.88417.1256

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 319-335

Detection and Classification of Some Diseases of Tomato Crops Using Transfer Learning

I. Ahmadi [1*]

1- Department of Genetics and Plant Production Engineering, Institute of Agriculture, Water, Food and Nutraceuticals, Isf. C., Islamic Azad University, Isfahan, Iran
(*- Corresponding Author Email: imanahmadi1358@iau.ac.ir)

Received: 14 June 2024
Revised: 13 July 2024
Accepted: 29 July 2024
Available Online: 31 May 2025

How to cite this article:
Ahmadi, I. (2025). Detection and Classification of Some Diseases of Tomato Crops Using Transfer Learning. *Journal of Agricultural Machinery, 15*(3), 319-335. https://doi.org/10.22067/jam.2024.88500.1258

Abstract

In the context of plant diseases, the selection of appropriate preventive measures, such as correct pesticide application, is only possible when plant diseases have been diagnosed quickly and accurately. In this study, a transfer learning model based on the pre-trained EfficientNet model was implemented to detect and classify some diseases in tomato crops, using an augmented training dataset of 2340 images of tomato plants. The study's findings indicate that during the model's validation phase, the rate of image categorization was roughly 5 fps (frames per second), which makes sense for a deep learning model operating on a laptop computer equipped with a standard CPU. Furthermore, the model was learned well because increasing the number of epochs no longer improved its accuracy. After all, the curves of the train and test accuracies, as well as the losses versus epoch numbers, remained largely horizontal for epoch numbers greater than 20. Notably, the highest coefficient of variation across these four cases was only 7%. Furthermore, the cells of the primary diagonal of the confusion matrix were filled with larger numbers in comparison with the values of the other cells; precisely, 88.8%, 7.7%, and 3.3% of the remaining cells of the matrix (cells of the primary diagonal excluded) were filled with 0, 1, and 2, respectively. The model's performance metrics are: sensitivity 85%, specificity 98%, precision 86%, F1-score 84%, and accuracy 85%.

Keywords: Confusion Matrix, EfficientNet Model, Model Accuracy

Introduction

In the context of plant diseases, the selection of appropriate preventive measures, such as correct pesticide application, is only possible when plant diseases have been diagnosed quickly and accurately. If plant diseases are not controlled on time, a significant reduction in crop quantity and quality will result.

One of the methods used to detect plant diseases is through human observation of disease symptoms on different parts of the plant. Since different diseases may have similar symptoms, an amateur inspector may falsely diagnose a disease, and the wrong chemical may be chosen to cure the disease (Shah, Harshadkumar, Prajapati, & Dabhi, 2016); however, machine learning (ML) techniques such as feature extraction and classification can help an amateur inspector in this regard (Jena, Sethy, & Behera, 2021). Ali, Bachik, Muhadi, Tuan Yusof, and Gomes (2019) highlighted that utilizing machine learning techniques to evaluate plant diseases leads to enhanced precision, reliability, and accuracy. The inability of machine learning

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https://doi.org/10.22067/jam.2024.88500.1258

techniques to reliably detect subtle indications of plant illnesses and early-stage disease detection, and the requirement for complex and high-resolution images, are drawbacks of using feature extraction approaches for plant disease diagnosis (Anjna, Sood, & Singh, 2020; Genaev *et al.*, 2021).

Using deep learning (DL) techniques such as Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) can overcome the limitations of traditional ML methods (Khan, Khan, Albattah, & Qamar, 2021; Liu & Wang, 2021); however, DL models need high computational power, a limiting factor for some applications.

Another Artificial Intelligence (AI) model that has been recently used for plant disease detection is a model based on the transfer learning (TL) concept. In the TL paradigm, a pre-trained DL model is used to develop a custom model on another dataset that has the same function as the first pre-trained model. In other words, TL entails refining pre-trained models using a custom dataset to boost the performance of a model developed specifically for that dataset.

The accuracies obtained in studies conducted on plant disease identification using AI methods range from above 50% to nearly 100%. For example, Burhan, Minhas, Tariq, and Nabeel Hassan (2020) performed a study on five different modern DL models to identify rice diseases and obtained accuracies of 70.42%, 73.6%, 51.99%, 61.6%, and 87.79% on VGG16, VGG19, ResNet50, ResNet50v2, and ResNet101v2 models, respectively. Agarwal, Singh, Arjaria, Sinha, and Gupta (2020) carried out a study to classify 9 groups of tomato diseases and obtained accuracy values of 63.7%, 63.4%, and 90% using InceptionV3, MobileNet, and VGG16 models, respectively. Batool, Hyder, Rahim, Waheed, and Asghar (2020) aimed to detect and classify tomato leaf diseases using a training dataset of 450 images. Results showed that among the models used, the AlexNet model was superior, with an accuracy of 76.1%. Kirola *et al.* (2022) compared the performance of five ML models and one DL model for plant disease prediction. They stated that the accuracies of ML models such as LR, SVM, KNN, RF, and NB were 71.89%, 75.76%, 82.17%, 97.12%, and 81.12%, respectively; while the accuracy of the deep learning CNN model was 98.43%. Bharali, Bhuyan, and Boruah (2019) developed a new architecture called plant disease detection neural network (PDDNN). An 86% accuracy was obtained for detecting diseases of maize, grape, apple, and tomato plants using this architecture. Balaji *et al.* (2023) utilized an enhanced CNN technique to detect rice diseases. For the TL, CNN+TL, ANN, and ECNN+GA models, they attained accuracies of 80%, 85%, 90%, and 95%, respectively. A fully connected CNN method was employed by Upadhyay and Kumar (2022) to identify three rice illnesses. Four thousand photos of each sick leaf and four thousand photos of healthy rice leaves were used to train the model. This study's accuracy rate was 99.7%.

To sum up, the development of a deep learning model for diagnosing some groups of tomato diseases, in order to assist in the curing process of diseased plants, is the main challenge followed in this study. Another challenge of this study is the lack of modern hardware resources required for running a deep learning model. In this study, it is necessary to run the model on a regular computer with a CPU instead of a modern GPU. It appears that the only deep learning model that may satisfy these criteria is the transfer learning (TL) model. As a result, a TL model based on the EfficientNet pre-trained model was implemented to distinguish between healthy tomatoes and nine groups of diseased plants. The original small custom dataset contained 320 images of tomato plants, divided into 234 images for the training dataset and 86 images for the test dataset; however, the training dataset was augmented, and the final number of images in it was increased to 2340 images. The following justifies the use of EfficientNet as a pre-trained model: EfficientNet emerges as a superior model for image classification tasks due to its efficient network structure and

ingenious mechanisms. It utilizes a triplet attention mechanism to enhance feature expression and acquire channel and spatial attention information, leading to improved accuracy. Additionally, the model enhances transfer learning by loading pre-trained parameters, accelerating convergence, and reducing training time, resulting in strong robustness and generalization ability. These specifications make EfficientNet a powerful choice for image classification tasks, surpassing other models in accuracy and efficiency (Huang, Su, Wu, & Chen, 2023).

Materials and Methods

Preparation of raw images

Nine predominant diseases of the tomato plant (*Solanum lycopersicum*) along with healthy crops, were considered as targets for diagnosis. The names of these diseases served as the classifier groups' names: Anthracnose, Bacterial_Speck, Blossom_End_Rot, Buckeye_Rot, Damping_Off, Gray_Wall, Healthy_Tomato, Leaf_Mold, Southern_Blight, and Tomato_Pith_Necrosis. Some of the pictures belonging to each group were considered for developing the model. While the total number of images was 2426, they were divided into 2340 pictures in the train folder and 86 pictures in the test folder. The exact number of pictures in the train and test datasets of each classifier group are as follows: Anthracnose (300, 11), Bacterial_Speck (170, 6), Blossom_End_Rot (350, 13), Buckeye_Rot (200, 7), Damping_Off (220, 9), Gray_Wall (120, 5), Healthy Tomato (230, 10), Leaf_Mold (320, 11), Southern_Blight (140, 4), and Tomato_Pith_Necrosis (290, 10). The first number in the parentheses indicates the number of images in the training dataset for that classifier group, while the second number indicates the number of images in the test dataset. Images of the "train" folder will be used for training the model (i.e. changing weights of the model in the convergence direction so that the model predictions on train images match reality), while the unseen images of the "test" folder will be used to test the goodness of those weights for diagnosing tomato diseases.

Model development procedure

Development of the model was conducted using code written in the PyCharm environment, using the PyTorch package of the Python programming language. The codes are attached to this paper as an appendix. Some functions in the PyTorch package make it suitable for creating models based on the transfer learning concept.

The architecture of the TL model to classify 10 groups of tomato diseases is shown in Table 1.

As shown, the parameters of the feature extraction section are not trainable during the model's training process, and only the parameters of the classifier section are trainable. This leads to a significant decrease in the model's training time. Numerically, the number of trainable parameters decreased from 4,020,358 parameters of the EfficientNet model to 12,810 parameters of the model based on the transfer learning concept. This feature of the TL model allows it to run efficiently on a regular computer with a standard CPU in a reasonable time.

Other informative data about the TL model are summarized in Table 2.

Model evaluation criteria

Sensitivity (Recall): This criterion measures how well a model can detect positive instances; in mathematical terms, it can be calculated using the formula:

$$Sensitivity\ (Recall) = \frac{TP}{TP+FN} \quad (1)$$

Where TP is the number of instances that are truly predicted as positive, and FN is the number of instances that are falsely predicted as negative.

Specificity: This criterion measures the model's ability to predict true negatives in each of the available categories. In mathematical terms, it can be calculated using the formula:

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

Table 1- The architecture of the TL model based on the EfficientNet pre-trained model

```
==========================================================================================
Layer (type (var_name))          Input Shape          Output Shape        Param #     Trainable
==========================================================================================
EfficientNet (EfficientNet)      [32, 3, 224, 224]    [32, 10]            --           Partial
├─Sequential (features)          [32, 3, 224, 224]    [32, 1280, 7, 7]    --           False
│    └─Conv2dNormActivation (0)  [32, 3, 224, 224]    [32, 32, 112, 112]  --           False
│    │    └─Conv2d (0)           [32, 3, 224, 224]    [32, 32, 112, 112]  (864)        False
│    │    └─BatchNorm2d (1)      [32, 32, 112, 112]   [32, 32, 112, 112]  (64)         False
│    │    └─SiLU (2)             [32, 32, 112, 112]   [32, 32, 112, 112]  --            --
│    └─Sequential (1)            [32, 32, 112, 112]   [32, 16, 112, 112]  --           False
│    │    └─MBConv (0)           [32, 32, 112, 112]   [32, 16, 112, 112]  (1,448)      False
│    └─Sequential (2)            [32, 16, 112, 112]   [32, 24, 56, 56]    --           False
│    │    └─MBConv (0)           [32, 16, 112, 112]   [32, 24, 56, 56]    (6,004)      False
│    │    └─MBConv (1)           [32, 24, 56, 56]     [32, 24, 56, 56]    (10,710)     False
│    └─Sequential (3)            [32, 24, 56, 56]     [32, 40, 28, 28]    --           False
│    │    └─MBConv (0)           [32, 24, 56, 56]     [32, 40, 28, 28]    (15,350)     False
│    │    └─MBConv (1)           [32, 40, 28, 28]     [32, 40, 28, 28]    (31,290)     False
│    └─Sequential (4)            [32, 40, 28, 28]     [32, 80, 14, 14]    --           False
│    │    └─MBConv (0)           [32, 40, 28, 28]     [32, 80, 14, 14]    (37,130)     False
│    │    └─MBConv (1)           [32, 80, 14, 14]     [32, 80, 14, 14]    (102,900)    False
│    │    └─MBConv (2)           [32, 80, 14, 14]     [32, 80, 14, 14]    (102,900)    False
│    └─Sequential (5)            [32, 80, 14, 14]     [32, 112, 14, 14]   --           False
│    │    └─MBConv (0)           [32, 80, 14, 14]     [32, 112, 14, 14]   (126,004)    False
│    │    └─MBConv (1)           [32, 112, 14, 14]    [32, 112, 14, 14]   (208,572)    False
│    │    └─MBConv (2)           [32, 112, 14, 14]    [32, 112, 14, 14]   (208,572)    False
│    └─Sequential (6)            [32, 112, 14, 14]    [32, 192, 7, 7]     --           False
│    │    └─MBConv (0)           [32, 112, 14, 14]    [32, 192, 7, 7]     (262,492)    False
│    │    └─MBConv (1)           [32, 192, 7, 7]      [32, 192, 7, 7]     (587,952)    False
│    │    └─MBConv (2)           [32, 192, 7, 7]      [32, 192, 7, 7]     (587,952)    False
│    │    └─MBConv (3)           [32, 192, 7, 7]      [32, 192, 7, 7]     (587,952)    False
│    └─Sequential (7)            [32, 192, 7, 7]      [32, 320, 7, 7]     --           False
│    │    └─MBConv (0)           [32, 192, 7, 7]      [32, 320, 7, 7]     (717,232)    False
│    └─Conv2dNormActivation (8)  [32, 320, 7, 7]      [32, 1280, 7, 7]    --           False
│    │    └─Conv2d (0)           [32, 320, 7, 7]      [32, 1280, 7, 7]    (409,600)    False
│    │    └─BatchNorm2d (1)      [32, 1280, 7, 7]     [32, 1280, 7, 7]    (2,560)      False
│    │    └─SiLU (2)             [32, 1280, 7, 7]     [32, 1280, 7, 7]    --            --
├─AdaptiveAvgPool2d (avgpool)    [32, 1280, 7, 7]     [32, 1280, 1, 1]    --            --
├─Sequential (classifier)        [32, 1280]           [32, 10]            --           True
│    └─Dropout (0)               [32, 1280]           [32, 1280]          --            --
│    └─Linear (1)                [32, 1280]           [32, 10]            12,810       True
==========================================================================================
Total params: 4,020,358
Trainable params: 12,810
Non-trainable params: 4,007,548
Total mult-adds (Units.GIGABYTES): 12.31
==========================================================================================
Input size (MB): 19.27
Forward/backward pass size (MB): 3452.09
Params size (MB): 16.08
Estimated Total Size (MB): 3487.44
==========================================================================================
```

Table 2- Complementary information about the TL model

Parameter	Setting
Training epoch	30
Batch size	32
optimizer	Adam
Learning rate	0.001
Loss function	Cross-Entropy

where TN is the number of instances that are truly predicted as negative, and FP is the number of instances that are falsely predicted as positive.

Precision: This criterion measures the ratio of the number of instances that are predicted as true positives to the total number of instances predicted as positive. In mathematical terms, it can be calculated using the formula:

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

F1 score: The F1 score is calculated by taking the harmonic average of recall and precision. In mathematical terms, we have:

$$F1\ score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (4)$$

If either precision or recall is zero, then the F1 score will be zero, but the arithmetic average of precision and recall will be a number greater than zero.

Accuracy: This criterion measures the ratio of the number of true predictions made by the model to the total number of predictions. In mathematical terms, we have:

$$Accuracy = \frac{\sum_{i=1}^{n}(TP_i)}{\sum_{i=1}^{n}(TP_i+FP_i)} \quad (5)$$

Where n is the number of classes; in this study, n is 10. During model training, this criterion was calculated after each epoch (there are 30 epochs during model training in this study), and then accuracy and loss values were charted against the corresponding epoch number. These charts can be used to be sure about the number of epochs for model training; in other words, if the curve of accuracy or loss versus epoch number remains horizontal for a few epochs, it is an indication for the completion of the model's training phase.

Confusion matrix: To obtain a complete understanding of where a false prediction has taken place, and with which group the prediction has been confused, a confusion matrix will be used. In this paper, a 10×10 confusion matrix was developed to show the location of false tomato disease predictions. In a confusion matrix, the greater the concentration of large numbers in the cells of the main diagonal of the matrix (the more zeros or small numbers in the other cells of the matrix), the better. The values of TP, FP, FN, and TN can be obtained from the confusion matrix. The values of the cells located on the main diagonal of the matrix comprise the TP values. If the TP value of each class is subtracted from the sum of cells for the corresponding column, the FP value for that class will result. On the other hand, if the TP value of each class is subtracted from the sum of the cells for the corresponding row, the FN value of that class will be obtained. Finally, the TN values can be obtained by subtracting the sum of the TP, FP, and FN values from the number of pictures in the test dataset.

Results and Discussion

Accuracy values versus corresponding epoch numbers: Figure 1 shows the train and test accuracies, as well as the losses of the model versus the corresponding epoch numbers.

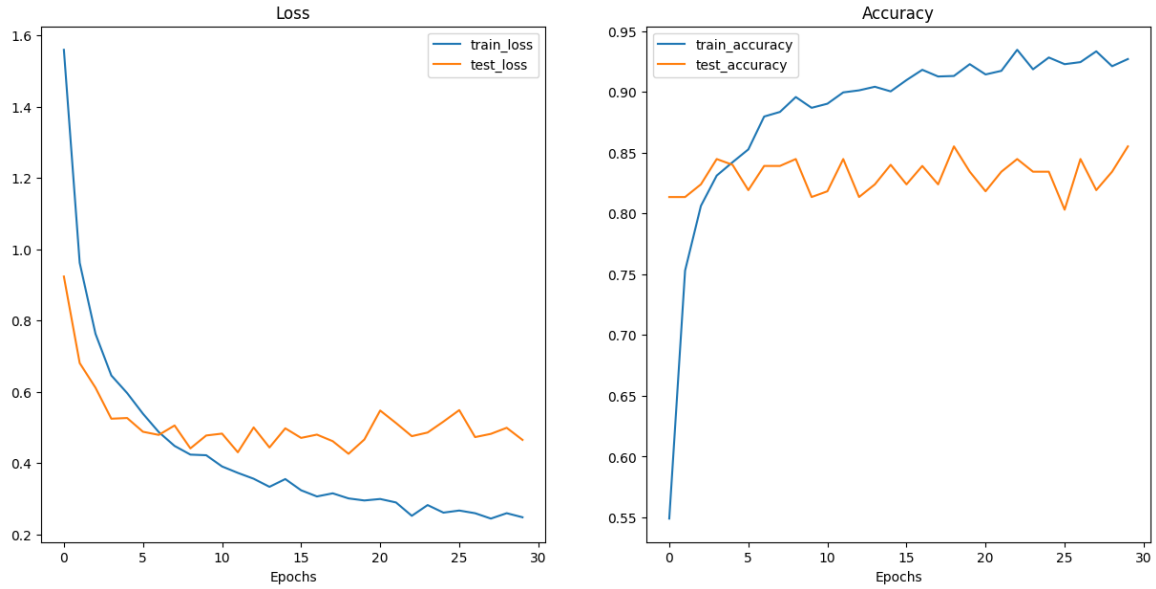


Fig. 1. Train and test losses and accuracies versus corresponding epoch number

The first point inferred from Figure 1 is that because the curves of train and test accuracies

have been approximately horizontal for epoch numbers greater than 20, the model has learned well, and increasing the epoch number cannot further increase model accuracy. Numerically, by recording values of model accuracies and losses in the training and testing phases for epoch numbers greater than 20, the worst coefficient of variation for these four cases was 7%. Another point that can be obtained from this chart is that since the distance between train and test accuracies is about 10%, and this situation has taken place for train accuracies near 95%, therefore, the model shows neither signs of under fitting nor over fitting.

Confusion matrix of the test instances: Figure 2 shows the confusion matrix obtained for the 86 images in the test dataset.

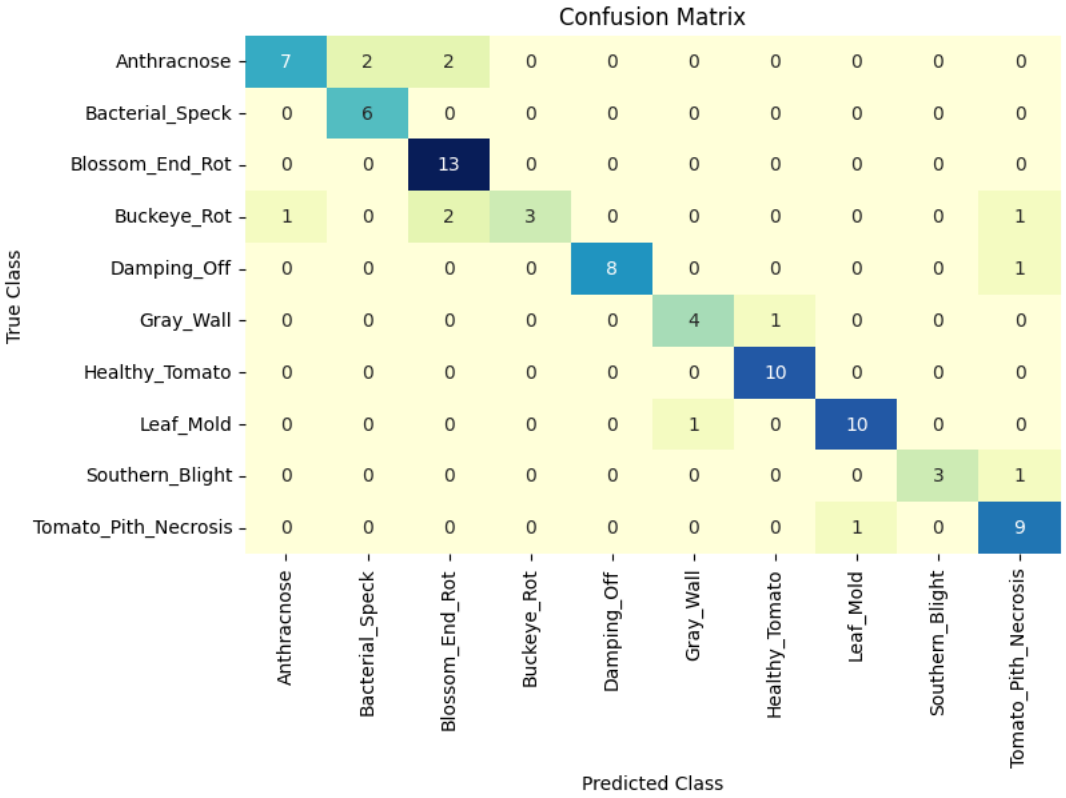


Fig. 2. Confusion matrix obtained in this study

This picture presents a matrix of real (ground truth) labels versus predicted ones. As shown, the elements along the primary diagonal of the matrix are filled with larger values compared to those in the other cells. The values of the primary diagonal of the matrix comprise the number of images in each disease's category that were predicted truly as positive; in other words, these values are the TP values of classes. The FP, TN, and FN values can be obtained from this matrix, too. Table 3 shows TP, FP, TN, and FN values of each category of tomato diseases considered in this study:

Calculation of sensitivity (recall), specificity, precision, F1 score, and accuracy of the model: The values presented in Table 3 can be used to obtain sensitivity (recall), specificity, precision, F1 score, and accuracy of the model. Table 4 shows the calculated values of the above-mentioned criteria.

The criteria values shown in Table 4 were calculated for each category of tomato diseases. To obtain corresponding criteria for the model, regular or weighted averaging can be carried out. Table 5 shows the sensitivity (recall), specificity, precision, and F1 score of

the model.

Table 3- Suitable data obtained from the confusion matrix

Disease category	TP	FP	FN	TN
Anthracnose	7	1	4	74
Bacterial Speck	6	2	0	78
Blossom_End_Rot	13	4	0	69
Buckeye Rot	3	0	4	79
Damping_Off	8	0	1	77
Gray Wall	4	1	1	80
Healthy Tomato	10	1	0	75
Leaf_Mold	10	1	1	74
Southern Blight	3	0	1	82
Tomato_Pith_Necrosis	9	3	1	73

Table 4- Calculated values of sensitivity (recall), specificity, precision, and F1 score

Disease category	Sensitivity (recall)	Specificity	Precision	F1 score
Anthracnose	0.64	0.99	0.88	0.74
Bacterial Speck	1	0.98	0.75	0.86
Blossom_End_Rot	1	0.95	0.76	0.86
Buckeye Rot	0.43	1	1	0.6
Damping_Off	0.89	1	1	0.94
Gray Wall	0.8	0.99	0.8	0.8
Healthy Tomato	1	0.99	0.91	0.95
Leaf_Mold	0.91	0.99	0.91	0.91
Southern Blight	0.75	1	1	0.86
Tomato_Pith_Necrosis	0.9	0.96	0.75	0.82

Table 5- Sensitivity (recall), specificity, precision, and F1 score of the model calculated from regular and weighted averaging

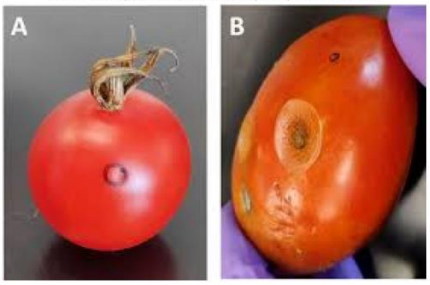
Average	Sensitivity (recall)	Specificity	Precision	F1 score
Regular	0.832	0.985	0.876	0.834
Weighted	0.85	0.982	0.868	0.841

The accuracy of the model was obtained from the formula of $accuracy = \frac{\sum_{i=1}^{10}(TP_i)}{\sum_{i=1}^{10}(TP_i+FP_i)} = \frac{73}{86} = 0.85$.

To assess the performance of the model visually, model predictions on some tomato images were considered. Figure 3 shows the predictions of the model on twenty randomly selected images in the test dataset.

Three acronyms are displayed on top of each image: Pred, Prob, and RPD. Pred is the acronym for prediction and shows the predicted group of the image. RPD is the acronym for real parent directory and shows the correct directory that the image belongs to. Prob is the acronym for probability and presents the probability value that the image belongs to the predicted group. In other words, the classifying algorithm calculates ten probabilities for each image that represent the belonging probabilities of the image to each of the tomato disease groups, and declares the tomato disease group with the highest probability value as the image's predicted group. As shown in Fig. 3, 3 out of 20 predictions were incorrect, which indicates the error rate of 15% (i.e. the accuracy of 0.85). On the other hand, there is a trade-off between the performance of a machine learning method and the time spent or computational resources devoted to training the model. Although the time spent training the model in this study was about 4.5 hours, which is high, the model was trained on a computer without a GPU. Additionally, it took just 16 seconds to classify 86 images from the test dataset during the model's validation phase.

Pred: Anthracnose | Prob: 0.692 |
RPD: data\tomato diseases4\test\Anthracnose



Pred: Anthracnose | Prob: 0.941 |
RPD: data\tomato diseases4\test\Anthracnose



Pred: Bacterial_Speck | Prob: 0.994 |
RPD: data\tomato diseases4\test\Bacterial_Speck



Pred: Bacterial_Speck | Prob: 0.598 |
RPD: data\tomato diseases4\test\Bacterial_Speck



Pred: Blossom_End_Rot | Prob: 0.939 |
RPD: data\tomato diseases4\test\Blossom_End_Rot



Pred: Blossom_End_Rot | Prob: 0.975 |
RPD: data\tomato diseases4\test\Blossom_End_Rot



Pred: Buckeye_Rot | Prob: 0.594 |
RPD: data\tomato diseases4\test\Buckeye_Rot



Pred: Blossom_End_Rot | Prob: 0.581 |
RPD: data\tomato diseases4\test\Buckeye_Rot



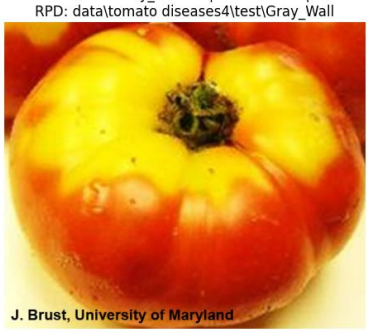
Pred: Damping_Off | Prob: 0.905 |
RPD: data\tomato diseases4\test\Damping_Off



Pred: Damping_Off | Prob: 0.848 |
RPD: data\tomato diseases4\test\Damping_Off



Pred: Healthy_Tomato | Prob: 0.849 |
RPD: data\tomato diseases4\test\Gray_Wall



Pred: Gray_Wall | Prob: 0.999 |
RPD: data\tomato diseases4\test\Gray_Wall



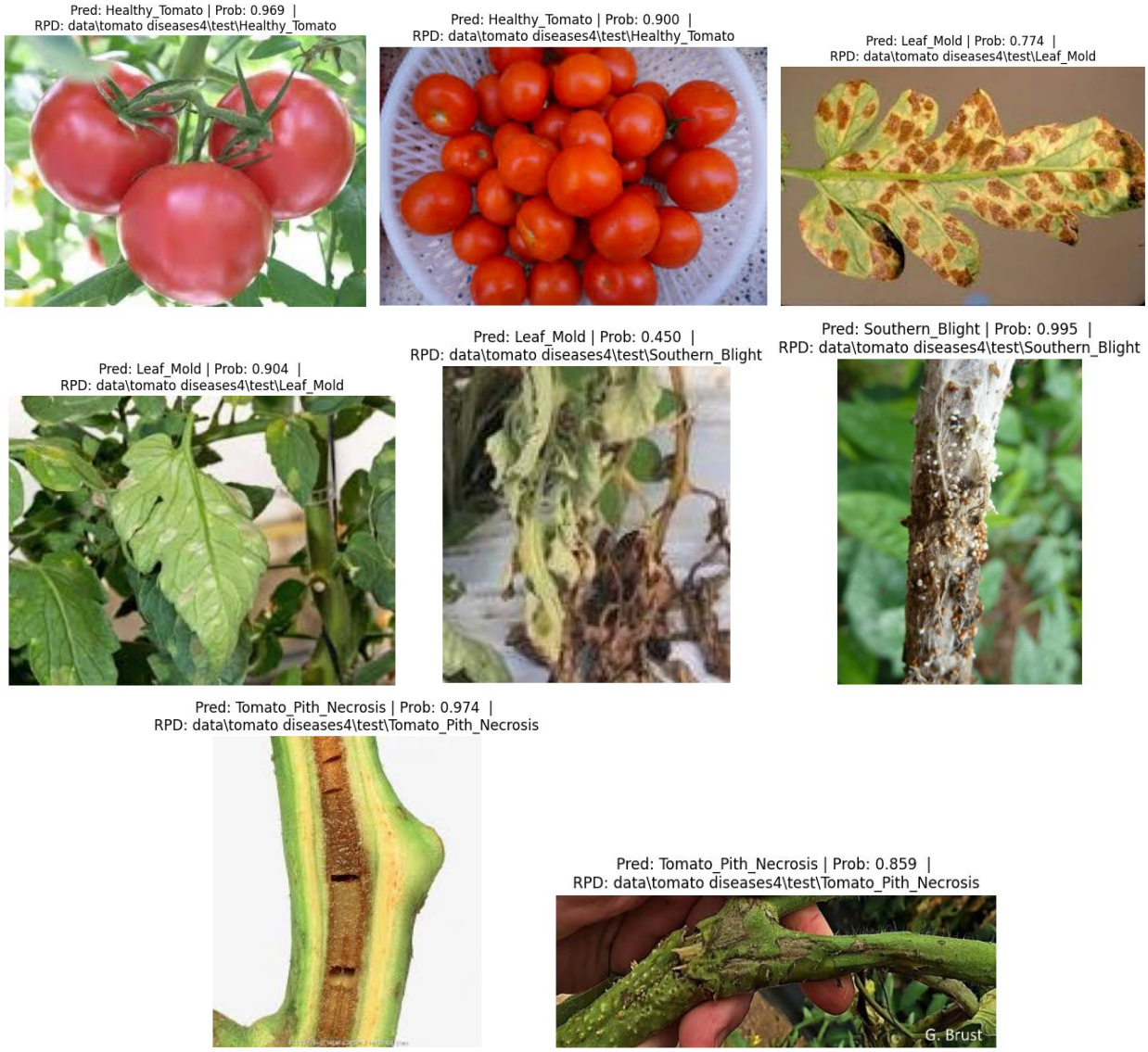


Fig. 3. Predictions of the model on some random images of tomato plants selected from the test dataset

This means that the model performed well during validation, achieving an image classification rate of about 5 frames per second (fps). Furthermore, the model's accuracy was comparable to some of the findings made by other researchers (Burhan *et al.*, 2020; Batool *et al.*, 2020); however, in some similar studies, higher accuracies were obtained (Jasim & Al-Tuwaijari, 2020; Guerrero-Ibanez & Reyes-Munoz, 2023; Ahmed & Yadav, 2023; Zhao, Peng, Liu, & Wu, 2021). To explain the observed differences, it should be noted that in the studies conducted by Jasim and Al-Tuwaijari (2020) and Guerrero-Ibanez and Reyes-Munoz (2023), they reached accuracies higher than 98% by training complete CNN models, instead of transferring the weights of a pre-trained model to a TL model and only training the classifier section of the model. On the other hand, in the studies conducted by Zhao *et al.* (2021), and Ahmed and Yadav (2023), more images capturing only the leaves of plants were used to train the model. This differs from the proportion of images examined in this study. Therefore, it is necessary to consider all the conditions surrounding a model and not focus on a single criterion in order to have a fair judgment about the model's performance.

Conclusion

In conclusion, in this study, a computationally inexpensive TL model trained on a dataset containing a mixture of images such as leaf, fruit, and stem was used to discriminate between healthy tomatoes and nine groups of diseased plants. According to the obtained results, the model's overall performance metrics are: sensitivity 85%, specificity 98%, precision 86%, F1-score 84%, and accuracy 85%, which is acceptable.

Conflict of Interest: The author declares no competing interests.

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Appendix: Python codes used in this study[1]:

```
# This script aims to create augmented images from one image to create a larger dataset for our transfer learning model

import PIL
import torch
from PIL import Image
from pathlib import Path
import matplotlib.pyplot as plt
import numpy as np
import sys
import torchvision.transforms as T
import os

#torch.transforms

#grayscale
grayscale_transform = T.Grayscale(3)

#random rotation
random_rotation_transformation_45 = T.RandomRotation(45)
random_rotation_transformation_85 = T.RandomRotation(85)
```

1- The codes were developed based on the materials presented in the following websites:
https://anushsom.medium.com/image-augmentation-for-creating-datasets-using-pytorch-for-dummies-by-a-dummy-a7c2b08c5bcb
https://www.learnpytorch.io/06_pytorch_transfer_learning/

```
#Gausian Blur
gausian_blur_transformation_13 = T.GaussianBlur(kernel_size = (7,13), sigma = (6 , 9))
gausian_blur_transformation_56 = T.GaussianBlur(kernel_size = (7,13), sigma = (5 , 8))

#Gausian Noise
def addnoise(input_image, noise_factor = 0.3):
    inputs = T.ToTensor()(input_image)
    noisy = inputs + torch.rand_like(inputs) * noise_factor
    noisy = torch.clip (noisy,0,1.)
    output_image = T.ToPILImage()
    image = output_image(noisy)
    return image

#Colour Jitter
colour_jitter_transformation_1 = T.ColorJitter(brightness=(0.5,1.5),contrast=(3),saturation=(0.3,1.5),hue=(-0.1,0.1))
colour_jitter_transformation_3 = T.ColorJitter(brightness=(0.5,1.5),contrast=(2),saturation=(1.4),hue=(-0.1,0.5))

#Random invert
random_invert_transform = T.RandomInvert()

#Main function that calls all the above functions to create 9 augmented images from one image

def augment_image(img_path):

    #orig_image
    orig_img = Image.open(Path(img_path))

    #grayscale

    grayscaled_image=grayscale_transform(orig_img)
    #grayscaled_image.show()

    #random rotation
    random_rotation_transformation_45_image=random_rotation_transformation_45(orig_img)
    #random_rotation_transformation_45_image.show()

    random_rotation_transformation_85_image=random_rotation_transformation_85(orig_img)
    #random_rotation_transformation_85_image.show()

    #Gausian Blur
    gausian_blurred_image_13_image = gausian_blur_transformation_13(orig_img)
    #gausian_blurred_image_13_image.show()

    gausian_blurred_image_56_image = gausian_blur_transformation_56(orig_img)
    #gausian_blurred_image_56_image.show()

    #Gausian Noise
    gausian_image_3 = addnoise(orig_img)
    #gausian_image_3.show()

    gausian_image_9 = addnoise(orig_img,0.9)
    #gausian_image_9.show()

    #Color Jitter
    colour_jitter_image_1 = colour_jitter_transformation_1(orig_img)
    #colour_jitter_image_1.show()

    colour_jitter_image_3 = colour_jitter_transformation_3(orig_img)
```

```
        #colour_jitter_image_3.show()

        return [orig_img,grayscaled_image,random_rotation_transformation_45_image,
random_rotation_transformation_85_image,gausian_blurred_image_13_image,gausian_blurred_image_56_image,gausi
an_image_3, gausian_image_9,colour_jitter_image_1, colour_jitter_image_3]

    #augmented_images = augment_image(orig_img_path)

    def creating_file_with_augmented_images(file_path_master_dataset,file_path_augmented_images):

        master_dataset_folder = file_path_master_dataset
        files_in_master_dataset = os.listdir(file_path_master_dataset)
        augmented_images_folder = file_path_augmented_images

        counter=0

        for element in files_in_master_dataset:
            os.mkdir(f"{augmented_images_folder}/{element}")
            images_in_folder= os.listdir(f"{master_dataset_folder}/{element}")
            counter = counter+1
            counter2 = 0
            for image in images_in_folder:
                counter
                required_images = augment_image(f"{master_dataset_folder}/{element}/{image}")
                counter2=counter2+1
                counter3 = 0
                for augmented_image in required_images:
                    counter3 = counter3 +1
                    augmented_image =
augmented_image.save(f"{augmented_images_folder}/{element}/{counter}_{counter2}_{counter3}_{image}")

    """images = augment_image("dog.png")

    for element in images:
        element.show()"""

    #augmented dataset path
    augmented_dataset = "C:\\Users\\acer\\PycharmProjects\\pythonProject2\\augmented_tomato"

    # master dataset path
    master_dataset = "C:\\Users\\acer\\PycharmProjects\\pythonProject2\\tomato"

    # run the program

    creating_file_with_augmented_images(master_dataset,augmented_dataset)

    # This script aims to perform the main goal of the study i.e. tomato crop diseases classification

    import torch
    import torchvision
    import matplotlib.pyplot as plt
    from torch import nn
    from torchvision import transforms
    !pip install going_modular
    import going_modular
    try:
        from torchinfo import summary
    except:
        print("[INFO] Couldn't find torchinfo... installing it.")
```

```
    !pip3 install -q torchinfo
    from torchinfo import summary
try:
    from going_modular.going_modular import data_setup, engine
except:
    print("[INFO] Couldn't find going_modular scripts... downloading them from GitHub.")
    !git clone https://github.com/mrdbourke/pytorch-deep-learning
    !mv pytorch-deep-learning/going_modular .
    !rm -rf pytorch-deep-learning
    from going_modular.going_modular import data_setup, engine
device = "cuda" if torch.cuda.is_available() else "cpu"
device
import os
import zipfile
from pathlib import Path
import requests
data_path = Path("data/")
image_path = data_path / "tomato_diseases"
train_dir = image_path / "train"
test_dir = image_path / "test"
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT
auto_transforms = weights.transforms()
auto_transforms
train_dataloader, test_dataloader, class_names = data_setup.create_dataloaders(train_dir=train_dir,
                                                                               test_dir=test_dir,
                                                                               transform=auto_transforms,
                                                                               batch_size=32)
train_dataloader, test_dataloader, class_names
weights = torchvision.models.EfficientNet_B0_Weights.DEFAULT
model = torchvision.models.efficientnet_b0(weights=weights).to(device)
summary(model=model,
        input_size=(32, 3, 224, 224),
        col_names=["input_size", "output_size", "num_params", "trainable"],
        col_width=10,
        row_settings=["var_names"]
)
for param in model.features.parameters():
    param.requires_grad = False
torch.manual_seed(42)
torch.cuda.manual_seed(42)
output_shape = len(class_names)
model.classifier = torch.nn.Sequential(
    torch.nn.Dropout(p=0.2, inplace=True),
    torch.nn.Linear(in_features=1280,
                    out_features=output_shape,
                    bias=True)).to(device)
summary(model,
        input_size=(32, 3, 224, 224),
        verbose=0,
        col_names=["input_size", "output_size", "num_params", "trainable"],
        col_width=20,
        row_settings=["var_names"]
)
loss_fn = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
torch.manual_seed(42)
torch.cuda.manual_seed(42)
from timeit import default_timer as timer
start_time = timer()
```

```
    results = engine.train(model=model,
                           train_dataloader=train_dataloader,
                           test_dataloader=test_dataloader,
                           optimizer=optimizer,
                           loss_fn=loss_fn,
                           epochs=5,
                           device=device)
    end_time = timer()
    print(f"[INFO] Total training time: {end_time-start_time:.3f} seconds")
    try:
        from helper_functions import plot_loss_curves
    except:
        print("[INFO] Couldn't find helper_functions.py, downloading...")
        with open("helper_functions.py", "wb") as f:
            import requests
            request = requests.get("https://raw.githubusercontent.com/mrdbourke/pytorch-deep-learning/main/helper_functions.py")
            f.write(request.content)
        from helper_functions import plot_loss_curves
    plot_loss_curves(results)
    from typing import List, Tuple
    from pathlib import Path
    def get_folder(dataset):
        parent = Path(dataset).parent
        if "." in parent.name:
            return str(parent.parent)
        return str(parent)
    from PIL import Image
    def pred_and_plot_image(model: torch.nn.Module,
                            image_path: str,
                            class_names: List[str],
                            image_size: Tuple[int, int] = (224, 224),
                            transform: torchvision.transforms = None,
                            device: torch.device=device):
        img = Image.open(image_path)
        if transform is not None:
            image_transform = transform
        else:
            image_transform = transforms.Compose([
                transforms.Resize(image_size),
                transforms.ToTensor(),
                transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                     std=[0.229, 0.224, 0.225]),
            ])
        model.to(device)
        model.eval()
        with torch.inference_mode():
          transformed_image = image_transform(img).unsqueeze(dim=0)
          target_image_pred = model(transformed_image.to(device))
        target_image_pred_probs = torch.softmax(target_image_pred, dim=1)
        target_image_pred_label = torch.argmax(target_image_pred_probs, dim=1)
        plt.figure()
        plt.imshow(img)
        plt.title(f"Pred: {class_names[target_image_pred_label]} | Prob: {target_image_pred_probs.max():.3f} | Real Parent Directory: {get_folder(image_path)}")
        plt.axis(False);
    import random
    num_images_to_plot = 30
    test_image_path_list = list(Path(test_dir).glob("*/*.jpg"))
```

```
test_image_path_sample = random.sample(population=test_image_path_list,
                                       k=num_images_to_plot)
for image_path in test_image_path_sample:
    pred_and_plot_image(model=model,
                        image_path=image_path,
                        class_names=class_names,
                        image_size=(224, 224))
```

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۳۳۵-۳۱۹

تشخیص و دسته‌بندی تعدادی از بیماری‌های گوجه‌فرنگی با استفاده از یادگیری انتقالی

ایمان احمدی [1*]

تاریخ دریافت: ۱۴۰۳/۰۳/۲۵
تاریخ پذیرش: ۱۴۰۳/۰۵/۰۸

چکیده

در موضوع بیماری‌های گیاهی، انتخاب روش‌های پیشگیری مناسب مانند کاربرد علف‌کش‌ها تنها زمانی امکان‌پذیر است که نوع بیماری به سرعت و به دقت تشخیص داده شود. در این مطالعه یک مدل یادگیری انتقالی بر مبنای مدل از پیش آموزش‌دیده EfficientNet به‌منظور تشخیص و دسته‌بندی برخی از بیماری‌های گوجه‌فرنگی با استفاده از ۲۳۴۰ تصویر از گیاه گوجه‌فرنگی به‌عنوان پایگاه تصاویر آموزشی توسعه یافت. برمبنای نتایج این مطالعه در مرحله اعتبارسنجی مدل، نرخ دسته‌بندی تصاویر در حدود 5 fps (۵ فریم در ثانیه) بود که برای مدل یادگیری عمیقی که روی رایانه مجهز به CPU معمولی اجرا می‌شود، منطقی است. به‌علاوه چون منحنی‌های صحت و هزینه مربوط به مراحل آموزش و آزمایش در عددهای دوره بیش از ۲۰ تقریباً افقی شده بودند (از نظر عددی، بدترین ضریب تغییرات داده‌های مربوط به این چهار حالت ۷٪ بود)، مدل به‌خوبی آموزش دیده است و افزایش عدد دوره به افزایش صحت مدل منجر نخواهد شد. به‌علاوه سلول‌های واقع در قطر اصلی ماتریس در هم‌ریختگی مربوط به عملکرد مدل روی تصاویر آزمون با اعداد بزرگتری در مقایسه با محتوای سایر سلول‌های ماتریس پر شده بودند، به‌طور دقیق ۸۸/۸٪، ۷/۷٪، و ۳/۳٪ از سلول‌های باقیمانده (جایی‌که سلول‌های مربوط به قطر اصلی ماتریس کنار گذاشته شده بودند) به‌ترتیب با اعداد ۰ و ۱ و ۲ پر شده بودند. در نهایت مقادیر حساسیت، اختصاصیت، دقت، نمره F1 و صحت مدل به‌ترتیب برابر با ۸۵٪، ۹۸٪، ۸۶٪، ۸۴٪ و ۸۵٪ بود.

واژه‌های کلیدی: صحت مدل، ماتریس درهم ریختگی، مدل EfficientNet

۱- گروه مهندسی تولید و ژنتیک گیاهی، دانشکده کشاورزی، آب، غذا و فراسودمندها، واحد اصفهان (خوراسگان)، دانشگاه آزاد اسلامی، اصفهان، ایران
(*- نویسنده مسئول: Email: imanahmadi1358@iau.ac.ir)

https://doi.org/10.22067/jam.2024.88500.1258

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 337-361

Sustainability of Traditional Paddy Rice Processing Techniques Among Smallholder Rice Farmers in Southeast Nigeria

C. N. Onwusiribe [1*], J. Mbanasor [1], P. O. Nto [1], M. C. Ndukwu [2]

1- Department of Agribusiness & Management, Michael Okpara University of Agriculture, Abia State, Nigeria
2- Department of Agricultural and Bioresources Engineering, Michael Okpara University of Agriculture, Abia State, Nigeria
(*- Corresponding Author Email: onwusiribe.chigozirim@mouau.edu.ng)

Received: 29 July 2024
Revised: 29 October 2024
Accepted: 30 October 2024
Available Online: 31 May 2025

How to cite this article:
Onwusiribe, C. N., Mbanasor, J., Nto, P. O., & Ndukwu, M. C. (2025). Sustainability of Traditional Paddy Rice Processing Techniques Among Smallholder Rice Farmers in Southeast Nigeria. *Journal of Agricultural Machinery*, *15*(3), 337-361. https://doi.org/10.22067/jam.2024.89115.1267

Abstract

Rice is a major staple food consumed worldwide, but its processing has significant environmental impacts due to water and energy consumption and greenhouse gas emissions. As a result, rice producers are adopting sustainable processing techniques to reduce negative environmental impacts and increase profitability. This study analyzed the sustainability of modern and traditional paddy rice processing techniques among smallholder rice farmers in Southeast Nigeria. The data was collected from 240 rice producers using statistical approaches such as descriptive statistics, sustainability indicator (Weight Assessment Ratio Analysis), and multinomial regression analysis. The results showed that 34.7% of rice farmers used modern processing techniques while 65.3% used traditional methods. Traditional milling produced substantial carbon emissions, according to 77% of small-scale farmers, while 68% rated noise pollution as high. 80-100% of small-scale farmers using modern techniques cared about the environment and wanted to reduce their gas emissions, solid waste, energy use, and water use. The sustainability index for farmers using traditional and modern processing techniques was affected by gender experience, labor size, investment, income, cost of production, understanding of climate change, and environmental sustainability. The study recommends using renewable energy sources to increase productivity and reduce environmental effects.

Keywords: Emissions, Energy consumption, Environmental impacts, Investment, Productivity, Profitability

Introduction

Rice is a staple food for millions of Nigerians and plays a crucial role in food security across West Africa (Akinbile, Ogunmola, Abolude, & Akande, 2020; Soullier, Demont, Arouna, Lançon, & Del Villar, 2020). Rice consumption in Nigeria is projected to rise by 4% to 7.8 MMT in MY (Million Metric Tons in Marketing Year) 2023/24, marking an increase in consumption compared to other African staples like wheat and corn (United United States Department of Agriculture Foreign Agricultural Service, 2023).Smallholder farmers are the primary producers of rice in Nigeria (Esiobu, Onubuogu, Njoku, & Nwachukwu, 2020; Onyeneke, Amadi, Njoku, & Osuji, 2021), and the government has implemented policies to boost local production and reduce imports (Ikebudu, 2021; Karkare, Odijie, Ukaoha, & van Seters, 2022).

The production and processing of rice

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https://doi.org/10.22067/jam.2024.89115.1267

involve complex procedures requiring various technologies (Sethy, Barpanda, Rath, & Behera, 2020). While large-scale operations utilize highly-mechanized processes (Materne & Reddy, 2007), most smallholder farmers in Nigeria still rely on traditional, labor-intensive methods (Bello, Baiyegunhi, & Danso-Abbeam, 2021; Obianefo *et al.*, 2021). These traditional techniques, though less efficient, are perceived to preserve food quality and nutrition better than modern methods (Adekoyeni, Fagbemi, & Ismaila, 2018; Danbaba *et al.*, 2019; Zhao, Lin, & Chen, 2020).

However, the increasing costs of labor and resources are pushing more smallholder farmers towards adopting more efficient rice production methods to remain competitive (Akite, Okello, Kasharu, & Mugonola, 2022; Bello *et al.*, 2021; Obianefo *et al.*, 2021). This shift presents opportunities for the sustainable development of Nigeria's small-scale modern rice processing industry (Kosemani & Bamgboye, 2020; Onyekwena, 2016; Salisu, Gao, & Quan, 2021).

Both traditional and modern rice processing techniques have environmental implications, including carbon emissions, solid waste generation, water pollution, and noise pollution (Chungsangunsit, Gheewala, & Patumsawad, 2005; Kumar, Priyadarshinee, Roy, Dasgupta, & Mandal, 2016; Lenis Rodas, Morales Rojas, Jaramillo Marín, Salcedo Jiménez, & Pérez Bayer, 2022; Lim, Manan, Hashim, & Alwi, 2013). The sustainability of these processes must be evaluated considering environmental, economic, and organizational factors (Batista & Francisco, 2018; Dzhengiz, 2020; Gowda & Jayaramaiah, 1998; Roy, Chan, & Xenarios, 2016).

While previous studies have examined various aspects of rice processing techniques, there are several gaps in the existing literature. First, there is limited research specifically focusing on the sustainability of traditional paddy rice processing among smallholder farmers in Southeast Nigeria. Second, many studies have focused on either environmental or economic aspects, but few have integrated all three dimensions of sustainability (environmental, economic, and organizational) in their analysis. Third, while some researchers have used econometric models to study the effects of various factors on sustainability (De La Maza, Davis, & Azevedo, 2021; Rajabov & Mustafakulov, 2020), there is a lack of comprehensive studies applying both Multinomial Logistic Regression and Weight Assessment Ratio Analysis (WARA) to assess the sustainability of rice processing techniques. Lastly, the existing literature often fails to provide a clear comparison between traditional and modern processing techniques in terms of their overall sustainability within the context of smallholder farming in Nigeria.

Given these gaps, the objectives of this study are:

1. To examine the distribution of modern and traditional rice processing techniques among smallholder farmers in Southeast Nigeria.
2. To assess the environmental effects of both traditional and modern rice processing methods in the study area.
3. To evaluate the sustainability of traditional paddy rice processing techniques using a comprehensive approach that integrates environmental, economic, and organizational factors.
4. To identify the key determinants influencing the adoption and sustainability of different rice processing techniques among smallholder farmers.
5. To provide evidence-based recommendations for policymakers and stakeholders to promote sustainable rice processing practices in Nigeria.

Materials and Methods

The study was carried out at three locations: Abia, Ebonyi, and Imo states in southeastern Nigeria. These states are predominantly agrarian and major producers of paddy rice (see Figure 1). A two-stage sampling technique was used to select the rice processors. The first stage was the purposive selection of the state's rice-producing communities. The second stage was randomly

selecting 240 rice farmers from the selected communities. The researchers visited each farm periodically to collect data about the sustainability performance of the modern and traditional paddy processing systems. Data were collected using a survey and focused group discussion. The data collected were analyzed using statistical tools such as descriptives, sustainability index (Weight Assessment Ratio Analysis), and multinomial regression analysis. The farmers' perception of organizational sustainability was characterized by conducting a content analysis of the transcripts of their responses (Baccar, Bouaziz, Dugué, Gafsi, & Le Gal, 2020). To estimate the factors affecting the sustainability index of traditional rice milling, the following multinomial logit model was adopted.

$$\text{Pij} = \frac{e\ B_j X_i}{1+\sum_{k=0}^{j} X^B k X_i} \quad \ldots \quad (1)$$

The explicit form of the model is stated as:

$$\log\left(\frac{pij(categoryi)}{Pij(categoryref)}\right) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + e_i \quad (2)$$

where:
P= probability
i = 1, 2, 3, ..., n variables
j= categories
Y= high=1, average =2, and Y*ref*= low =5
X_1= level of education of the small-scale farmers, measured in years
X_2=sex (male=1 and female=0)
X_3 = experience of the small-scale farmers,measured in years
X_4 =labor size of traditional rice mills,measured in numbers
X_5 =investment of traditional rice mills in naira
X_6 =income of traditional rice mills in naira
X_7 = cost of production of traditional rice mills in naira
X_8=knowledge of climate change of small-scale farmers using traditional rice mills (yes =1, no=0)
X_9 =knowledge of economic sustainability of small-scale farmers using traditional rice mills (yes =1, no=0)
X_{10}=knowledge of organizational sustainability of small-scale farmers using traditional rice mills (yes =1, no=0)
b_i = the parameter
e_i = the error term

To estimate the factors affecting the sustainability index of modern rice milling, the following multinomial logit model was adopted

$$\text{Pij} = \frac{e\ B_j X_i}{1+\sum_{k=0}^{j} X^B k X_i} \quad (3)$$

The explicit form of the model is stated as

$$\log\left(\frac{pij(categoryi)}{Pij(categoryref)}\right) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + e_i \quad (4)$$

where:
P= probability
i = 1, 2, 3, ..., n variables
j= categories
Y= high=1, average =2, and Y*ref*= low =5
X_1= level of education of the small-scale farmers, measured in years
X_2=sex (male=1 and female=0)
X_3= experience of the small-scale farmers using modern mills,measured in years
X_4= labor size of modern rice mills, measured in numbers
X_5= investment of modern rice mills in naira
X_6= income of modern rice mills in naira
X_7 = cost of production of modern rice mills in naira
X_8=knowledge of climate change of small-scale farmers using modern rice mills (yes =1, no=0)
X_9 =knowledge of economic sustainability of small-scale farmers using modern rice mills (yes =1, no=0)
X_{10}= knowledge of organizational sustainability of small-scale farmers using modern rice mills (yes =1, no=0)
b_i = the parameter
e_i = the error term

The Weight Assessment Ratio Analysis (WARA) model (Dehnavi, Aghdam, Pradhan, & Varzandeh, 2015; Ghenai, Albawab, & Bettayeb, 2020; Zavadskas, Stević, Tanackov,

& Prentkovskis, 2018) is specified as follows:

$$W_j = \frac{q_i}{\sum_{k=1}^{m} q_k} \quad (5)$$

where:

W_j = relative weight criteria of the farmer's response to sustainability questions

i = individual farmer response

j = 1, 2, …, n

q = the rank of the farmer response

m= sample size

Endogenous variables: Information was gathered through questionnaires and interviews with the rice farmers. The data collected is based on the processing activities of rice farmers. The data collected on environmental sustainability was computed using the Weight Assessment Ratio Analysis (see equation 5) to get an index score to measure the environmental impact of rice processing using modern and traditional methods. The high index score is 0.7-1, the average is 0.5-0.69, while the low index is <0.5 (Daniel, Tsoulfas, Pappis, & Rachaniotis, 2004). This indicates the adverse impact of processing rice on the farmer and the environment. The index is the dependent variable for the multinomial logit models (see equations 2 and 4) performed in this study.

Exogenous variables: The exogenous variable is the independent variable included in equations 2 and 4, which influences the environmental sustainability of traditional and modern rice processing, respectively. The first variable is the level of education of the farmers. Some reports on environmental sustainability considered education as a factor (Anabaraonye, Okafor, & Hope, 2018; Baur, 2022; Jayne, Snapp, Place, & Sitko, 2019; Mancini, Termorshuizen, Jiggins, & van Bruggen, 2008). The sex of the farmers was considered as another variable. Gender, the roles assigned to different sexes that vary across societies and cultures, is an essential component of any sustainability study involving farmers (Aluko, 2018; Jellason, Conway, & Baines, 2021). The experience of the farmers in rice processing and their knowledge of the traditional and modern methods of rice processing were also considered important variables for the study (Ojo & Baiyegunhi, 2020a; Ojo, Baiyegunhi, Adetoro, & Ogundeji, 2021). Moreover, labor size, a measure of the number of workers used to process the paddy, has been included as an important variable as it affects the total time spent on processing the paddy (Kulyakwave, Xu, Yu, & Mwakyusa, 2022; Mujeyi, Mudhara, & Mutenje, 2021). Amount of investment in the processing as an exogenous variable was also considered because the amount of investment in the equipment used in the processing of paddy affects the processing time, which in turn affects the environmental impact of the entire process (Salisu, Gao, & Quan, 2021). Lastly, the cost of production and income are important as they affect the ability of the farmer to purchase inputs needed in the processing of paddy, affecting the processing time and the environment of the process (Onyeneke, 2021).

Results and Discussion

Distribution of rice processing methods among farmers

The distribution of the farmers according to their use of the traditional or modern method of rice processing is presented in Table 1. The table showed that 34.7% of rice farmers use modern rice processing methods, while 65.3% use the traditional method of rice processing. The percentage split showed that the two rice processing methods are popular with rice farmers in Nigeria. However, the data reveals that the percentage of farmers employing traditional rice processing methods in the region is nearly double that of those utilizing modern techniques. The higher number of traditional processing techniques can be associated with the cost of purchase and maintenance of modern processing equipment. Additionally, there is this perception among local processors that the traditional processing of paddy rice is more efficient and reliable than modern rice processing methods (Anthony, Alabi, Ebukiba, & Gamba, 2021; Sissoko, Ohene-Yankyera, & Wongnaa, 2021; Tahir, Onewo, & Alkali, 2022). However,

according to Hasan, Tanaka, Alam, Ali, and Saha (2020) and Soullier *et al.* (2020), this method results in lower throughput capacity compared to farmers who use modern machinery to process their rice. The results agreed with the finding of Yusuf (2018) that rice farmers in Nigeria use more traditional rice processing methods, which have resulted in a low level of processing output and quality of rice produced. This low yield is probably due to the daily drudgery with manual labor involving traditional techniques.

Table 1- Methods of paddy rice processing

Technique of paddy rice processing	Frequency	Percentage
Modern processing	83	34.72803
Traditional processing	156	65.27197
Total	239	100

Effect of processing techniques on riceyield and quality among farmers

The investigation strongly suggested that land availability determines the quantity of rice grown and the amount of rice processed. First, however, we categorize the rice farmers based on the quantity of rice processed (see Figure 2). From the questionnaire, we grouped the processors into three: those that process 0.5 to 5 tonnes of rice daily, 6 to 10 tonnes daily, and 11 to 15 tonnes daily. Then, each group was separated based on those that used modern processing techniques and those that used traditional techniques. Figure1 shows the quantity of rice produced using traditional and modern processing techniques for each category. According to the graph, in the 0 to 5 tonnes category, about 77% of rice farmers use traditional milling methods, while 8% use modern milling methods. In the6 to 10 tonnes daily category, 58% of processed rice was by modern milling methods, while 20% used traditional milling methods. Furthermore, in the11 to 15 tonnes daily category, 34% used modern milling methods, while 3% used traditional methods. The analysis revealed that the use of milling methods is correlated with the amount of rice produced. However, Figure 2 shows that processors are dominated by rice millers in the category of 0.5 to 5 tonnes daily. The reason is that the farming cluster is dominated by small farm holders whose first objective is to feed their families before selling the excess. This finding agreed with Kyaw, Ahn, & Lee (2018), who asserted that small-scale rice farmers typically mill less rice than is necessary to provide their families with sufficient income. Low-quantity rice milling can result from acombination of available quantity to mill, effective milling systems, and drudgery due to local milling techniques. However, Ndirangu & Oyange (2019) noted that the modern milling procedure could increase rice farmers' daily output from 1.5 to 3 tonnes. This increase in output is because of the availability of high-capacity modern mill machines and efficient material handling techniques, which enable rice farming to be more productive and profitable for small-scale farmers. However, the trend observed among most rice farmers in most Sub-Saharan countries is the continued use of traditional milling methods due to the limited access to reliable and affordable machines (Fatunbi & Kombat, 2020).

The information regarding these quality indices was provided by farmers and processors who were asked to rate the degree of acceptability on a scale of 0 to 5, with 0 being the lowest and 5 being the highest (refer to Figure 2). The participants willingly shared their insights to contribute to the research and provide valuable data on the perceived quality of rice produced using different processing methods. Concerning palatability, the average response from small-scale farmers using traditional milling techniques was 3.5, while those using modern milling techniques rated it at 3. This indicates that the traditionally milled

rice was perceived to have better palatability among the respondents. The farmers' input on this aspect helps in understanding the preference for rice processed through traditional methods. However, it is important to note that the nutritional content of traditional and milled rice was not the focus of this research and falls beyond its scope. This acknowledgment is necessary to avoid drawing conclusions regarding the nutritional differences between the two processing methods.

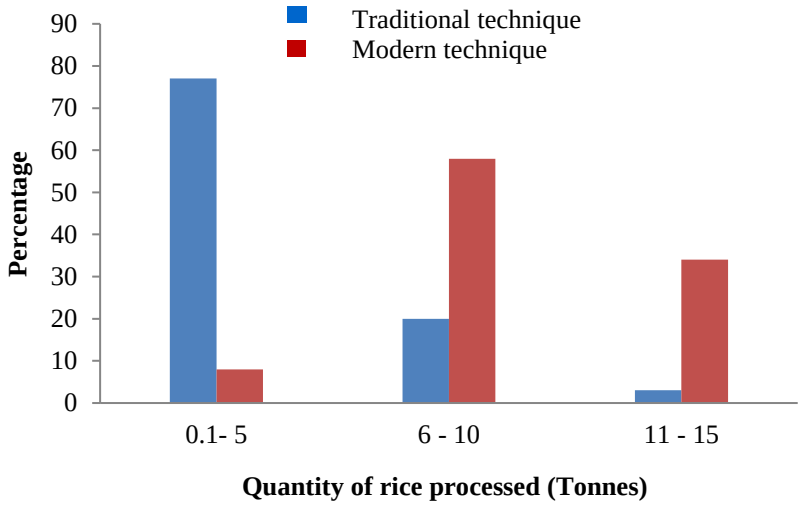


Fig.1. Quantity of rice produced using the traditional and modern method

Moving on to the assessment of appearance, a comparison between small-scale farmers using traditional milling techniques and those using modern mills revealed notable differences. Traditionally milled rice received a low rating with a mean response of 1.5, while modern milled rice scored significantly higher at 3.7. This difference in ratings can be attributed to the fact that traditionally milled rice retains more of the bran layer of the paddy kernel, as supported by previous studies (Dhankhar & Hissar, 2014; Tong, Gao, Luo, Liu, & Bao, 2019). The farmers and processors' input on appearance offers valuable insights into the visual appeal of rice processed using different methods.

In terms of taste, the respondents rated traditionally milled rice equal to modern rice mills. This implies that there was no significant difference in taste perception between the two processing methods. The input provided by the farmers and processors aids in understanding the taste-related aspects of rice quality and helps in evaluating the potential consumer preferences.

Considering cooking time, the farmers rated traditionally milled rice as having a faster cooking time, with a mean rating of 3.8, while modern milled rice received a slightly lower rating of 3.5 (refer to Figure 2). This information contributes to the understanding of the practical aspects of rice preparation and may influence consumer choices based on convenience and time-saving factors.

Access to available modern rice processing machines

The cluster of rice processing machines available from the respondents was a dehusking, pre-cleaning machine, aspiration or winnowing machine, destoner, paddy separator, weighing machine, sifter, grader, polisher, blender, and bagging/packaging machines. Farmers were questioned about access to each machine in the three study areas. The distribution of the respondents is shown in Figure 3. From the Figure, about 14% and 15% of the rice farmers had access to pre-cleaning and paddy separator machines,

respectively. Dehusking, de-stoning, packaging, and weighing machines were accessed by 10%, 12%, 13%, and 15% of the rice farmers, respectively (see Figure 4). The farmers who use length grading, husk aspiration, and polishing machines were 5% each, while 2% and 4% of the rice farmers have access to sifting and blending machines, respectively. There was a clear trend in which small-scale farmers with fewer machines have smaller farms with lower productivity. However, most farmers in the study areas had poor access to machinery. It has been reported that farmers with access to the highest numbers of machines also produced the most rice per hectare (Bello *et al.*, 2021; Panpluem, Mustafa, Huang, Wang, & Yin, 2019). This finding suggests that having access to multiple machines is crucial as it increases farm productivity and allows farmers to diversify their income streams. Moreover, it was observed that despite the few machines available to most farmers, they could produce a significant amount of rice and sell their products at a value higher than the market price and therefore earned higher incomes than imported rice. Thus, this positive correlation between the number of machines and average output can be achieved only when the farmers can use these machines effectively to carry out the desired tasks (Osabuohien, Okorie, & Osabohien, 2018). Therefore, these results suggest considerable room for improvement regarding farmer knowledge and proficiency with the various types of machines available in the study area.

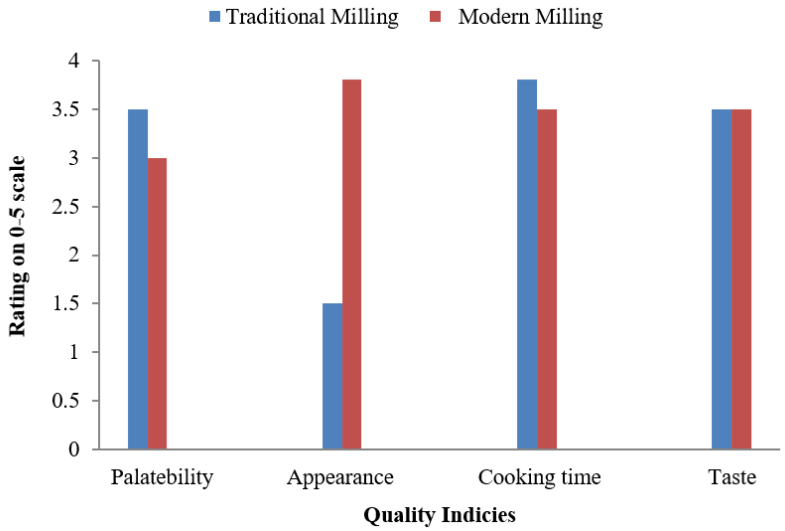


Fig.2. Quality of rice produced using the traditional and modern method

Environmental effects of rice processing

Modern rice processing can significantly impact the environment, particularly when inefficient machines and systems are used, resulting in a range of negative environmental consequences. These attributes were noise pollution, carbon emission due to fossil fuel use, wastewater discharge to the environment, high water usage, and high solid waste used to large amounts of processed rice. Farmers were asked how these indices affect them and the community where the processing machines are located. They were asked to rate these attributes in terms of low, moderate, and high among them and the community. Figure 4 shows that 68% of the respondents identified noise pollution as a primary concern, while 42% identified carbon emissions from the machines as a primary concern. Water usage and water pollution were of minor concern, while solid waste discharge was third in the least of their environmental concerns. The reason is that modern rice processing methods contribute minimally to water use, water pollution, and solid waste. When weighted as a single factor of environmental effects, the overall view indicated that about 31%, 30%,

and 39% of rice farmers rate the environmental effects of modern rice processing to be high, moderate, and low, respectively. It has been reported that rice mills operating with a single-cylinder engine and flat belt drives produce more noise than those being run using an electric motor along with flat belt drives, and the single-cylinder engine rice millers are more prevalent in sub-Saharan Africa (Nag & Gite, 2020; Oyedepo, 2019).

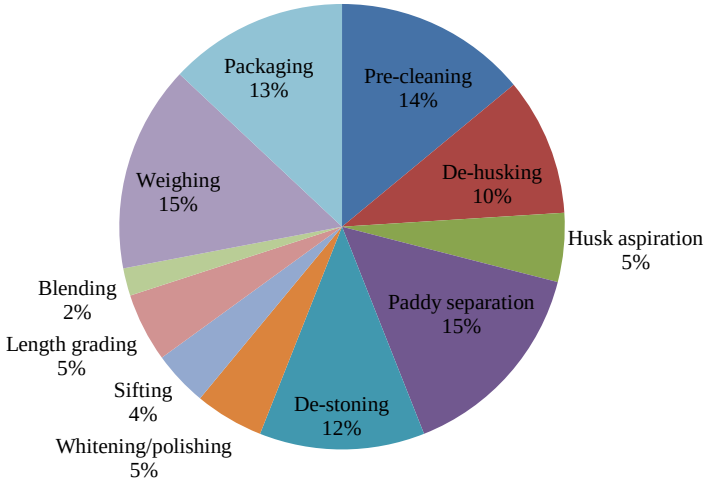


Fig.3. Machines used for modern processed rice

Furthermore, the commonly observed causes of high noise in the rice mills may be due to the use of a long flat belt drive, crank-and-pitman mechanism, absence of an electric motor enclosure, poor machine maintenance, and inadequate acoustic design of the workroom in the rice mill (Paudel & Baral, 2020). Studies have shown that excessive noise exposure can adversely affect human health, including hearing loss and other chronic health conditions (Mansor *et al.*, 2020; Seidman & Standring, 2010). Also, ithas been reported that modern mills emit low carbon compared to traditional mills, which are operated by direct combustion of rice straws and residues (pellets) (Field, Tanger, Shackley, & Haefele, 2016; Wassmann *et al.*, 2021). The water used by a modern rice mill is primarily forcleaning rice; therefore, the overall water usage is generally minimal. However, water used for cleaning purposes in rice mills may carry high levels of phosphorus, nitrogen, and organic matter (Sayanthan & Thusyanthy, 2018). Wastewater from rice mills also contains high levels of inorganic and organic contaminants, posing a hazard to the environment (Kumar & Deswal, 2021). Several chemical constituents present in the effluents from rice mills pose a potential threat to humans if present in high enough concentrations. In 2011, researchers in Thailand reported that rice grains might generate hazardous gases, which can replace oxygen (O_2) in confined spaces (Parnphumeesup & Kerr, 2011; Resanond, Jittsanguan, & Sriphraram, 2011). These gases may contribute to explosions and other severe accidents and adversely affect human health and the environment.

The traditional rice processing method has some environmental effects, too, as observed by the respondents. Using the same rating method in Figure 4 above, Figure 5 showed that about 76% of the respondents indicated that the level of carbon emission from the traditional milling method is high. In comparison, 67% of the farmers identified water use and water pollution as of significant concern. However, only 58% indicated that

solid discharge is of significant concern, while 52% mentioned noise pollution as a concern in traditional rice processing. When compared to the overall weighted average of the environmental effect of the modern methods, the overall environmental effect of the traditional method was 11% higher than the modern methods of rice processing among the respondents. It has been noted that waste generated during the milling process for most traditional millers ends up in streams or rivers. At the same time, some of the wastewater from the mills is releasedinto the environment without proper treatment (Rasheed *et al.*, 2020). Using outdated milling machines also leads to higher particulate matter emissions and greenhouse gases, such as methane and carbon dioxide (Motevali, Hashemi, & Tabatabaeekoloor, 2019).

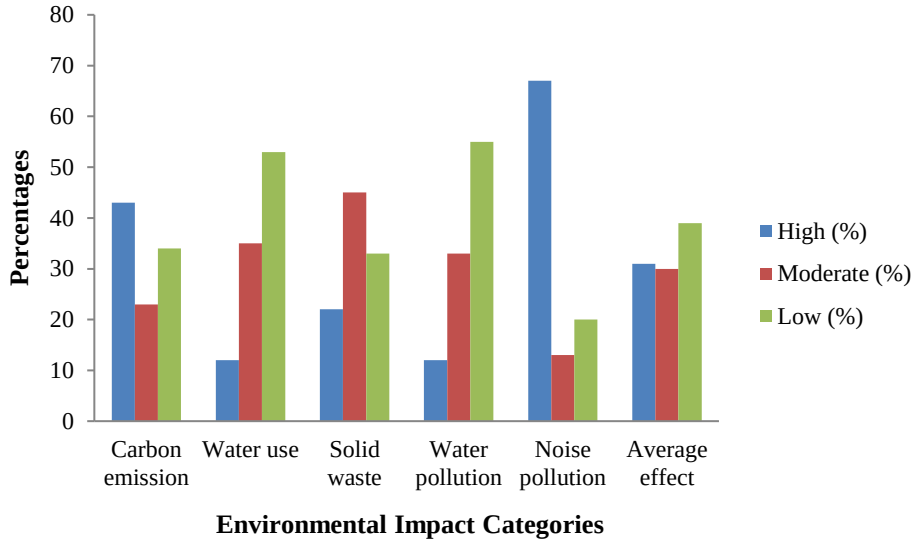


Fig.4. Environmental effects of modern processed rice

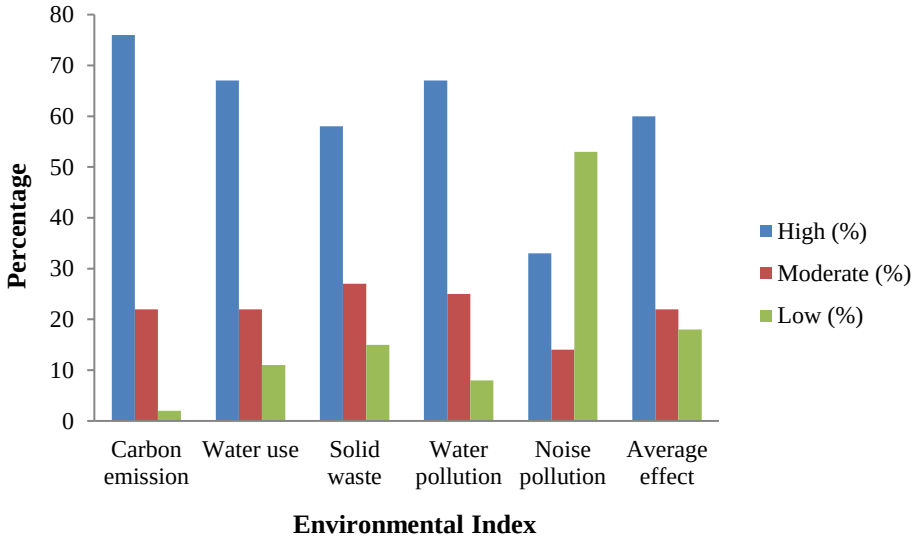


Fig. 5. Environmental effects of traditional rice processing technique

Farmers have reported that wastewater from their rice milling activities can reach the watercourses, thereby polluting the water sources and affecting the local people's health

(Akiwumi, 2019; Njoku, Nwali, & Ajana, 2017). Solid waste is a significant concern among rice farmers,as it is frequently dumped into the soil without proper treatment, resulting in soil degradation and loss of fertility (Nwachukwu, Ikeagwuani, & Adeboje, 2021; Ulakpaa & Eyankwareb, 2021).

This finding shows that farmers need to incorporate more sustainable practices into their operations by switching to eco-friendly and sustainable practices. Consequently, there is a decline in traditional mill operations, leading to the acquisition of more efficient and quieter equipment. Additionally, enhanced water management practices and reduced carbon emissions are achieved through better waste management. Farmers, therefore, should be open to learning new practices that could improve their agricultural operations and find ways to lower the cost and risk involved in implementing these new sustainable practices in their business operations, such as the utilization of improved equipment and machinery, allowing them to increase productivity while reducing their production costs and negative environmental impact (Vogel *et al.*, 2020).

The sustainability index of the traditional and modern rice milling methods

The sustainability index in wireframe contour plots (Figure 6), following the index computed by applying equation 5, shows that small-scale farmers using the traditional rice milling method care about the environment, with 80-100 percent willing to reduce their gas emissions, solid waste, energy use, and water use. At the same time, profit increases, an aspect of business sustainability.

From Figure 6, the average sustainability score of the rice farmers is 60 percent, which shows a moderate level of concern for the UN Sustainable Development Goals (Acosta, Maharjan, Peyriere, & Mamiit, 2020; Gil *et al.*, 2019). This finding shows that they need to improve their business and organizational sustainability and incorporate more sustainable practices into their operations. By reducing the number of traditional mill processes, investing in more efficient equipment, improving water management, reducing carbon emissions through better management of their waste, switching to eco-friendly and sustainable practices, and investing more time and planning on how to lower the cost of production. Collaborate with local environmental agencies to improve farm pollution management while maintaining good profit margins, and partner with other small-scale farmers. Moreover, a similar business model can help build a strong community that supports each other's ventures (Donner, Verniquet, Broeze, Kayser, & De Vries, 2021; Inman *et al.*, 2018; Sarkis, Cohen, Dewick, & Schröder, 2020; Zucchella & Previtali, 2019). To improve their overall sustainability score, small-scale farmers should be open to learning new practices that could improve their agricultural operations and find ways to lower the cost and risk involved in implementing these practices in their business operations, such as the utilization of improved equipment and machinery that would allow them to increase productivity while reducing their production costs and the reliance on manual labor and emissions (Vogel *et al.*, 2020).

The sustainability index in wireframe contour plots (Figure 7), derived by applying equation 5, shows that small-scale farmers use the modern method of rice milling. The small-scale farmers have a percentage of 80-100 focusing on environmental sustainability indicators such as energy and water use. Their organizational and business sustainability index indicates a high percentage for profit, investment, cost management, and long-term planning. The concern for carbon emission and solid waste was 20-40 percent. Their sustainability index focuses on environmental sustainability indicators, such as energy and water use. The sustainability index of the small-scale farmers using the modern method of rice milling shows a percentage above 80. According to researchers, modern rice processing is more economically and environmentally sustainable than manual rice processing (Devkota *et al.*, 2020; Kosemani & Bamgboye, 2020).

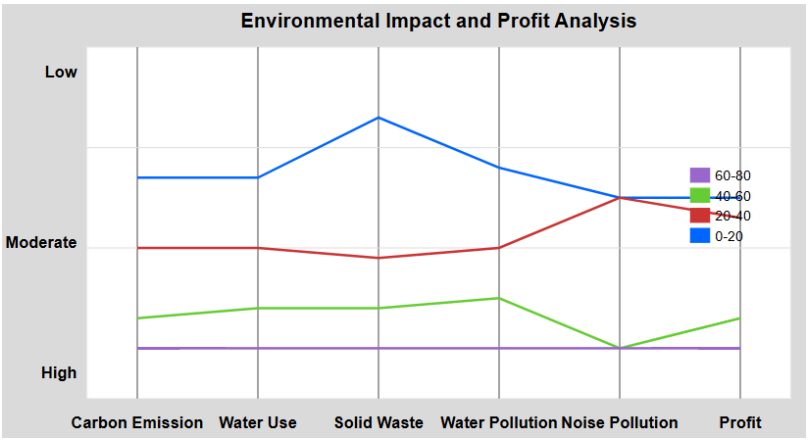


Fig. 6. Wireframe contour plots of the sustainability index of traditional processing technique

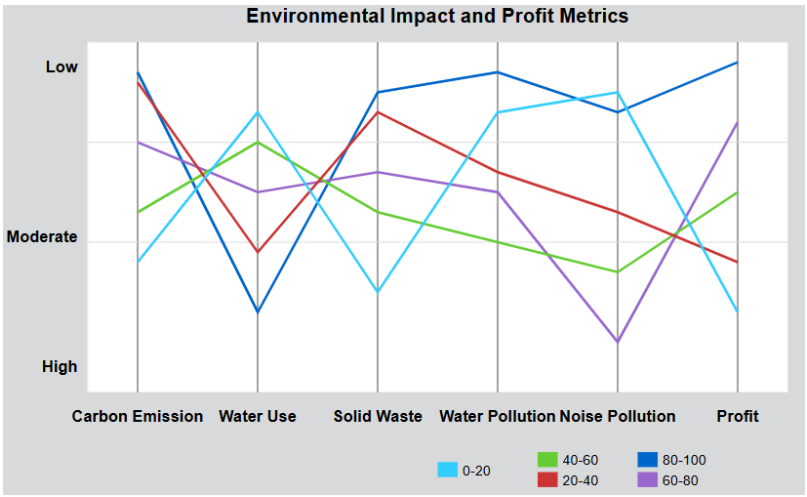


Fig.7. Wireframe contour plots of the sustainability index of modern processing technique

Factors affecting the sustainability index of paddy rice processing

Applying equations 1 and 2, the observed variables that might have an impact on the long-term viability of paddy rice processing are shown in Table 2. The distribution shows that the model's chi-square probability (124.93) was statistically significant at 1%. The independent variables that were included in the model had significant effects, leading to the rejection of the null hypothesis. So, we agree with the alternative theory that the independent factors that were included had a big impact on the dependent variable. The strength of the model is indicated by the Cox and Snell, McFadden, and Nagelkerkepseudo R-square values, which are 0.75, 0.853, and 0.656, respectively. This indicates that the collection of variables included in the model accounts for between 75.0, 85.3, and 65.6 percent of the variability. The model is 98 percent accurate, according to the proportionate by chance accuracy rate (Bayaga, 2010). The likelihood ratio test evaluates the overall relationship between the dependent and independent variables (Bayaga, 2010).

The gender (sex) of the small-scale farmers using the traditional rice mills was statistically significant at 1% and positively related to the level of sustainability. Gender has long been recognized as an essential factor in the production process of small-scale rice farmers in developing regions, where each gender has unique roles and responsibilities. These gender roles create significant advantages and disadvantages for female small-scale farmers of rice-growing communities in their

understanding and choice of sustainability practices. The heavy responsibilities placed on women contribute to the low participation rate of women in agriculture, making them less likely to adopt environmentally sustainable practices such as composting, not using chemicals, and planning the rice mill business. However, women tend to have a better understanding of household issues and are more likely to educate their children about environmental issues; they can be the driving force behind the adoption of sustainability practices and play a vital role in advancing environmental sustainability in their communities.

The traditional rice milling experience of the small-scale farmers was statistically significant at the 1% and positively related to the level of sustainability (see Table 2). The correlation between sustainable rice production and small-scale farmers' experience in the rice mills' production management is significant (Bello *et al.*, 2021). The experience of the rice producers in milling their rice at the mill is significant in the rice farming process because this is a critical process that contributes to the quality of rice and the sustainability of the process and environment. Improving small-scale farmers' experience and skill level in milling rice will create a better environment for sustainable rice production. Improved experience will make the production process more sustainable for farmers and improve the quality of the produced rice.

The labor size of the small-scale farmers using traditional rice mills was statistically significant at the 1% and positively related to the level of sustainability, as presented in Table 2. This finding is because, as the labor size increased, the efficiency in using energy in small-scale farms also increased (Stępień *et al.*, 2021). As a result, small-scale farmers could harvest more paddy from the land and process them, increasing rice production. In contrast, when the labor size decreased, the efficiency of the small-scale farmers in terms of energy consumption also fell, causing a drop in the sustainable production of rice. This finding can be attributed to the fact that farmers who use smaller quantities of laborers cannot achieve maximum efficiency of inputs in their operations, which affects the sustainability of their production (Dahlin & Rusinamhodzi, 2019; Houedjofonon *et al.*, 2020). However, the labor size of small-scale rice farmers using traditional mills also affects environmental sustainability. This finding is because the energy and manpower-intensive nature of the traditional rice milling processes means that the farmers will consume a small amount of non-renewable energy sources and high raw materials such as land and water. Non-renewable energy is the leading cause of climate change, and reducing the quantity used will improve environmental sustainability (Khan, Trinh, Khan, & Ullah, 2022). However, these resources are limited and cannot be replenished by natural means. Therefore, it is vital to use these resources responsibly to preserve the environment for future generations.

The investment of the small-scale farmers using traditional rice mills was statistically significant at the 1% and positively related to the level of sustainability, as shown in Table 2. This finding implies that the investment the small-scale farmers make increases the sustainability of the farmers using traditional rice mills. Based on the findings of Ritthaisong, Johri, and Speece (2014), investment in the mills results in the economic sustainability of the rice milling business. Jirapornvaree, Suppadit, and Kumar (2021), reported on the impacts of the sustainable production of jasmine rice. They concluded that the investment in modern rice mills positively impacts the environmental and economic sustainability of rice farming enterprises in Indonesia. The income of the small-scale farmers using traditional rice mills was statistically significant at 10% and negatively related to the level of sustainability, as presented in Table 2. This result implies that the income of small-scale farmers negatively affects their sustainability practices. Some reports are similar to our findings that income affects sustainability practices adversely (Ndayambaje *et al.*, 2019;

Olanipekun, Olasehinde-Williams, & Alao, 2019; Ojo & Baiyegunhi, 2020b). A study by Qadir *et al.* (2014) found in their research that as the income of farmers increased, the adoption of sustainable land management practices decreased. The study also found a negative relationship between household income and sustainability. Several reasons may explain this relationship between income and sustainability. Krishnankutty, Blakeney, Raju, and Siddique (2021) found similar results to our study, where lower-income farmers were less proactive in their agricultural management processes. In our study, we hypothesized that as the level of income increases for farmers, they would adopt more sustainable agricultural practices. However, Krishnankutty *et al.* found that this was not the case; instead, as income levels increased, sustainable practices decreased.

The cost of production was statistically high at 1% and negatively related to the level of sustainability. This result implies that the production cost impedes small-scale farmers' ability to adopt sustainability practices. Some researchers reported that higher production costs resulted in a lower adoption of sustainable practices by small-scale farmers in developing countries (Samson *et al.*, 2018). This finding is primarily due to the higher input costs required to implement and maintain sustainable agriculture and processing systems by rice farmers compared to conventional agriculture systems. In addition, most smallholder farmers are low-income earners who find investing in costly sustainable practices that improve socioeconomic well-being challenging. Thus, the long-term impact of adopting cost-reducing and sustainable practices on agricultural production is hard to predict due to the short-term costs associated with adopting such practices by rice farmers. Nonetheless, the long-term economic benefits of farmers' large-scale adoption of sustainable farming practices and food processing technologies would be significantly higher as it would contribute towards reducing the dependence on expensive chemicals.

Table 2- Factors affecting the sustainability index of the traditional rice processing technique (Equation 2)

Power of classification of the sustainability index of the traditional milling process				
	High	**Moderate**	**Low**	**Percent correct**
High	43	8	14	100
Moderate	23	15	10	95
Low	16	7	15	96
Overall percentage	53	20	25	98

Effect	**Model Fitting Criteria**	**Likelihood Ratio Tests**	
	-2 Log Likelihood of Reduced Model	**Chi-Square**	**p-value**
Intercept	67.896	2.251	0.025
Education level	22.134	0.612	0.462
Sex	70.775	5.131	0.001
Experience	72.717	7.073	0.000
Labor size	84.561	9.3321	0.000
Investment	72.214	6.57	0.002
Income	-67.536	-1.892	0.043
Cost of production	-73.921	-8.277	0.000
Knowledge of climate change	22.032	1.235	0.881
Perception of economic sustainability	58.036	3.021	0.021
Perception of business sustainability	66.547	2.418	0.075
Cox and Snell	**Nagelkerke**	**McFadden**	
0.75	0.853	0.656	
Chi-square	124.93		

The perception of sustainability was statistically significant at 10% and positively related to the level of sustainability. This result implies that the small-scale rice farmers' perception of economic sustainability promotes the ability of the small-scale farmers to adopt sustainability practices.

Equations 3 and 4 were used to obtain the result in Table 3. The distribution shows that the model's chi-square probability (89.254) was statistically significant at 1%. Therefore, the independent variables included in the model were significant effects, and the null hypothesis was rejected. So, we agree with the alternative theory that the independent variables that were included have a significant impact on the dependent variable. The model's strength is indicated by the pseudo R-square values of Cox and Snell, McFadden, and Nagelkerke, which are 0.65, 0.78, and 0.55, respectively. It indicates that the set of variables used in the model accounts for between 65.0, 78, and 55 percent of the variability. Therefore, the model is 98 percent accurate, according to the proportional by chance accuracy rate (Bayaga, 2010).

The level of education of the small-scale farmers using modern rice processing was statistically significant at 1% and positively related to the level of sustainability, as shown in Table 3. This result implies that the skills and training acquired, especially through collaboration with aid extension agents and information communication technologies by small-scale farmers using modern rice processing, positively impacted sustainability (Anugwa, Onwubuya, Chah, Abonyi, & Nduka, 2022). Rahman (2003) reported that when the education level was high, more farmers used modern rice processing than farmers with low education levels. Farmers with high education levels are more aware of the importance of adopting sustainable production practices such as modern rice processing because they are better informed about technological advances in agriculture and are more knowledgeable about the production and marketing of agriculture. On the other hand, low-education farmers tend to use traditional farming methods because they are unaware of the benefits of using modern rice processing methods (Amponsah, Addo, Dzisi, Asante, & Afona, 2018).

The modern rice milling experience of the small-scale farmers was statistically significant at 1% and positively related to the level of sustainability. Farmers utilizing modern rice processing techniques are embracing more sustainable practices. There are three main reasons for small-scale farmers in Nigeria choosing to adopt modern rice milling technologies over traditional rice processing techniques (Adisa, Ahmed, Ebenehi, & Oyibo, 2019; Obisesan, Salman, Adenegan, & Obi-Egbedi, 2018). Firstly, adopting new technologies reduces the time and effort involved in rice processing, ensuring that the rice is produced sustainably. Secondly, modern rice processing techniques produce better-quality rice (Joshi *et al.*, 2020). Thirdly, the high initial cost of adopting new machinery can be recovered through increased production. Therefore, small-scale farmers can improve their productivity and profitability by choosing the right rice processing technology.

The labor size of the small-scale farmers using modern rice processing was statistically significant at 1% and negatively related to the level of sustainability. Therefore, the smaller the labor size, the higher the sustainability level (Ahmed, Saha, Sarkar, & Alam, 2022). The sustainability index analysis strongly suggested that the level of sustainability was higher when the labor size of the farmers using modern rice processing was less than three laborers per hectare of paddy field. Therefore, indicating that optimizing labor size is crucial for enhancing sustainable agricultural practices among small-scale rice farmers.

The investment of the small-scale farmers using modern rice mills was statistically significant at 1% and positively related to the level of sustainability. The first contributing factor towards the sustainability of the small-scale farms that used the modern rice mill was their access to modern equipment through

increased investments. There was a strong correlation between the accessibility to modern equipment and the level of sustainability in the agricultural sector (Kumari & Garg, 2021). Farmers with more modern machinery were more likely to achieve higher yield levels and better production efficiency when compared to those who did not have access to such machinery. As a result, these farmers could produce large quantities of rice for market sale with minimal cost and effort.

Modern rice processing has been recently gaining popularity as an environmentally friendly process. The processors use several techniques to reduce the water and energy needed to process rice. These techniques are washing, drying, threshing, and milling. The income of the small-scale farmers using modern rice mills was statistically significant at 10% and positively related to the level of sustainability. This finding suggests that farmers who invest in higher-efficiency equipment tend to produce greater profits than those who stick with traditional equipment. This effect is likely due to economies of scale in processing, i.e., as production increases, it becomes easier to maximize efficiency and increase profit. When assessing the sustainability of farming operations, it is crucial to consider both costs and benefits because increased production may carry hidden costs such as pollution or depletion of natural resources. In the case of modern rice processing, most of the machinery used is low-cost items that can be built by the owner or purchased with a small loan.

The cost of production, or the amount that a producer must expend to produce a unit quantity of rice, is statistically high at 1% and negatively related to the level of sustainability of the rice farmer using a modern method of rice processing. This finding means that as the cost of production increases, a farmer's sustainability level decreases. However, this relationship could be stronger. Therefore, other factors, such as the amount of rice produced per harvest and the cost to the farmer of his machinery, may be more important than the cost of production in determining the sustainability of the rice farmer. The other major factor that affects the sustainability and profitability of the rice farmer is the quality of the rice he produces.

The farmers' perception of economic sustainability was statistically significant at 10% and positively related to the sustainability of modern rice processing (see Table 3). This result implies that the perception of the farmers on the economic sustainability of modern rice processing is correlated with the level of its sustainability (Escobar *et al.*, 2022). On the other hand, the study showed that the technical complexity of modern rice processing is not significantly related to the perception of the farmers on its economic sustainability. In other words, the level of technological complexity does not affect the reliability of the output generated by the system in its effort to earn a living for the farmers and sustain their business in the long run.

This finding explored the farmers' perception of organizational sustainability using modern rice processing. The farmers' perception of organizational sustainability was statistically significant at 10% and positively related to the sustainability of farmers using modern rice processing. Based on the results of this study, there is a positive relationship between organizational sustainability and the level of technical innovation in an organization. Hence, the need to develop more sustainable organizations in the agricultural sector. This study shows a relatively close but not strict link between farmers' perceptions of their farms' sustainability and their rice processors' technical innovation. However, stronger relationships may exist between farmers' perceptions of the sustainability of their farms and the levels of the organization's environmental performance, as well as how they implement new technologies to improve sustainability.

Table 3- Factors affecting the sustainability index of the modern rice processing technique (Equation 4)

Power of classification of the sustainability index of the modern milling process				
	High	**Moderate**	**Low**	**Percent correct**
High	25	5	5	98
Moderate	12	11	2	96
Low	14	3	1	100
Overall percentage	63	25	10	98

Effect	**Model Fitting Criteria**	**Likelihood Ratio Tests**	
	-2 Log Likelihood of Reduced Model	**Chi-Square**	**p-value**
Intercept	55.801	2.601	0.045
Education level	85.248	7.541	0.0001
Sex	23.214	0.124	0.632
Experience	59.214	4.214	0.00341
Labor size	32.124	2.457	0.054
Investment	99.215	10.254	0.000155
Income	25.214	2.413	0.012
Cost of production (excluding cost of energy)	-45.214	-3.241	0.012
knowledge of climate change	42.013	3.417	0.024
Knowledge of economic sustainability	58.036	3.021	0.0214
Knowledge of business sustainability	78.215	6.275	0.000125

Cox and Snell	**Nagelkerke**	**McFadden**
0.65	0.784	0.551
Chi-square	89.254	

Conclusion

1. Small-scale rice farmers prefer traditional processing. The traditional approach was chosen due to the expensive cost of modern processing machines, which have a higher output than the traditional method.
2. While the nutritional content of rice processed using traditional techniques was deemed superior, farmers recognized the appearance of rice produced by modern methods as the most outstanding. The farm employsthe modern technique using different machines for rice processing, which impacts the environment; carbon emission levels and noise pollution were the significant environmental impacts of the modern rice processing technique.
3. The traditional technique of rice processing released high carbon into the environment, resulting in high water usage and, consequently, water pollution. The farmers who use the traditional technique care for the environment by reducing carbon emission energy and water use, while the farmers that use the modern technique care for the environment by reducing their water and energy use significantly.
4. Factors such as gender experience, labor size, investment, income, cost of production, knowledge of climate change, and business economic sustainability were the significant factors that influenced the farmers using the modern and traditional rice processing techniques to have a sustainability index.
5. The education level of the farmers and their knowledge of sustainability practices prompt them to prefer modern technology to traditional techniques.

Recommendation

There is a need to make recommendations based on the findings.

The Government needs to develop a

support program to reduce the cost of acquiring the machines required to use a modern rice processing technique. It will reduce the production cost of the farmers. Alternative energy sources need to be explored to reduce the impact of high carbon emissions on the environment.

Farmers should be educated about the value of using renewable energy sources to improve production and the environmental impact. The use of more modern machinery for paddy rice production should be encouraged to improve the output and quality of rice produced and reduce production costs.

Farmers should be encouraged to adopt modern farming techniques to reduce the impact of chemicals on the environment and adopt improved techniques to produce high-quality, healthy produce that satisfies consumer demands. Measures should be taken to reduce the waste from food processing. Incentives should be provided to encourage the use of renewable energy and reduce the use of fossil fuels in production. The use of modern technology needs to be encouraged in order to increase production and decrease costs.

Conflict of Interest: The authors declare no conflict of interest.

Authors Contribution: The authors made equal contributions.

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نشریه ماشین‌های کشاورزی
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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱۴۰۴، ص ۳۶۱-۳۳۷

بررسی پایداری روش‌های سنتی فرآوری برنج در میان کشاورزان خرد برنج در جنوب شرق نیجریه

چیگوزیریم اونوسیریبه [۱*]، جود مباناسور [۱]، فیلیپس اِنتو [۱]، مک‌مانِس اندوکوو [۲]

تاریخ دریافت: ۱۴۰۳/۰۵/۰۸
تاریخ پذیرش: ۱۴۰۳/۰۸/۰۹

چکیده

برنج یکی از غذاهای اصلی در سراسر جهان است، اما فرآوری آن به دلیل مصرف آب و انرژی و انتشار گازهای گلخانه‌ای، اثرات قابل‌توجهی بر محیط‌زیست دارد. در نتیجه، تولیدکنندگان برنج سعی می کنند روش‌های فرآوری پایدار را برای کاهش اثرات منفی زیست‌محیطی و افزایش سودآوری اتخاذ کنند. این مطالعه میزان پایداری روش‌های فرآوری برنج شالیزاری (شالی) مدرن و سنتی را در میان کشاورزان خرده‌مالک شالیکار در جنوب شرق نیجریه تحلیل می‌کند. داده‌ها از ۲۴۰ تولیدکننده برنج با استفاده از رویکردهای آماری مانند آمار توصیفی، شاخص پایداری (تحلیل نسبت ارزیابی وزن‌دهی) و تحلیل رگرسیون چندجمله‌ای جمع‌آوری شد. نتایج نشان داد که ۳۴/۷ درصد از کشاورزان شالیکار از روش‌های نوین و ۶۵/۳ درصد از روش‌های سنتی فرآوری استفاده می‌کردند. از نظر ۷۷ درصد کشاورزان خرده مالک، آسیاب کردن سنتی باعث انتشار میزان قابل‌توجهی گاز کربن می‌شود و همچنین ۶۸ درصد کشاورزان آلودگی صوتی را در حد بالایی ارزیابی می‌کنند. ۸۰ تا ۱۰۰ درصد کشاورزان خرده مالک که از تکنیک‌های مدرن استفاده می‌کنند به محیط‌زیست اهمیت می‌دهند و می‌خواهند انتشار گاز، زباله‌های جامد، مصرف انرژی و مصرف آب خود را کاهش دهند. شاخص پایداری در کشاورزانی که از روش‌های فرآوری سنتی یا مدرن استفاده می‌کنند تحت‌تاثیر جنسیت، تعداد نیروی کار، سرمایه‌گذاری، درآمد، هزینه تولید، میزان درک تغییرات آب و هوا و پایداری محیطی قرار می‌گیرد. این مطالعه استفاده از منابع انرژی تجدیدپذیر را برای افزایش بهره‌وری و کاهش اثرات زیست‌محیطی توصیه می‌کند.

واژه‌های کلیدی: آلاینده، اثرات زیست‌محیطی، انتشار گازهای گلخانه‌ای، سوددهی، سرمایه‌گذاری، مصرف انرژی

۱- دانشکده کسب‌وکارهای کشاورزی و مدیریت، دانشگاه کشاورزی مایکل اوکپارا، ایالت آبیای نیجریه
۲- دانشکده مهندسی کشاورزی و منابع زیستی، دانشگاه کشاورزی مایکل اوکپارا، ایالت آبیای نیجریه
(*- نویسنده مسئول: Email: onwusiribe.chigozirim@mouau.edu.ng)

https://doi.org/10.22067/jam.2024.89115.1267

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 363-377

Evaluating the Effect of Soil Deformation Rate on the Estimation of the Energy Consumption in Soil-Tire Interactions Using the Pressure-Sinkage Equation

H. Asadollahi [1], B. Mohammadi-Alasti [1*], A. Mardani [2], M. Abbasgholipour [1]

1- Department of Mechanical Engineering of Biosystems, Bon.C., Islamic Azad University, Bonab, Iran
2- Department of Mechanical Engineering of Biosystems, Faculty of Agriculture, Urmia University, Urmia, Iran
(*- Corresponding Author Email: behzad.alasti@iau.ac.ir)

Received: 02 August 2024
Revised: 15 October 2024
Accepted: 20 October 2024
Available Online: 31 May 2025

How to cite this article:
Asadollahi, H., Mohammadi-Alasti, B., Mardani, A., & Abbasgholipour, M. (2025). Evaluating the Effect of Soil Deformation Rate on the Estimation of the Energy Consumption in Soil-Tire Interactions Using the Pressure-Sinkage Equation. *Journal of Agricultural Machinery*,*15*(3), 363-377. https://doi.org/10.22067/jam.2024.89154.1269

Abstract

Understanding soil deformation dynamics is critical in various fields, such as off-road vehicle mobility, agriculture, and soil mechanics. In particular, evaluating soil-tire interactions is essential for optimizing energy consumption and minimizing the negative effects of soil compaction. This study investigates the effect of soil deformation rates on the pressure-sinkage relationship and energy consumption using a controlled soil bin environment and a bevameter system. The primary objective of the study is to examine how different traffic levels and varying penetration rates influence the energy required to achieve specific sinkage depths. The study employed a completely randomized block design, with each treatment replicated three times to ensure precision and reliability. Quantitative measurements were obtained using a load cell attached to a bevameter, capturing the forces at a sampling frequency of 30 Hz. Results demonstrated a significant influence of both traffic level and penetration velocity on soil resistance and energy consumption. For the larger plate, the pressure required for penetration increased with higher velocities and traffic levels. At the highest velocity (45 mm s^{-1}) and with 8 passes, the pressure needed for sinkage was maximal. The energy consumption for each scenario was calculated by integrating the area under the force-sinkage curve. The analysis of variance (ANOVA) revealed that the number of wheel passes, plate size, and penetration velocity significantly affected energy consumption. At the highest sinkage depth (60 mm), the energy consumption for the larger plate at 45 mm s^{-1} and with 8 passes was nearly double that of the smaller plate. These results emphasize the importance of considering both traffic-induced compaction and velocity when designing off-road vehicles or agricultural machinery that interact with deformable terrains.

Keywords: Bevameter, Penetration rate, Soil deformation, Terramechanics, Multiple passes

Introduction

The understanding of soil deformation holds paramount importance in various fields, such as soil mechanics, traction theory, soil compaction, and sustainable agriculture practices. The dynamics of soil deformation are inherently complex, particularly when considering the interaction between off-road vehicles and soil, which typically exhibits dynamic behavior (Golanbari & Mardani, 2024; Majdoubi, Masmoudi, & Elharif, 2024). The quality of soil deformation is influenced by factors such as load parameters, device

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https://doi.org/10.22067/jam.2024.89154.1269

geometry, and the dynamic characteristics of soil interaction (Golanbari & Mardani, 2023; Taheri & Tatsuoka, 2015). Moreover, an in-depth study of soil deformation dynamics is indispensable for practitioners, such as agricultural workers and off-road vehicle operators, who encounter diverse and often unfamiliar terrain conditions during their operations (Gonzalez & Iagnemma, 2018). The main advantage with a bevameter is that it is designed to measure several parameters with the same equipment (Mardani & Golanbari, 2024). Earl and Alexandrou (2001) used a tractor-mounted bevameter for outdoor measurement of soil pressure-sinkage parameters using three different shapes of pressure plates.

The study conducted by Taghavifar and Mardani (2014) investigated the influence of tire characteristics on energy consumption management in terramechanics. They utilized a soil bin facility under controlled conditions and examined the effects of tire vertical load, velocity, and tire inflation pressure on energy consumption. In contrast with earlier literature reports, their findings revealed discrepancies regarding the impact of tire parameters on wasted energy and rolling resistance.

The complex influence of diverse factors on pressure-sinkage relationship, particularly across varied penetration rates and probe sizes, was explored in the study conducted by Apfelbeck, Kuß, Rebele, and Schäfer (2011). The importance of these variables in determining the optimal testing conditions necessary to validate soil contact models for specific wheel types under defined operational parameters was highlighted in their study.

Schematic diagrams are utilized to illustrate the dynamic forces involved in off-road wheel mechanics, facilitating a comprehensive understanding of the phenomenon. Fig. 1 depicts the gross traction (GT), which can be calculated as the summation of the net traction (NT) and the rolling resistance (RR) forces (ASAE Standard S296.5, 2018).

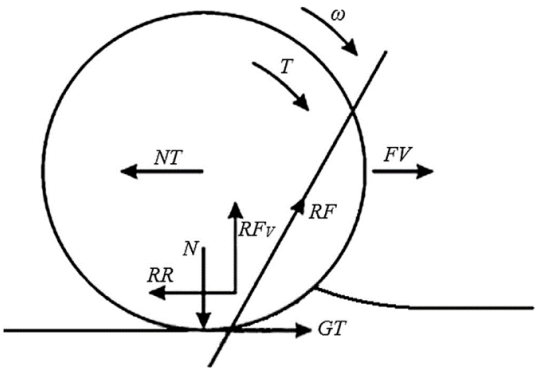


Fig. 1. Illustration of the fundamental forces and velocities acting upon a wheel, encompassing the resultant soil reaction force

It is notable that, to set the wheels in motion, the torque generated by the engine is used to create traction so that the rolling resistance is neutralized. Additionally, Bekker established the basis for quantifying rolling resistance from a mechanical soil strength perspective. He proposed that at the tire-soil contact area, the wheel acts like a continuously penetrating plate to a depth equal to the rut depth formed by the wheel's load. Equations 1 and 2 were introduced to calculate the average pressure applied to the soil from a plate pressed into the soil as a function of sinkage depth (Z), and the energy loss of the process, respectively, as outlined by Bekker (1969).

$$P_{ave} = \left(\frac{k_c}{b} + k_\varphi\right).Z^n \quad (1)$$

$$W_o = l\frac{(k_c + bk_\varphi)}{n+1}\left[\frac{F}{l(k_c + bk_\varphi)}\right]^{\frac{n+1}{n}} \quad (2)$$

Eq. 2 is used to theoretically calculate the

work required for penetrating a plate into soil, where W_0 represents the work done by the load of F (kN) acting on the plate at the maximum sinkage depth of Z_0. Furthermore, this equation encompasses pivotal factors such as soil sinkage coefficients (k_c and k_ϕ), plate width (b) and length (l), and a sinkage exponent (n) derived from sinkage tests.

However, this oversimplified explanation only scratches the surface of the complex phenomenon known as rolling resistance. Recent research has delved deeper into understanding the factors influencing rolling resistance, particularly focusing on tire characteristics. In a notable experiment conducted by Taghavifar and Mardani (2013), the relationship between tire characteristics and rolling resistance was thoroughly investigated. Their study emphasized the crucial role of the contact area in determining rolling resistance, proposing it as a practical metric for quantifying this phenomenon.

The primary objective of this study is to evaluate the effects of varying soil deformation rates on pressure distribution and energy consumption during interactions with different plate sizes in a controlled environment. Specifically, this research aims to assess how different traffic levels (no pass, 4 passes, and 8 passes) and varying penetration velocities (15 mm s^{-1}, 30 mm s^{-1}, and 45 mm s^{-1}) affect soil compaction and resistance at different sinkage depths. By analyzing the energy consumption patterns and pressure-sinkage relationships, this study seeks to provide deeper insights into the mechanical behavior of soils under repeated loads. The findings aim to enhance models of soil-structure interactions for applications in off-road mobility and agricultural machinery.

Materials and Methods

For the measurement of soil parameters, a 200 kg capacity S-shaped load cell was accurately calibrated and positioned vertically between the sinkage plate and the bevameter shaft. This load cell served as a critical component for accurately quantifying soil resistance. The data obtained from the load cell were transmitted to a data acquisition system, which comprised a data logger, digital indicators, and a laptop. The data transmission occurred at a sampling frequency of 30 Hz, ensuring high-resolution data capture throughout the experiment process.

Fig. 2 provides a visual representation of the system, illustrating the arrangement of the equipment within the soil bin facility.



Fig. 2. Overall configuration of the soil bin



Fig. 3. Tools used for soil preparation: ploughing (top left), rake (top right), leveling board (bottom left), and rolling (bottom right)

Soil preparation

Before conducting the experiments, soil preparation was carried out using loosening and leveling tools (Fig. 3). Table 1 shows some properties of the soil used for the bevameter tests.

In this study, two plates were used to determine the pressure-sinkage relationship. Also, the independent variables of penetration rate and the number of passes, according to Table 1, were considered in performing the experiments.

The soil bin was filled with clay-loam soil to ensure precise experimental outcomes. Various tools, including a harrow, leveler, and roller, were used to meticulously prepare the soil bed within the soil channel, thereby guaranteeing the reliability and accuracy of the experimental results.

Fig. 4 and Fig. 5 illustrate the complete soil bin-mounted bevameter unit, along with the details of its design and construction.

Penetration velocity tests

This study investigates the influence of penetration velocity and tool geometry on soil parameters within bevameter test configurations, alongside the estimation of wasted energy under varying traffic passes. Two distinct rectangular plates are employed for each penetration velocity. Testing procedures contain three penetration velocities, spanning from the maximum attainable velocity of the bevameter to the lower velocities typical of agricultural implements. Each test includes three replications to ensure precision and reliability.

Table 1- Experimental soil texture and properties

Parameter	Value
Sand	35%
Silt	22%
Clay	43%
Moisture content (dry base)	8%
Bulk density	1460 kg cm^{-3}
Young's modulus	0.3 MPa
Poisson's ratio	0.29
Angle of internal friction	32

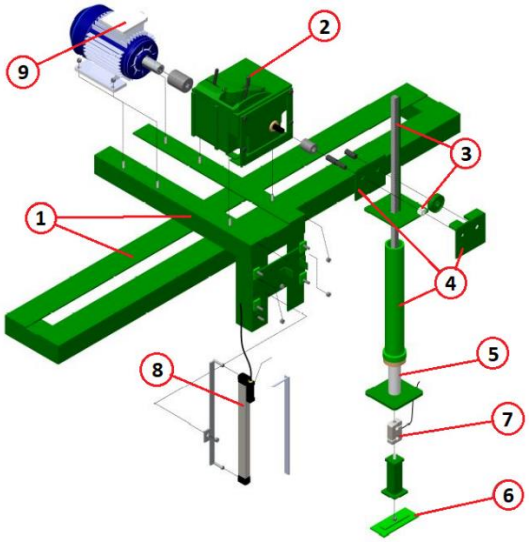


Fig. 4. Construction of the bevameter unit for soil characterization: 1. Chassis, 2. Gearbox, 3. Rail, 4. Support and Guide, 5. Shaft, 6. Bekker Plate, 7. Load cell, 8. Linear Encoder, and 9. 5.5 kW electromotor

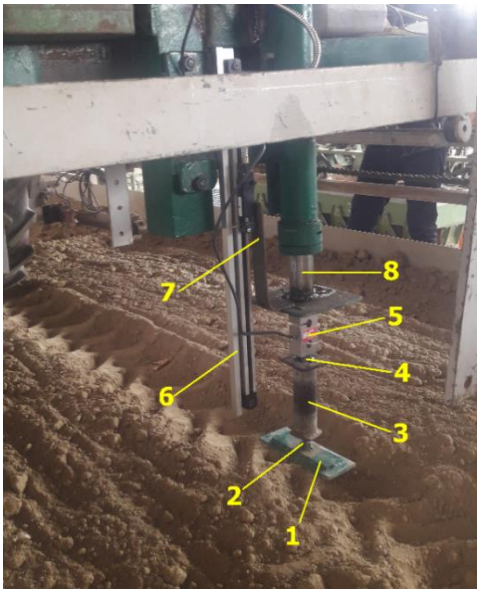


Fig. 5. A photograph of the bevameter mounted on the soil bin chassis: 1. Bekker Plate, 2. Screw, 3. Connection Rod 4. Screw, 5. Load cell, 6. MLC320 Linear Encoder, 7. Connector, and 8. Shaft

To ensure precise collection of rolling resistance data, a soil bin facility was utilized rather than conducting field experiments. This experimental setup provided a controlled environment and allowed for the inclusion of essential equipment such as a wheel carriage, single-wheel tester, bevameter, and various tillage tools along the track. The wheel carriage was propelled by a three-phase, 22 kW electromotor, which was powered by a chain system. Additionally, an inverter was employed to facilitate speed adjustments during testing procedures.

The bevameter system is a comprehensive setup designed to measure and analyze soil behavior under vehicle loads. It consists of various components that work together to ensure accurate and reliable testing results. The chassis and main frame, mounted on the soil bin carrier, provide structural support and stability against mechanical loads. They are constructed using L-shape and rectangular

profiles, ensuring the system's integrity during testing. The power unit of the bevameter applies a vertical load to penetrate the pressure plates into the soil at different sinkage velocities. It includes a three-phase 5 kW electromotor connected to a mechanical jack. The motor's revolution control is achieved through a gearbox and an inverter, allowing for the adjustment of penetration velocity levels. To measure the applied vertical load, an S-type load cell (DBBP, Bongshin, South Korea), with a capacity of 10 kN was used. The load cell can be customized to accommodate various load requirements, providing precise measurements during testing. Additionally, a linear position transducer (MLC320, Atek, Türkiye), with a displacement of 400 mm and a resistance of 4 kΩ is used to measure the vertical displacement or sinkage of the pressure plates. This enables accurate assessment of the plates' penetration depth into the soil. The data acquisition system plays a crucial role in collecting and storing force and displacement data. It incorporates an interface that powers the transducers and processes the output signals in real-time. This interface (Azma120, Abzar Azma, Iran) also facilitates the storage of data in up to 10 different channels as an Excel file on external memory, enhancing data management and analysis capabilities.

The vertical motion of the shaft initiates the displacement of the bevameter probe into the soil. Consequently, load cells are activated, transmitting signals to the data acquisition system. The bevameter test is widely used in soil mechanics to measure the mechanical properties of soil under loading, such as its bearing capacity, pressure-sinkage relationships, and shear strength. This test typically involves pressing a circular or rectangular plate into the soil to evaluate how the soil reacts under varying loads. In performing Bekker bevameter tests, two different plate sizes are used to understand the soil's response at varying surface contact areas (Fig. 6). The test involves applying vertical pressure to the soil through these plates while monitoring the sinkage, which is the depth of penetration into the soil. The primary reason for using two plate sizes in the bevameter test is to evaluate the pressure-sinkage exponent, represented as *n* in Eq. 1, a key parameter in Bekker's pressure-sinkage model. This exponent helps determine the nonlinear relationship between the applied load and the resulting deformation in the soil. Moreover, by comparing the results of the two plate sizes, the cohesion modulus (k_c) and friction modulus (k_φ) of the soil can be estimated (Eq. 1).

Calculation of Soil Parameters Using the Bekker's Method

Following the collection of pressure-sinkage data, Bekker's equations can be expressed separately for each plate, as shown in equations 3 and 4.

$$P_1 = \left(\frac{k_c}{b_1} + k_\varphi\right).{Z_1}^n \quad (3)$$

$$P_2 = \left(\frac{k_c}{b_2} + k_\varphi\right).{Z_2}^n \quad (4)$$

To solve Bekker's equations, the logarithms of these equations can be written as linear equations 5 and 6.

$$logP_1 = nlog(Z_1) + log\left(\frac{k_c}{b_1} + k_\varphi\right) \quad (5)$$

$$logP_2 = nlog(Z_2) + log\left(\frac{k_c}{b_2} + k_\varphi\right) \quad (6)$$

First, by using one of each plate at two different penetration depths, two pressures are obtained. Then by writing two Becker equation relations for these two states and calculating the ratio of the two sides of the relations, *n* is directly obtained as the slope of the line with a similar amount for both plates.

In the next step, by using two Becker equations obtained from two plates with different widths and considering a certain amount of sinkage for each of them (Z_1 and Z_2) and the resulting pressures (P_1 and P_2), a two-equation system with two unknowns in terms of k_c and k_φ will be obtained as:

$$k_c = \frac{(P_1 - P_2)b_1 b_2}{(b_2 - b_1){Z_2}^n} \quad (7)$$

$$k_\varphi = \frac{P_1}{Z_1^n} - \frac{k_c}{b_1} \quad (8)$$

These parameters are essential for understanding the soil bearing capacity and behavior under different loading scenarios.

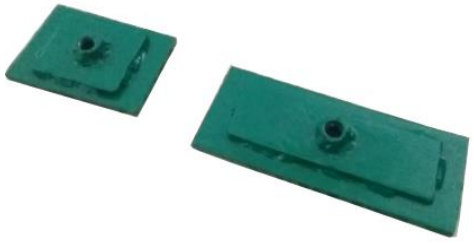


Fig. 6. Sinkage plates with two different sizes (70 × 105 mm and 70 × 175 mm)

Pressure–sinkage tests

The methods for determining soil parameters outlined in the preceding section offer a means to characterize the soil under analysis with dependable values based on the selected pressure-sinkage relationship. Prior to commencing measurement operations aimed at identifying the influence of the test setup on soil parameters, it is imperative to ascertain an appropriate soil preparation method. This ensures the attainment of reproducible and reliable measurement outcomes.

The experiment investigated the impact of different vertical bevameter probe rates (15, 30, and 45 mm s^{-1}), in conjunction with the number of wheel passages (0, 4, and 8), utilizing two sizes of sinkage plates.

Table 2 presents the details of the experimental treatments. The experiments were carried out in a completely randomized block design, with each treatment replicated three times.

Table 2- Summary of experimental parameters

Independent parameters		
Wheel passage	**probe velocity (mms^{-1})**	**Sinkage plates (mm)**
0	15	70×105, 70×175
4	30	70×105, 70×175
8	45	70×105, 70×175

Top of Form

The analysis of variance (ANOVA) was done on the experimental data using Minitab software. Variables were included in the model if they exhibited statistical significance at the 0.01 level. The investigated variables were traffic, probe velocity, and their interaction.

Results and Discussion

Analysis of Variance

The Analysis of Variance (ANOVA) is a statistical method used to analyze the differences among group means and their associated variances. It helps in determining whether there are any statistically significant differences between the means of categorical independent variables affecting a dependent variable. In experimental studies, ANOVA is commonly used to assess the influence of different factors and their interactions on the observed outcomes. It is particularly effective when dealing with multiple factors and levels, as in this study, where multiple variables like plate size, number of passes, sinkage, and penetration rate are evaluated for their effect on energy consumption in soil deformation tests.

In the provided ANOVA table (Table 3), the primary factors affecting the energy consumption and pressure response during soil deformation tests are sinkage, plate size, and number of passes. Among these, sinkage has the most significant impact, as evidenced by its extremely high F-value (4980.76) and a p-value of less than 0.0001. This indicates that changes in the sinkage depth greatly influence the pressure-sinkage relationship and energy requirements. Similarly, plate size and number of passes also show significant effects, with F-values of 1439.35 and 1391.50, respectively, both with p-values less than 0.0001. These findings suggest that larger plate sizes and increased numbers of passes over the soil contribute substantially to increased soil compaction and energy consumption.

Table 3- Analysis of variance of the effect of parameters on energy consumption

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Plate size (mm)	1	33419	33419	1436.17	0.000
Number of passes	2	64616	32308	1388.43	0.000
Sinkage (mm)	3	346934	115645	4969.76	0.000
Penetration rate (mm s^{-1})	2	5301	2650	113.90	0.000
Plate size (mm)×Number of passes	2	5900	2950	126.76	0.000
Plate size (mm)×Sinkage (mm)	3	20356	6785	291.60	0.000
Plate size (mm)×Penetration rate (mm s^{-1})	2	123	62	2.65	0.074
Number of passes×Sinkage (mm)	6	37116	6186	265.84	0.000
Number of passes×Penetration rate (mm s^{-1})	4	1564	391	16.80	0.000
Sinkage (mm)×Penetration rate (mm s^{-1})	6	2866	478	20.53	0.000
Error	184	4282	23		
Total	215	522478			

Furthermore, several interaction effects are also significant. For instance, the interaction between plate size and number of passes ($F = 127.05$, $p < 0.0001$) indicates that the combined effect of these two factors significantly alters the energy consumption. The number of passes and sinkage interaction is also highly significant ($F = 266.43$, $p < 0.0001$), suggesting that the effect of the number of passes becomes more pronounced with increased sinkage depths. Overall, the ANOVA results highlight that these factors and their interactions must be carefully considered to optimize energy consumption and soil resistance in practical applications, such as off-road mobility or agricultural operations.

During the initial stage of plate sinkage, there is observable soil compaction, as illustrated in Figures 7 to 10. In the pressure-sinkage curves, within the range of 0 to 15 mm, compaction remains consistent, showing no significant variation across different penetration rates or pass levels. At this stage, soil compaction occurs directly beneath the plates, and the curve characteristics remain unaffected by the plate dimensions. As sinkage increases, as shown in Fig. 7, particularly between depths of 25 to 60 mm, the pressure-sinkage curves exhibit a consistent and smooth slope. At this point, the rectangular fracture area beneath the loading plate's transitions from a rectangular shape into an incomplete or full cone-shaped form. This transformation occurs due to the initiation of lateral compression and soil flow, which marks the shift of the failure zone into a conical shape.

Fig. 7 illustrates the effect of varying penetration rates (15 mm s^{-1}, 30 mm s^{-1}, and 45 mm s^{-1}) and passage levels (no pass, 4 passes, and 8 passes) on the pressure required to achieve specific sinkage depths. Fig. 7A, with a smaller plate (70 × 105 mm), illustrates a clear trend where the pressure required for penetration increases with higher velocities and passage levels. The graphs obtained from a penetration rate of 15 mm s^{-1} at all pass levels show the minimum pressure required to increase penetration. However, by increasing the number of passes to 4 and 8, the pressure

increases at a higher penetration rate for the same level of sinkage.

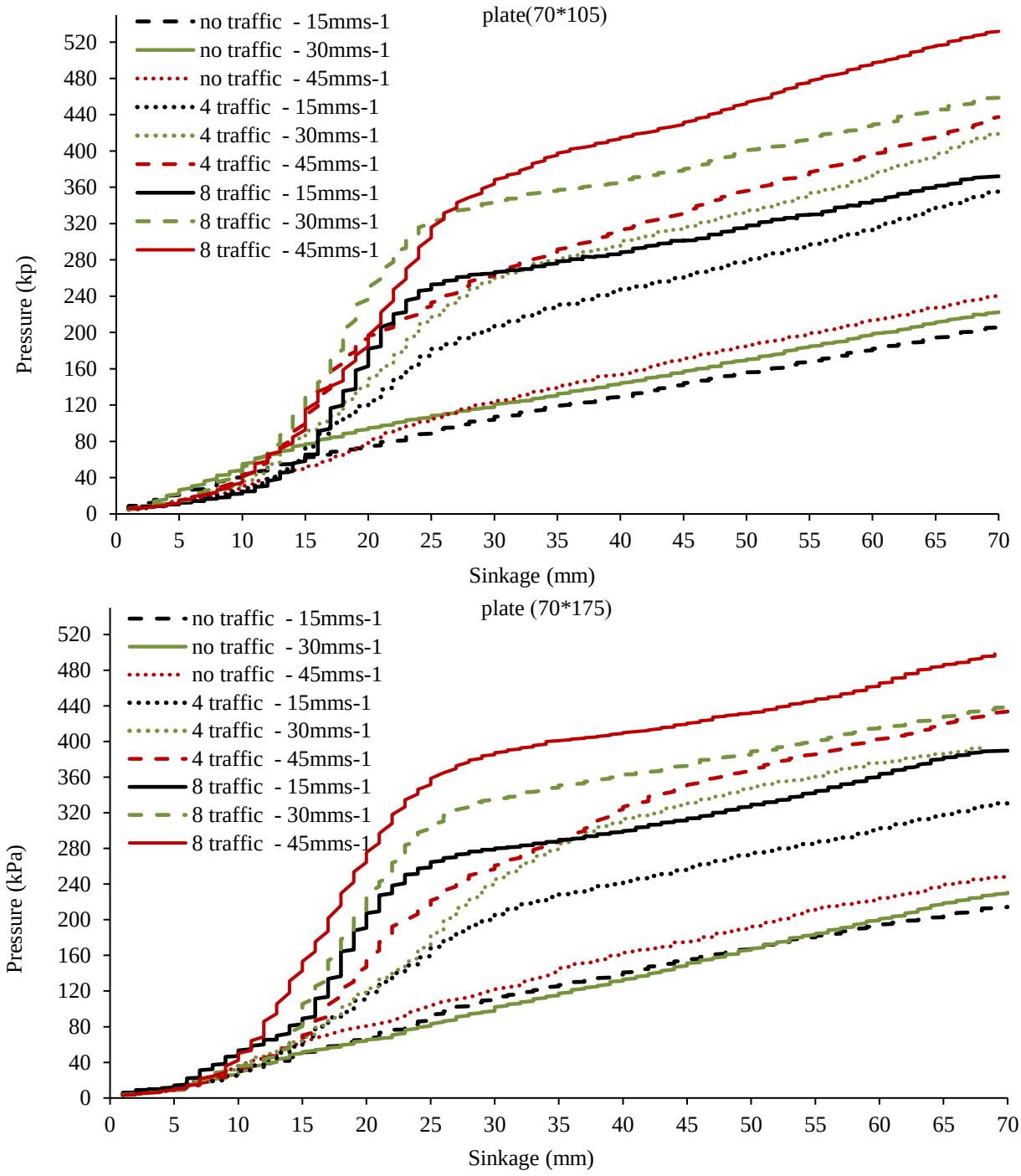


Fig. 7. Pressure-sinkage curves for two different rectangular plates: (A) 70 × 105 mm, and (B) 70 × 175 mm

This change signifies a modification in the soil's initial condition and an enhancement of soil compaction due to repeated loading. The 45 mm/s velocity plots exhibit the highest pressures at all penetration levels, indicating that higher penetration rates require more pressure for a given amount of soil deformation than lower penetration rates.

Fig. 7B shows the resulting soil pressure-settlement curves from the larger plate (70 x

175 mm). The overall trend is similar, but the pressure required for the same amount of sinkage is significantly lower than the smaller plate. This occurs while the force applied to reach a certain sinkage is much higher for the larger plate than for the smaller plate. The stabilization of the sinkage occurs more quickly with a larger plate, suggesting that an increased contact area reduces deformation, even under high-pressure conditions. The pressure difference required for plate penetration between 4 and 8 passes becomes more pronounced when using the larger plate, highlighting the increased compaction pressure with a larger surface contact area. In both graphs, as the penetration rate increases, the pressure required to achieve similar levels of soil sinkage rises across all pass conditions, with the 45 mm s^{-1} penetration rate exhibiting the highest resistance. These findings indicate that larger plate sizes and higher speeds exacerbate traffic-induced soil compaction, making soil deformation under pressure progressively more difficult.

The results of the pressure-sinkage data from the experiments showed a similar trend aligned with research in this field (Brunskill *et al.*, 2011; Golanbari, Mardani, Hosainpour, & Taghavifar, 2023; Kruger, Els, & Hamersma, 2023). This shows that the designed bevameter has significant capability for data acquisition.

To estimate Bekker coefficients (k_c, k_φ, and n), at least two penetration experiments using different lengths of plates are required (Bekker, 1960).

The average soil parameters for three replicates were determined using Bekker's equations presented in Table 4.

As indicated in Table 4, the values of n have an increasing trend with increasing traffic and penetration velocity, and the reason for this is the increase in the slope of the pressure-sinkage curves with the increase of the above two independent parameters.

Table 4- Identified Bekker parameters for different wheel passes and penetration velocities

Pass	**0**			**4**			**8**		
Penetration rate (mm s^{-1})	15	30	45	15	30	45	15	30	45
n	0.973	0.976	1.08	1.243	1.287	1.319	1.223	1.278	1.425
k_ϕ (kN $(m^{n+1})^{-1}$)	620	665	778	808	757	666	913	745	772
k_c (kN $(m^{n+2})^{-1}$)	264.34	211.84	29.40	-47.15	21.77	135.98	153.04	72.45	39.63

The impact of multiple passes on energy consumption

In this section, according to the pressure-sinkage data acquired from the bevameter and the calculation of the area below the pressure-sinkage curves, the cumulative energy consumption of each experiment was extracted in the range of 0-15, 0-30, 0-45, and 0-60 mm of plate sinkage into the soil.

Fig**. 8.** Effect of multiple passes on energy consumption in different depths and constant penetration rate for the 70 × 175 plateFig. 8 illustrates the variation in energy required for the penetration of the large plate into the soil at different depths, corresponding to various penetration rates.

As illustrated in the figure, the general trend in penetration energy for the large plate penetration is similar to that of the small plate. However, as expected, the energy consumption is significantly higher for the large plate due to its larger surface area and higher soil penetration resistance.

The Analysis of Variance (ANOVA) examining the effect of parameters on energy consumption at a fixed penetration rate, using a completely randomized design, is presented in Table 4. The results indicate that the number of passes has a statistically significant effect on energy consumption across all depth intervals for both plate sizes. Significance was determined at the 1% level for most depths, except the 15 mm sinkage depth of the small plate, where significance was observed at the 5% level.

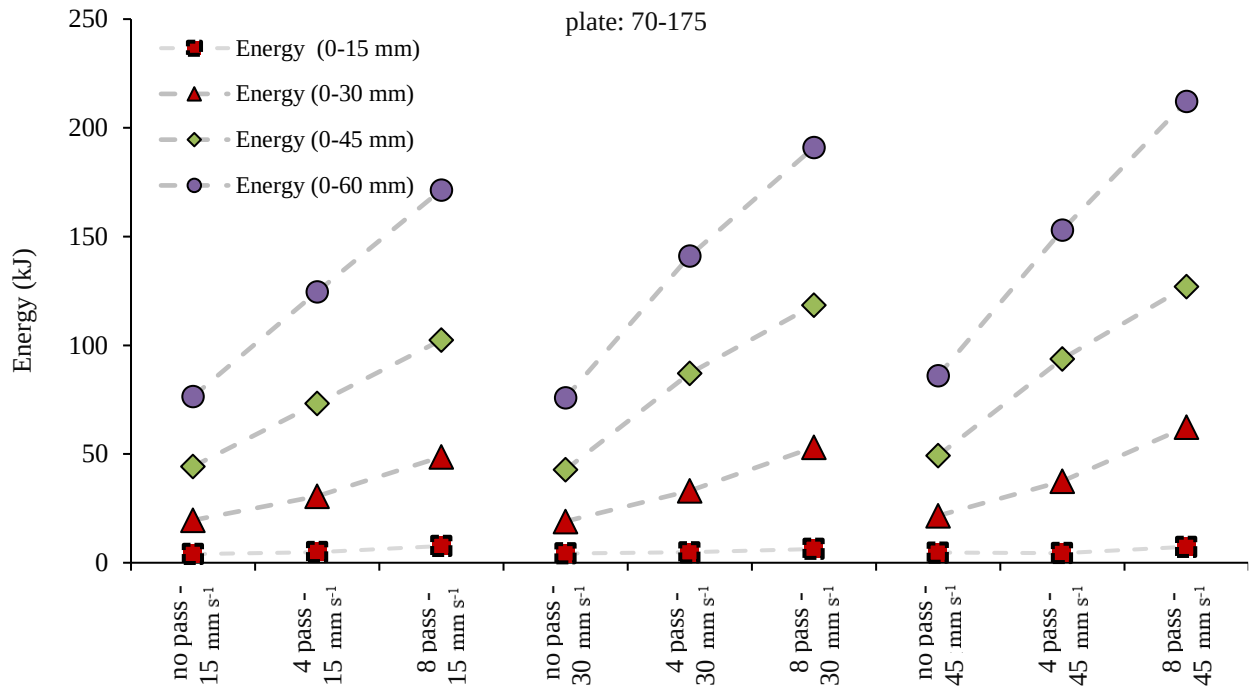


Fig. 8. Effect of multiple passes on energy consumption in different depths and constant penetration rate for the 70 × 175 plate

The impact of penetration rate on energy consumption

Although various approaches exist to account for the penetration rate in the Bekker equation (Grahn, 1996), there is limited information regarding its effect on the pressure-sinkage relationship. To address this gap, a modified bevameter was used to control the penetration velocity in a soil bin. Tests were conducted at different plate velocities, as outlined in Table 2. This section examines the effect of penetration velocity on energy consumption under constant traffic conditions, focusing on its influence through the pressure-sinkage relationship.

As demonstrated in Figures Fig. 9 and Fig. 10, changes in penetration rate (15 mm s^{-1}, 30 mm s^{-1}, and 45 mm s^{-1}) significantly influence energy consumption. With increasing speed, the energy required to achieve the same level of sinkage increases. This is likely due to the higher resistance generated between the plate and the soil at higher penetration rates, leading to increased energy expenditure. This trend is evident across both plate sizes. However, the larger plate (70 x 175 mm) exhibits a more pronounced increase in energy consumption as penetration rate and pass levels rise. For instance, at the 8th pass and a velocity of 45 mm s^{-1}, the energy consumption by the larger plate is nearly double that of the smaller plate under the same conditions, for a sinkage depth ranging from 0 to 60 mm. Similar results are reported by Apfelbeck *et al.* (2011).

Conclusion

The present study corroborates earlier findings regarding the influence of passes and penetration velocity on energy loss. The results reveal that traffic load and velocity are key factors in determining the pressure and energy required for soil penetration. Increased traffic leads to greater soil compaction, making the terrain more resistant to further deformation and requiring higher energy input, especially at higher speeds. The larger plate size (70 × 175 mm) consistently consumed more energy compared to the smaller plate (70 × 105 mm), indicating that surface contact area

plays a crucial role in the interaction dynamics.

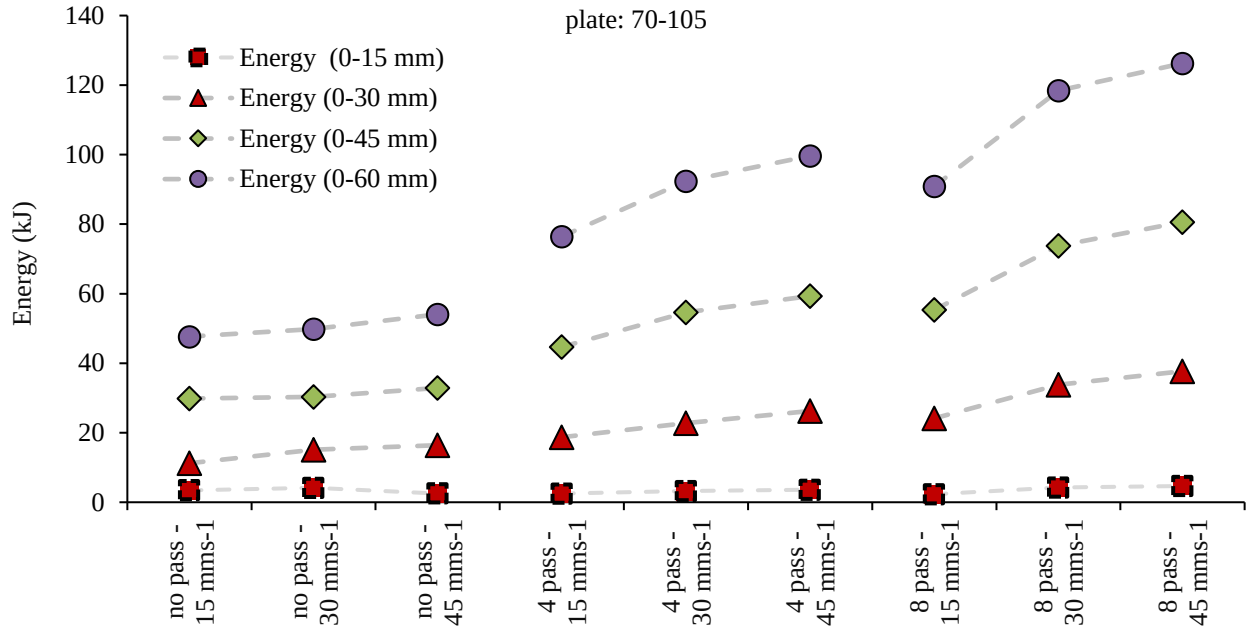


Fig. 9. The effect of penetration velocity on energy consumption in constant traffic in specified intervals, and constant traffic on the 70 × 105 plate

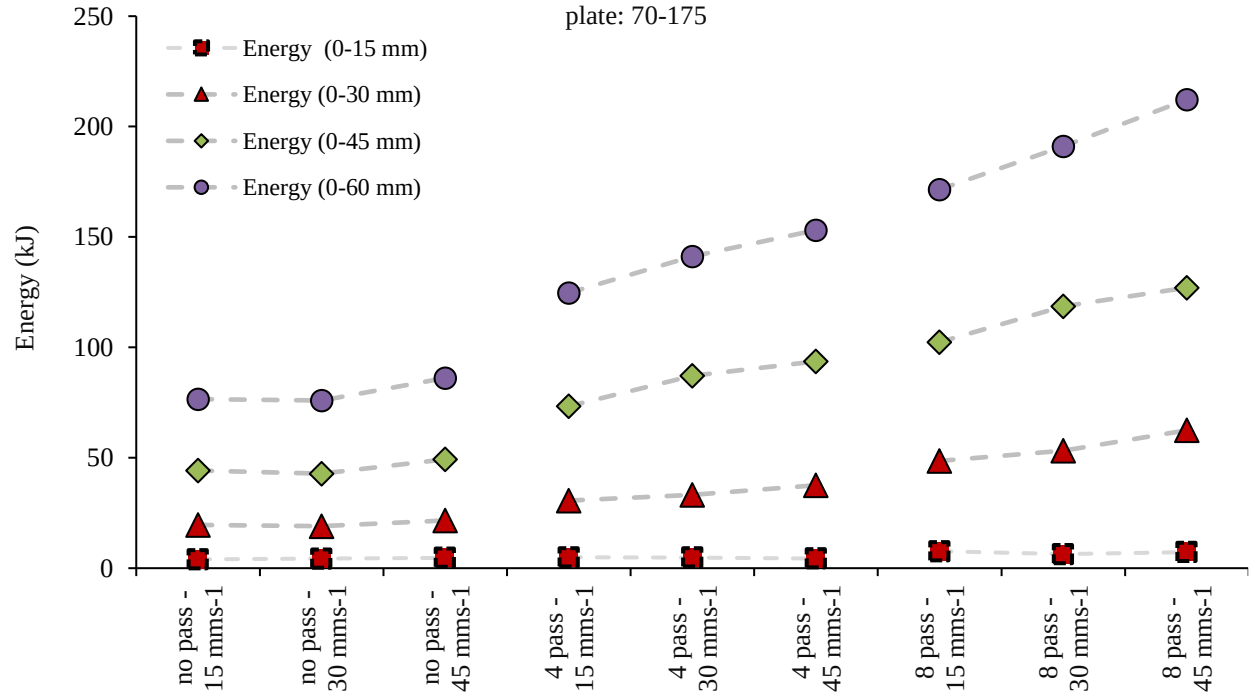


Fig. 10. The effect of penetration velocity on energy consumption in constant traffic in specified intervals, and constant traffic on the 70 × 175 plate

These findings are essential for optimizing vehicle performance in off-road environments, where minimizing energy consumption is crucial for efficiency. The study also provides valuable insights for soil management practices, particularly in agriculture and construction, where mitigating the negative effects of soil compaction is important. Future

research could explore the long-term effects of repeated traffic and higher speeds on soil properties, contributing to the development of more sustainable land-use strategies.

Acknowledgments

The authors would like to express their gratitude to Urmia University for supporting this research project and to thank the team of the soil bin testing facility at Urmia University, who sincerely assisted in data collection.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

H. Asadollahi: Methodology, Conceptualization, Data collection, Data processing, Extraction, and Preparation of the original text

B. Mohammadi-Alasti: Supervision and management, Conceptualization, Methodology, Validation, Text editing

A. Mardani: Supervision and management, Conceptualization, Validation, Text editing, Methodology, Technical advice

M. Abbasgholipour: Methodology, Technical advice, Statistical analysis, Visualization of results, Text editing

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۳۷۷-۳٦۳

ارزیابی تاثیر نرخ تغییر شکل خاک برای تخمین مصرف انرژی برهمکنش خاک و تایر با استفاده از رابطه فشار-نشست خاک

هادی اسدالهی [۱]، بهزاد محمدی الستی [۱*]، عارف مردانی [۲]، مهدی عباسقلی پور [۱]

تاریخ دریافت: ۱۴۰۳/۰۵/۱۲
تاریخ پذیرش: ۱۴۰۳/۰۷/۲۹

چکیده

درک دینامیک تغییر شکل خاک در زمینه‌های مختلف مانند تحرک وسایل نقلیه خارج از جاده، کشاورزی و مکانیک خاک بسیار مهم است. به‌طور خاص، ارزیابی فعل و انفعالات خاک و تایر برای بهینه‌سازی مصرف انرژی و به حداقل رساندن اثرات منفی تراکم خاک ضروری است. این مطالعه تأثیر نرخ تغییر شکل خاک بر رابطه فشار- نشست و مصرف انرژی را با استفاده از یک محیط انباره خاک و یک سیستم بوامتر بررسی می‌کند. هدف اصلی این مطالعه بررسی این است که چگونه سطوح مختلف عبور و نرخ‌های نفوذ متفاوت بر انرژی مورد نیاز برای دستیابی به عمق نشست مشخص تأثیر می‌گذارند. این مطالعه از یک طرح بلوک کاملا تصادفی استفاده کرد که هر تیمار سه بار تکرار شد تا از دقت و قابلیت اطمینان، اطمینان حاصل شود. اندازه‌گیری‌های کمی با استفاده از یک لودسل متصل به بوامتر انجام شد. نتایج نشان داد که سطح ترافیک و سرعت نفوذ بر مقاومت خاک و مصرف انرژی تأثیر معناداری دارد. برای صفحه بزرگتر، فشار مورد نیاز برای نفوذ با سرعت‌ها و سطوح عبور بالاتر افزایش می‌یابد. در بالاترین سرعت (۴۵ میلی‌متر بر ثانیه) و عبور هشتم، نیروی مورد نیاز برای نشست خاک حداکثر بود. مصرف انرژی برای هر سطح با اندازه‌گیری سطح زیر منحنی نیرو- نشست محاسبه شد. تجزیه و تحلیل واریانس (ANOVA) نشان داد که تعداد عبور چرخ، اندازه صفحه و سرعت نفوذ به‌طور قابل‌توجهی بر مصرف انرژی تأثیر می‌گذارد. به‌عنوان مثال، در بالاترین عمق نشست (۶۰ میلی‌متر)، مصرف انرژی برای صفحه بزرگ‌تر با سرعت ۴۵ میلی‌متر بر ثانیه و عبور هشتم تقریبا دو برابر صفحه کوچک‌تر بود. این نتایج بر اهمیت در نظر گرفتن تراکم و سرعت ناشی از تعداد عبور در هنگام طراحی وسایل نقلیه خارج از جاده یا ماشین‌های کشاورزی که با زمین‌های تغییر شکل‌پذیر تعامل دارند، تأکید می‌کند.

واژه‌های کلیدی: انرژی تغییر شکل خاک، بوامتر، عبورهای متعدد، مکانیک خاک، نرخ نفوذ

۱- گروه مهندسی مکانیک بیوسیستم، واحد بناب، دانشگاه آزاد اسلامی، بناب، ایران
۲- گروه مهندسی مکانیک بیوسیستم، دانشکده کشاورزی، دانشگاه ارومیه، ارومیه، ایران
(*- نویسنده مسئول: Email: behzad.alasti@iau.ac.ir)

https://doi.org/10.22067/jam.2024.89154.1269

Journal of Agricultural Machinery

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Research Article
Vol. 15, No. 3, 2025, p. 379-395

Sweet Pepper Detection Using Fast Point Features Histogram and Unsupervised Learning

O. Doosti-Irani [1*], M. H. Aghkhani [1], M. R. Golzarian [1]

1- Department of Biosystems Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran
(*- Corresponding Author Email: omiddoostiirani@gmail.com)

Received: 21 June 2023
Revised: 05 August 2023
Accepted: 16 August 2023
Available Online: 11 May 2025

How to cite this article:
Doosti-Irani, O., Aghkhani, M. H., & Golzarian, M. R. (2025). Sweet Pepper Detection Using Fast Point Features Histogram and Unsupervised Learning. *Journal of Agricultural Machinery*, *15*(3), 379-395. https://doi.org/10.22067/jam.2023.83054.1174

Abstract

Robotic harvesting in agriculture is an effective method for producing healthy fruit, reducing costs, and increasing productivity. Detecting and harvesting sweet peppers, however, remains a challenging task. This study aims to develop an unsupervised machine vision algorithm to recognize colored sweet peppers using a combination of geometric features (Fast Point Feature Histogram- FPFH) and color features (H, S, and V). Depth images were captured using a Kinect v2 sensor, and a 3D model was reconstructed. After extracting the geometric and color features, data preprocessing involved undersampling to ensure balance and applying the Z-score criterion to eliminate outliers. Principal component analysis (PCA) was used to reduce the feature dimensions, and the K-means clustering model was implemented to categorize the data using six geometric features and three color features. The silhouette coefficient was employed to evaluate clustering quality, and human evaluation demonsterated that the algorithm achieved a detection accuracy of 95.10% for sweet peppers.

Keywords: Fast point feature histogram, Fruit detection, Machine vision, Sweet pepper, Unsupervised learning

Introduction

Agriculture is increasingly moving towards automation, which requires smarter frameworks and technologies (Tang *et al.*, 2020). The use of agricultural robots has become a popular topic in farming, alongside emerging ideas like digital and intelligent agriculture (Ball *et al.*, 2016). Manual fruit harvesting poses risks such as injuries, falls from heights, bee stings, and other hazards, in addition to the high labor cost. However, robotic harvesting still remains a challenge (Shamshiri, Hameed, Karkee, & Weltzien, 2018). Challenges in robotic harvesting include high-precision fruit recognition, building robots with high speed and accuracy, and the ability to harvest while preserving fruit quality. Smart agriculture uses AI technologies like machine vision and robots for decision-making in real-time (Chidambaranathan, Handa, Ramanamurthy, & Ramanamurthy, 2018; Dharmaraj, & Vijayanand, 2018). Accurate fruit recognition by machines is affected by various environmental factors including light, canopy structure, fruit color, occlusion, plant care, fruit maturity, and leaf density (Gongal, Amatya, Karkee, Zhang, & Lewis, 2015). RGB cameras are commonly

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https://doi.org/10.22067/jam.2023.83054.1174

used for fruit harvesting in robots, as they can capture images in three channels simultaneously and extract color, geometric, and texture features (Kurtulmus, Lee, & Vardar, 2014; Hemming, Bac, & Van Tuijl, 2011; Fu, Majeed, Zhang, Karkee, & Zhang, 2020). Kurtulmus *et al.* (2014) used RGB color imaging to detect green immature fruits under natural illumination conditions in their study. The green color of peaches was identified as a major challenge. The maximum accuracy of detecting immature fruits obtained in this study was 84.6%, and the processing time was in the range between 72.8 and 112 s for individual images in the validation set. *Sa et al.* (2016) used deep convolutional neural networks to develop an accurate and efficient fruit detection system. However, this method requires a large number of images for model training and significant time for labeling these images. Previous studies indicate that RGB cameras struggle to perform effectively and yield satisfactory results when the color of the fruit closely resembles that of the background. Stein, Bargoti, and Underwood (2016), proposed a framework based on multi-sensor for identifying mango fruit. The aim of this research was to estimate the farm yield using a 3D model of each tree. A total of 522 trees were captured in the images. The R-CNN method has been used for object detection. The error rate obtained for each tree was 1.36%. In this, they address the problem of detecting fruits enclosed by leaves. To detect immature green citrus, Gan, Lee, Alchanatis, Ehsani, and Schueller (2018) proposed a new algorithm based on the combination of color and thermal features to distinguish green fruit from the background. The detection accuracy has increased from 86.6% to 95.5% by combining color and thermal images. But sensors such as Lidar and thermal imaging are costly; therefore, utilizing these sensors is often impractical for fruit detection. In research Mohamadzamani, Javidan, Zand, and Rasouli (2023) developed a deep neural network for cucumber detection. Testing this method on 120 samples showed that the accuracy of the network in correctly identifying the position of the cucumber fruit in the images was 95.3%.

Depth cameras have become increasingly popular among researchers in recent years. These cameras can capture both color and depth images of the target simultaneously, providing information about the target's position. This allows for the computation of three-dimensional geometric features of objects, which is useful for detecting fruits. In one study, depth cameras have been used in combination with RGB cameras to detect repetitious apples and achieve a precision of 87.0% (Gongal *et al.*, 2016). In another research, an algorithm was developed to detect apples on trees using an RGB-D camera and clustering with Euclidean distance (Nguyen, Vandevoorde, Kayacan, De Baerdemaeker, & Saeys, 2014). Point cloud data was used to detect apples with different 3D descriptors and classification methods, achieving acceptable results (Tao & Zhou, 2017). A depth camera was also used to detect sweet peppers and their pedicels, achieving a reported area under the curve of 0.71% with an acceptable accuracy (Sa *et al.*, 2017). In a different study, a dense point cloud of crops was created using an RGB-D camera to recognize red sweet peppers, and the algorithm accuracy was 90.69% (Zhao *et al.*, 2020). Researchers also evaluated approach strategies for sweet pepper harvesting robots. (Ringdahl, Kurtser, & Edan, 2019). Moghimi, Aghkhani, and Golzarian (2015) used RGB images to detect green sweet peppers. By utilizing texture features, the accuracy of detection reached 86%. Moreover, by combining texture features with color features, the accuracy increased to 92%. Doosti-Irani, Golzarian, and Aghkhani (2023) used 3D geometric features and K–NN classification algorithm to detect green sweet peppers. The F1-score of the model was 82.85%, and the accuracy of detection based on human evaluation was 83.07%. Ning *et al.* (2022) proposed a new algorithm named AYDY, which achieved a 9.14% improvement in F1-score compared to YOLO-V4. The algorithm demonstrated high accuracy in sweet pepper detection and localization, with an average localization accuracy of

89.55% and a collision-free harvesting success rate of 90.04%.

While various sensors (e. g. 2D and 3D) and descriptors (e. g. color, texture, and geometric) have been used to detect fruits and crops, several challenges remain, mainly due to changing environmental conditions and plant growth (Javidan, Banakar, Vakilian, & Ampatz, 2023). Sweet pepper detection and harvesting, in particular, pose a lot of difficulties such as complex and non-uniform backgrounds due to varying illumination intensity, fruits and pedicels covered by foliage, the fruits' color variations throughout their growth phases, sunburn, blotchy patches, and color fade. Therefore, relying solely on color characteristics to detect products is not always efficient or accurate. To tackle these challenges, it is essential to consider other information beyond color, such as three-dimensional geometric features, which can be easily obtained and to a great extent address the challenges of color images (Mohammadi, Massah, & Asefpour Vakilian, 2023). The data for this study were collected in the summer season of 2021, using a Kinect v2 sensor in a greenhouse located in Mohsen Abad, a suburb of Mashhad, Iran. Three-dimensional models of point clouds were then created and used to preprocess information and extract geometric features. Finally, unsupervised clustering was employed to detect colored sweet peppers. Figure 1 provides a summary of the objectives of this research. The main objective of this study is to present a method for real-time detection of sweet peppers in a greenhouse environment based on 3D models. The innovation of this study lies in using a new method for noise reduction in depth images and employing a combination of geometric and color features to cluster 3D models and recognize sweet peppers.

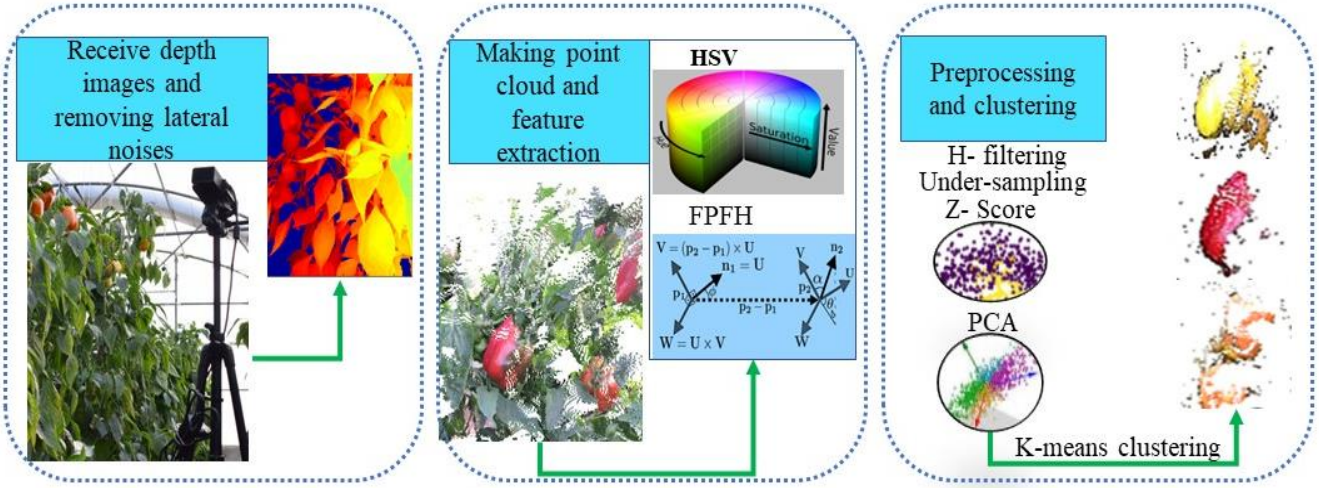


Fig.1. The summary of research steps

Materials and Methods

Point cloud obtainment

The Kinect v2 sensor was used to acquire depth and color images of sweet peppers in a greenhouse environment. After installing the related drivers for the Kinect v2 sensor in MATLAB 2018a software (MathWorks Inc, US), the samples were imaged from a distance of 80 cm. 3-D models were developed using depth maps, and color images were utilized for adding color to individual pixels in the 3-D models. The value of each pixel in this two-dimensional image indicates the distance from that point to the camera's center (Shen, Wu, & Suk, 2017). The characteristics of this sensor are shown in (Table 1).

Table 1- The characteristics of Kinect v2 sensor

Depth map resolution (pixels)	RGB map Resolution (pixels)	Operative measuring range (meter)	Filed of view (degrees)
512×424	1920×1080	0.5-4.5	70×60

Removing lateral noise

One of the challenges associated with depth images is the presence of pixels with zero values located at the edges of the image. The existence of the zero pixels in the depth image can affect the accuracy of the subsequent processing (Rusu, Blodow, & Beetz, 2009; Wan, Li, Jiang, & Xu, 2020). The noise present in the depth images was computed using Algorithm 1, which is based on the change in sign of the first derivative in the neighborhood of each point. In this algorithm, ΔZ represents the difference between the depth values of next pixels (Np) and previous pixels (Pp). By dividing ΔZ by ΔX, the first derivative of the depth function is obtained. If the sign of the first derivative is positive, the zero values of edge pixels are substituted with Np; otherwise, with Pp.

Algorithm 1: Correcting zero pixels based on the first derivative of depth function:

%Input= X: A $\boldsymbol{n \times m}$ matrix contains zero and nonzero values

%Output= X: A $\boldsymbol{n \times m}$ matrix contains nonzero values

for $\boldsymbol{i = 1:n}$
for $\boldsymbol{j = 2:m-1}$
if $\boldsymbol{X(i,j) == 0}$
Pp=$\boldsymbol{X(i,j-1)}$
$\boldsymbol{h}$ =0
for $\boldsymbol{k = 1:3}$
$\boldsymbol{h = h+1}$
if $\boldsymbol{X(i,j+h) \neq 0}$
break
end
end
Np=$\boldsymbol{X(i,j+h)}$
$\boldsymbol{\Delta z = (Np-Pp)/(h+1)}$
$\boldsymbol{if\ \Delta z > 0}$
$\boldsymbol{X(i,j:j+h-1) = Np}$
else
$\boldsymbol{X(i,j:j+h-1) = Pp}$
end
end
end
end

To demonstrate how this algorithm corrects the zero pixels, the algorithm was applied to a one-row depth map (a vector of pixels) (Figure 2(a)). The corrected depth vector is shown in Figure 2(b).

In order to validate the proposed algorithm, the Monte Carlo method was employed. In this method, different inputs are applied to the algorithm using randomly generated numbers, and the results obtained from each run of the algorithm are compared with each other. (Adams *et al.*, 2015). In order to assess the effectiveness of the proposed algorithm in substituting zero-valued points in depth maps, N points were randomly chosen from each depth map, which contained non-zero values, and then converted to zero. Next, the values of these converted points were estimated using the proposed algorithm and subsequently compared with the original non-zero values. The Root Mean Square Error (RMSE) index was computed to measure the accuracy of the algorithm. In this method, 50 images were utilized, and 20 samples were randomly selected from each image. In order to assess the performance of the proposed algorithm in estimating missing data, its RMSE value was compared with those of the commonly used B-fill and F-fill methods.

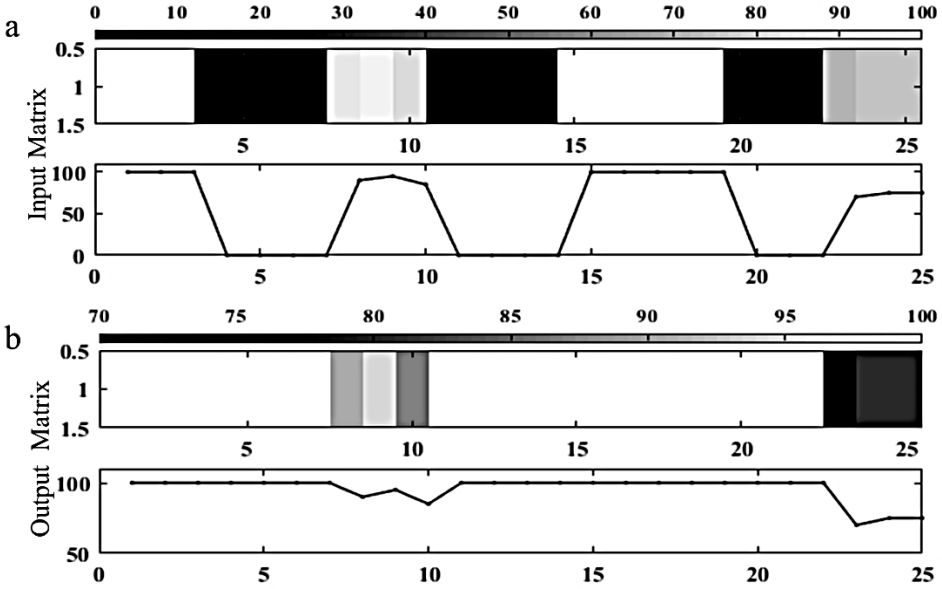


Fig.2. Simulation of first order derivative of depth function on a matrix: a) Input matrix, and b) Output matrix

Making the 3-D model

Calculate x and y

The positions x and y of the point $P\ (x, y, z)$ correspond to each pixel $p\ (j, k)$ in the depth map, as calculated using Eq. (1-2) (Lachat, Macher, Mittet, Landes, & Grussenmeyer, 2015):

$$x = \frac{j - Cx}{Fx} \times z \quad (1)$$

$$y = \frac{k - Cy}{Fy} \times z \quad (2)$$

where, (j, k) are parameters representing the position of pixel p in the depth map. In addition, (Cx, Cy) and (Fx, Fy) are internal parameters representing the coordinates of the focal point and focal length, respectively. Z represents the depth value for each pixel in the depth map. After calculating x and y for each pixel in the depth map, it is possible to have a point cloud.

3D Features extraction

In recent years, extensive research has been carried out on extracting descriptive 3D features. Local descriptors, such as PFH (Point Feature Histogram) (Rusu, Marton, Blodow, & Beetz, 2008) and FPFH (Fast Point Feature Histogram) (Rusu *et al.*, 2009) which are extracted from the key points in the object's point cloud, are more suitable for instance recognition and object classification. In this research, the FPFH descriptor was used to describe the surface of objects in the point cloud. The relative deviation between normal n1 and n2, which corresponded to two points P1 and P2, was calculated by defining a fixed local Darboux frame coordinate system *(UVW)* at one point, as shown in (Figure 3). A set of angle values was used to indicate the deviations between the two points using *UVW* coordinates, as shown in Eq. (3-6) (Han, Sun, Song, & Xiao, 2018; Sa *et al.*, 2017).

$$\alpha = V.\ n2 \quad (3)$$

$$\phi = U.\ \frac{P2 - P1}{d} \quad (4)$$

$$\theta = \arctan(W.n2,\ U.n2) \quad (5)$$

$$d = \|p2 - p1\|2 \quad (6)$$

where, d is the Euclidean distance between two points (p1 and p2). α, ϕ, and θ are descriptor angles in the UVW coordinate system. Furthermore, density was utilized as a geometric feature in the clustering process (Eq. 7). The coordinates of all point clouds are then considered as candidate cluster centers. Thus, each point pi with coordinates (xi, yi, zi) is potentially a cluster center whose density Di is given by the following equation (Zhao *et al.*, 2020):

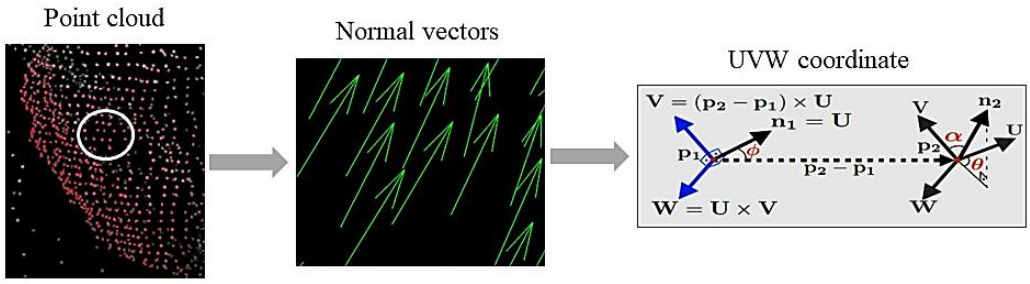


Fig.3. UVW Coordinates from a point cloud

$$D_i = \sum_{j=1}^{N} \exp\left(-\frac{(xi-xj)^2}{(\frac{Rax}{2})^2} - \frac{(yi-yj)^2}{(\frac{Ray}{2})^2} - \frac{(zi-zj)^2}{(\frac{Raz}{2})^2}\right) \quad (7)$$

where, d is the Euclidean distance between two points (p_1 and p_2). α, ϕ, and θ are descriptor angles in the *UVW* coordinate system. Furthermore, density was utilized as a geometric feature in the clustering process (Eq. 7). The coordinates of all point clouds are then considered as candidate cluster centers. Thus, each point p_i with coordinates (x_i, y_i, z_i) is potentially a cluster center whose density D_i is given by the following equation (Zhao *et al.*, 2020):

Color features extraction

In order to extract color features, the RGB color model was converted to the HSV model, and the three color components including H, S, and V were extracted. HSV color space was consistent with human eye color perception and showed fairly good light interference resistant capability. In general, the use of the HSV color space is useful in many areas of image processing because separate color features are easily accessible, which can help in object detection by providing more distinctive features.

Preprocessing

Data balancing with color filter

It is natural that simply using all the extracted values does not lead to a correct diagnosis. Therefore, it is necessary to conduct pre-processing on the data. Considering that the three-dimensional models were developed in greenhouse and under uncontrolled conditions, a wide range of data points across the X and Y axes has been obtained. Therefore, the ratio of sweet pepper points is very low compared to the points related to branches, leaves, and the surrounding environment. Due to the imbalanced nature of the dataset, clustering may favor non-pepper data. To address this issue, the data were balanced using the sample reduction method and the under-sampling module in Python software. Therefore, the threshold values for color distinction between pepper and other parts of the plant were determined for orange pepper at H > 0.13 and for yellow pepper at H > 0.17 by checking the histogram of this color channel. Labeling and balancing were done based on this threshold value. After this step, the image background was removed by applying a depth filter of Z < 120 cm. Finally, the Z-Score criterion was used to remove outlier data that were far from the overall average in each feature. Using the Z-Score criterion, data points that fell outside the range ($\bar{X}$-3σ, $\bar{X}$+3σ) were identified as outlier data and removed.

Principal Component Analysis (PCA)

The number of extracted features is 36, which comprise three color features (H, S, and V) along with 33 geometric features. Due to the high dimensionality of the geometrical features, a PCA analysis was performed, and the number of dimensions of the geometrical features was reduced to five. Therefore, the final features for entering the clustering model include five PCA components, three components from the HSV color channel, and Di.

Unsupervised Learning

Unsupervised *K*-means clustering method was used for clustering. The K-means algorithm is a popular clustering algorithm in unsupervised learning. Its goal is to divide input data into k different clusters so that the data in each cluster are similar to each other and distinct from the data in other clusters. The algorithm works by randomly initializing k cluster centroids, assigning each data point to the nearest centroid, and then computing the new centroid for each cluster as the mean of all data points assigned to it. This process is repeated until the centroids converge to a stable solution. Based on the research problem of detecting sweet peppers, which is the focus of this study, the number of clusters is considered to be two. In order to check the correctness of the clustering, the degree of cluster divergence was calculated using the silhouette coefficient (Rousseeuw, 1987). The silhouette coefficient ranges from -1 to 1, where a value closer to 1 indicates better clustering. A negative value suggests unsuitable clustering. To identify the pepper cluster, it is necessary to perform clustering first. By identifying the cluster, the 3D model corresponding to it can be retrieved using a threshold value, H, which is defined and utilized. The resulting 3D image is shown in Figures 6 and 7. After forming a 3D model of the sweet pepper class and comparing it with the initial model, it underwent human evaluation and its accuracy is reported in Table 3.

Dataset

The dataset comprised 20 3D models, including five orange and yellow pepper models for algorithm development, with the remaining fifteen models reserved for algorithm evaluation.

Results and Discussion

Results of removing lateral noise

Based on the results in Table 2, both the lower and upper bounds for the mean of RMSEs were found to be smaller than those of the other two methods (B-fill and F-fill). Therefore, this method was confirmed to be superior to the other two in terms of detecting the embeded noisy data.

Table 2- Descriptive statistics of obtained RMSEs

	F-Fill	B-Fill	Proposed algorithm
Minimum	1.85	2.01	1.89
Maximum	27.18	24.61	4.85
Average	5.43	5.25	3.97
Standard deviation	2.58	2.24	0.66
First quartile	4.09	4.07	3.56
Second quartile(median)	4.89	4.82	4.11
Third quartile	5.84	5.75	4.52
Lower bound of 95 % CI	4.92	4.81	3.8
Upper bound of 95 % CI	5.94	5.69	4.10

The smaller standard deviation observed in the proposed method suggests higher reliability compared to the other two methods, as demonstrated in the box plot presented in Figure 4. Additionally, Figure 5 displays the RMSE values obtained by the three methods in different iterations, highlighting the differences among them.

After eliminating noise from the depth maps, it becomes possible to carry out further processing on 3D models with fewer errors. By removing noise from depth images and replacing erroneous values with accurate ones, creating 3D models, object detection, background removal, and feature extraction can be performed with greater precision. In the context of object detection in 3D models, the geometric properties of points in a local neighborhood are utilized, and the presence of noise can significantly complicate the

estimation of surface properties like curvature and surface normals (Rusu & Cousins, 2011).

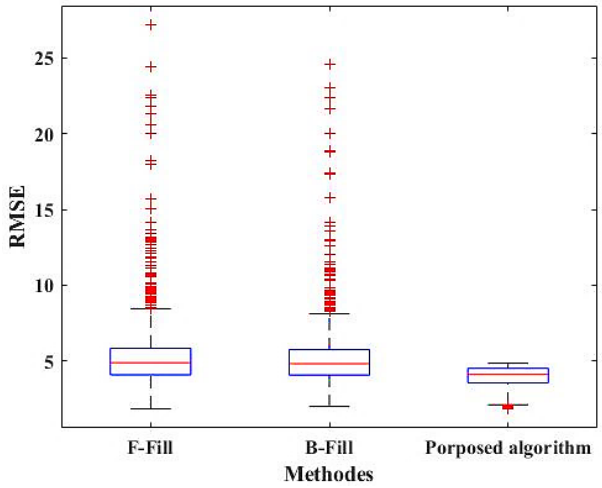


Fig.4. Results from the Monte Carlo method

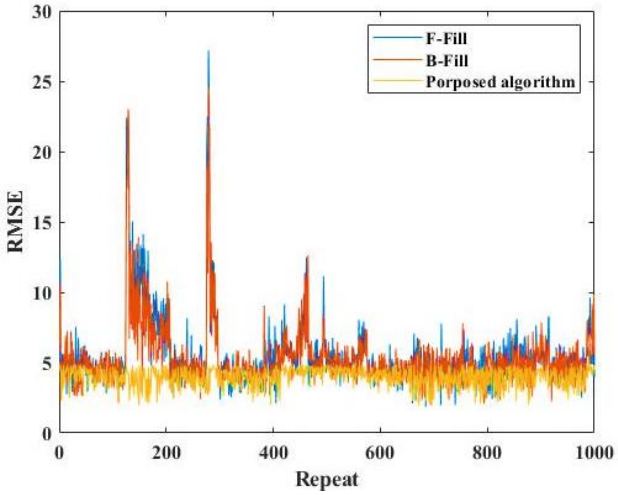


Fig.5. Root mean square error (RMSE) results from Monte Carlo simulations with 1,000 Iterations

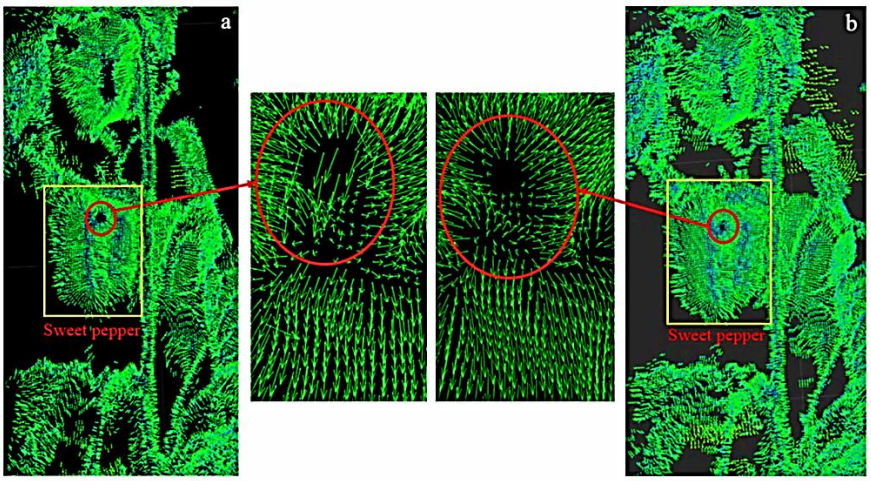


Fig.6. Demonstrate the normal vectors in 3D models: (a) before, and (b) after removing noises

The quality of extracted features such as PFH and FPFH (Sa *et al.*, 2017; Zhao *et al.*, 2020), SHOT (Muja, Rusu, Bradski, & Lowe, 2011), and VFH (Behley, Steinhage, & Cremers, 2012) is heavily dependent on the quality of the input data. In Zhao *et al.*'s (2020) study on detecting sweet peppers in a greenhouse environment, it was noted that the extraction of normal vectors is susceptible to noise from RGB-D sensors, leading to poor expression of surface curvature. Figure 6 displays two 3D models alongside their respective surface normal vectors. In Figure 6(b), the normal vectors in the 3D model are displayed after noise removal. As indicated, the normal vectors in Figure 6(b) appear more regular compared to those in Figure 6(a), which contains noisy points, and they more accurately illustrate changes in surface curvature for sweet peppers. Therefore, the methods presented in this study can be utilized for preprocessing depth data in the robotic harvesting of agricultural products. Hence, the techniques proposed in this study can be employed for preprocessing depth data in robotic harvesting of agricultural products.

Result of preprocessing

Point cloud models consist of a large number of points, and using all of them for clustering may not result in optimal accuracy. To enhance clustering accuracy, data preprocessing was performed in this study. The Z-Score method was employed to eliminate outlier points, and data balancing was achieved by reducing samples based on the H color channel. Figure 7 illustrates the reduction in the number of prototype points achieved by balancing each model, indicating a significant decrease in the number of points for the balanced models compared to the initial models. In addition, the silhouette coefficient values displayed in Figure 7 demonstrate that including a higher number of points in the clustering model leads to lower clustering quality.

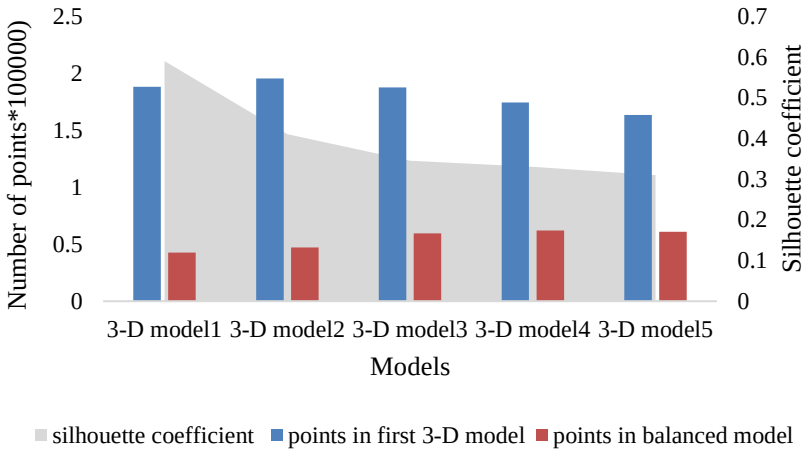


Fig.7. The reduction in points and silhouette coefficient for each model after dataset balancing

Results of PCA

The scree plot for PCA applied to the data is presented in Figure 8. The plot reveals that in this particular model, dimensions have been reduced to five components. This resulted in a considerably reduced slope and a minimal increase in the variance.

Results of K-means clustering

The K-means method was utilized as one of the unsupervised learning techniques in this study. The clustering quality was measured using the silhouette coefficient, and a human observer was employed to accurately identify

sweet peppers. In Figure 7, the silhouette coefficient plot is depicted for five models, with the maximum value equal to 0.59 and the minimum value equal to 0.31. These values indicate that the K-means clustering algorithm was able to effectively differentiate between the two clusters examined in this study (pepper and other plant components). Figure 9 illustrates the silhouette coefficient diagram for a clustered model, where the horizontal axis represents the silhouette coefficient and the vertical axis shows the number of points in each cluster. The majority of the points on the graph fall within a range greater than zero, providing evidence for the successful clustering achieved using the K-means algorithm.

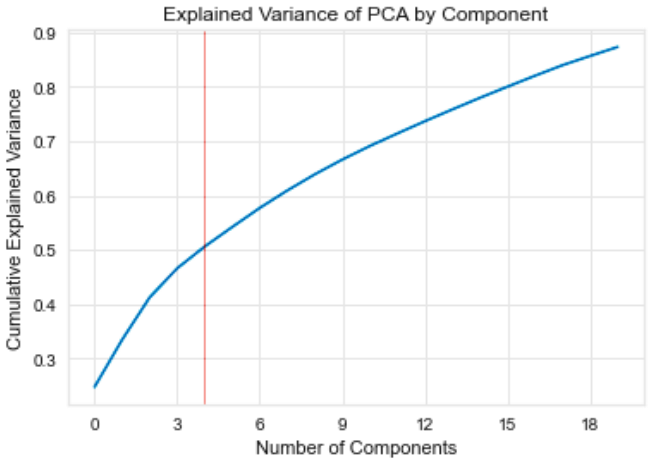


Fig.8. The graphic of the number of main components compared to the compressed variance is explained

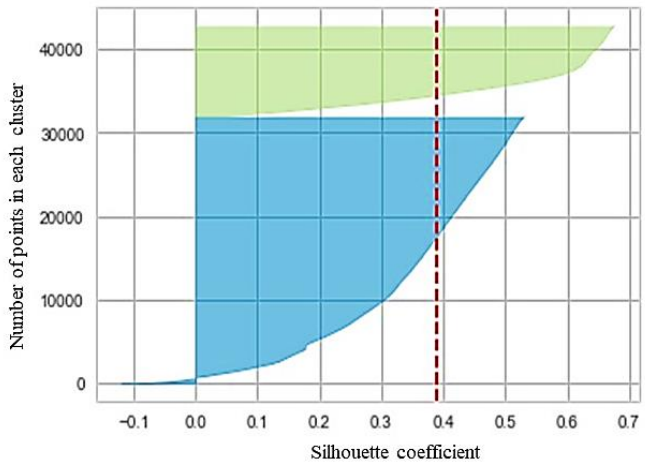


Fig.9. Silhouette analysis for K-means clustering on sample data with two cluster

To evaluate the performance of the proposed method in detecting sweet peppers, Figures 10 and 11 display the initial 3D model along with the number of detected sweet peppers. It is important to consider that the field of view for harvesting robots has limitations, and the harvesting operation can only be performed within a specific range. Therefore, in this study, if the target is located at the margins of the image, it is not included in the final count. Figure 10 shows the results of pepper counting for two models of orange pepper, while Figure 11 shows the results for two models of yellow pepper. As demonstrated, the algorithm utilized in this study is capable of effectively differentiating

pepper points from those belonging to branches and leaves in the 3D point cloud model. In the examined 3D models, all available peppers were successfully identified. However, it should be noted that some points belonging to branches and leaves were also classified as peppers. This may lead to errors when a harvesting robot encounters these points, and it may mistakenly treat branches and leaves as peppers. Figure 12 demonstrates this issue. The presence of these misclassified points in the clustering process has resulted in a decrease in the silhouette coefficient value. It is worth mentioning that the quality of clustering may vary across different models depending on various environmental factors, such as fruit-leaf overlap, lighting conditions, leaf density, maturity level, and so on. In this study, 3D models were created using the Kinect sensor without controlling these environmental conditions. Hence, the proposed algorithm is effective in tackling environmental challenges and can be employed in similar environments.

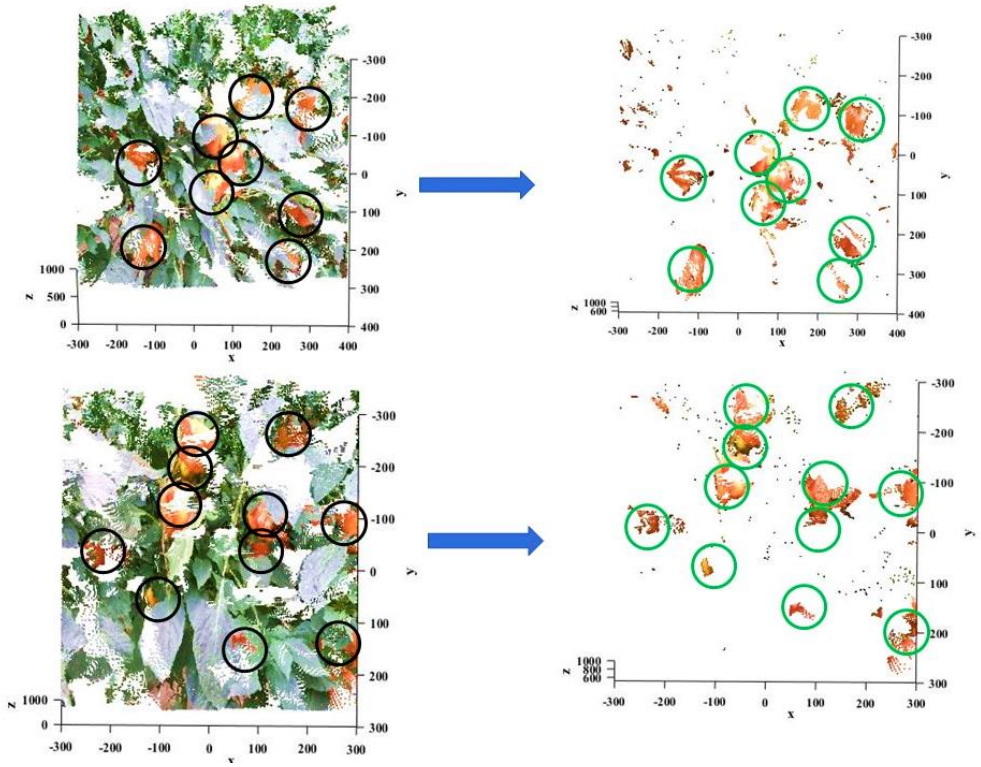


Fig.10. The initial 3-D model (left), and identified orange peppers (right) used for human monitoring

To detect sweet peppers in complex environments, various techniques were employed, including noise removal, data balancing via color filtering, 3D feature extraction, PCA, and unsupervised *K*-means clustering. To assess the performance of the k-means algorithm, the silhouette coefficient was utilized (as shown in Table 3). The maximum value of the silhouette coefficient was 0.59, while the minimum value was 0.35. Out of the 99 peppers present in the point cloud models, 93 peppers were detected. Finally, the average accuracy of human-supervised detection was found to be 95.10% for the sweet pepper dataset. The average execution time of the algorithm was determined to be 33.32 seconds. Comparable levels of accuracy to the results for sweet pepper detection have been reported in similar studies. For example, (Zhao *et al.*, 2020) used R-G filter and the Euclidean distance to detect color sweet pepper, and the accuracy of their human monitoring was 90.69%. In a study, (Sa *et al.*, 2017) used PFH features to detect sweet peppers with 0.71%

accuracy, considered acceptable because they used only 3D features, without incorporating any color features. Ning *et al.* (2022) achieved a precision of 91.84% in detecting sweet peppers using the YOLO-V4 model. Nan *et al.* (2023) used the YOLOv5l model for detecting green sweet peppers and achieved a detection accuracy of 81%. Compared to supervised detection of colored sweet peppers (Doosti *et al.*, 2023), the detection accuracy in this study increased from 83.07% to 95.1%, mainly due to appropriate preprocessing applied to the point cloud, including reducing the sample size.

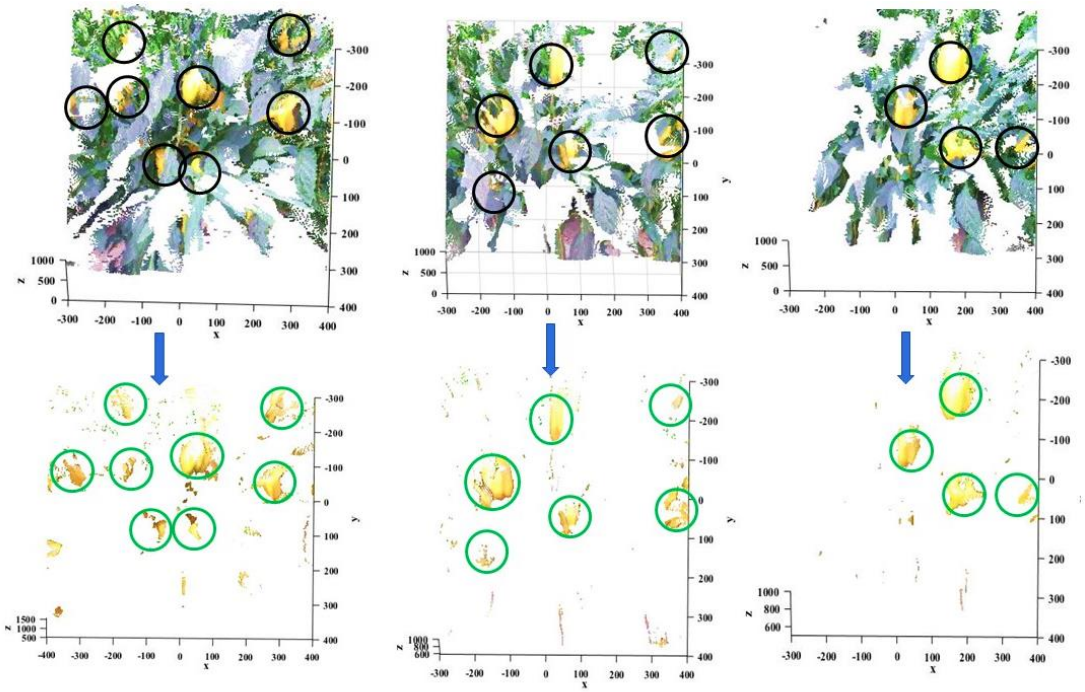


Fig.11. Detection of yellow pepper for human monitoring: initial 3D model (top), and detected peppers (buttom)

Table 3- The results of the human monitoring

3-D model number	Silhouette coefficient	Total number of sweet peppers	Number of identified sweet peppers	Detection accuracy (%)	Time (s)	Cumulative variance
1	0.59	9	9	100	37.36	50.76
2	0.41	11	11	100	31.29	51.55
3	0.44	4	4	100	34.85	54.92
4	0.40	6	6	100	29.45	54.14
5	0.40	8	8	100	30.67	54.83
6	0.51	7	6	85.71	33.11	63.36
7	0.46	8	7	87.5	32.62	66.16
8	0.52	3	3	100	13.45	64.28
9	0.44	5	5	100	32.12	65.97
10	0.58	2	2	100	16.84	65.74
11	0.44	10	9	90	46.64	60.2
12	0.38	6	6	100	47.54	60
13	0.48	4	4	100	20.12	60.78
14	0.39	6	5	83.33	54.20	59.8
15	0.35	10	8	80	50.66	60.30
Average	0.45	99	93	95.10	33.32	51.59

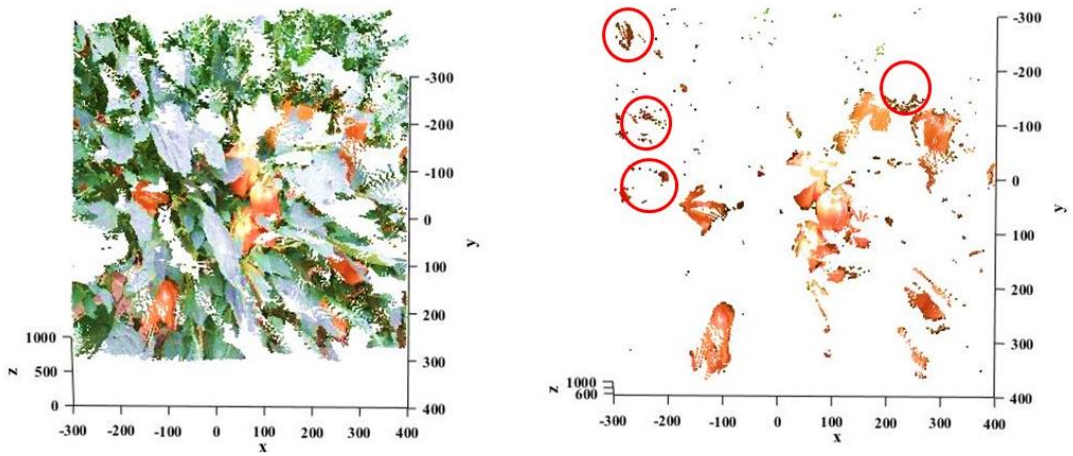


Fig.12. Recognition of the points of the branches and leaves as sweet pepper

The use of unsupervised learning algorithms in detecting agricultural products is prioritized over supervised learning algorithms. This is because, in supervised learning, changes in environmental conditions can affect the accuracy of detection and reduce it. In the detection of agricultural products, color supervision is mostly used, which can be influenced by changes in environmental lighting. Therefore, the superiority of unsupervised algorithms is due to the lack of need for supervision. Thus, these algorithms are more resistant to environmental changes, and their accuracy will be less affected.

Conclusion

Automatic detection and harvesting of sweet pepper is a challenging task in greenhouse cultivation due to the high density of branches and leaves, variations in lighting and environmental conditions, the presence of pests and diseases, and differing levels of maturity. In this study, a combination of geometric and color features using 3D models was used as a highly accurate method for detecting sweet peppers. The results showed that the algorithm used was capable of detecting sweet peppers with an accuracy of 95.1%. The algorithms used in this study can be used to detect other products with similar challenges such as green sweet peppers, cucumbers, green apples, and generally any product that is geometrically different from other plant components. The authors aimed to investigate whether geometric features are capable of distinguishing fruit from other plant components in order to provide a solution for detecting green sweet peppers in future studies. As detecting green sweet peppers is also a challenging task, it is suggested that the detection of green sweet peppers based on local 3D descriptors be investigated in a separate study.

Acknowledgment

We would also like to thank Dr. Amirhossein Nayebi Astaneh for his guidance and the following organizations for their financial support of this research.

1- Ferdowsi University of Mashhad

2- Khorasan Science and Technology Park

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

O. Doosti Irani: Study design, 3D imaging, Data preprocessing, Programming, Data analysis and modeling, Writing - original draft.

M. H. Aghkhani: Supervision, Scientific oversight, Review & editing.

M. R. Golzarian: Supervision, Scientific oversight, Technical consultation, Review & editing.

All authors reviewed and approved the final manuscript.

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ۳۹۵-۳۷۹

تشخیص فلفل دلمه‌ای با استفاده از هیستوگرام ویژگی سریع نقطه و یادگیری بدون نظارت

امید دوستی ایرانی [۱*]، محمدحسین آق خانی [۱]، محمودرضا گلزاریان [۱]

تاریخ دریافت: ۱۴۰۲/۰۳/۳۱
تاریخ پذیرش: ۱۴۰۲/۰۵/۲۵

چکیده

برداشت رباتیک محصولات کشاورزی فرآیندی مهم و موثر برای تولید میوه سالم، کاهش هزینه‌های برداشت و افزایش بهره‌وری است. با پیشرفت بینایی ماشین، استفاده از اطلاعات سه‌بعدی به‌جای اطلاعات دوبعدی در حال گسترش است. با این حال، برداشت فلفل دلمه‌ای به‌عنوان یکی از محصولات گلخانه‌ای، به دلیل دقت پایین سنسورهای دوبعدی با چالش‌هایی مواجه است. هدف این مطالعه توسعه یک الگوریتم بینایی ماشین بدون نظارت برای تشخیص فلفل دلمه رنگی با استفاده از ترکیبی از ویژگی‌های هندسی (هیستوگرام ویژگی نقطه سریع- FPFH) و ویژگی‌های رنگی (HSV) است. تصاویر عمق با استفاده از حسگر Kinect-v2 دریافت و مدل سه‌بعدی بازسازی شده است. پس از استخراج ویژگی‌های هندسی و رنگ، داده‌ها با استفاده از روش زیر نمونه‌گیری و با اعمال معیار Z-score برای فیلتر کردن نویزها، پیش‌پردازش شدند. تحلیل مؤلفه اصلی (PCA) برای کاهش ابعاد ویژگی‌ها استفاده شد و مدل خوشه‌بندی k-means با استفاده از شش ویژگی هندسی و سه ویژگی رنگ، به داده‌ها اعمال شد. ضریب سیلوئت برای ارزیابی کیفیت خوشه‌بندی استفاده شد و ارزیابی انسانی نشان داد که الگوریتم با دقت ۹۵/۱۰ درصد قادر به تشخیص فلفل دلمه‌ای است.

واژه‌های کلیدی: برداشت رباتیک، بینایی ماشین، فلفل دلمه‌ای، هیستوگرام ویژگی سریع نقطه، K-means

۱- گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران
(*- نویسنده مسئول: Email: omiddoostiirani@gmail.com)

https://doi.org/10.22067/jam.2023.83054.1174

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article
Vol. 15, No. 3, 2025, p. 397-418

Energy, Environmental, and Economic Evaluation of a Novel Building Integrated Green System: Insights from Residents and Social Perspectives

M. M. Naserian[1], R. Khodabakhshian[1*]

1- Department of Biosystems Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran
(*- Corresponding Author Email: Khodabakhshian@um.ac.ir)

Received: 10 August 2024
Revised: 19 October 2024
Accepted: 26 October 2024
Available Online: 01 June 2025

How to cite this article:
Naserian, M. M., & Khodabakhshian, R. (2025). Energy, Environmental, and Economic Evaluation of a Novel Building Integrated Green System: Insights from Residents and Social Perspectives. *Journal of Agricultural Machinery*, *15*(3), 397-418. https://doi.org/10.22067/jam.2024.89307.1274

Abstract

The buildings and the agri-food sectors nearly consume 40% and 21% of the world's total energy, respectively. This research aims to combine these two significant energy-consuming sectors to decrease the total society's energy consumption. For this purpose, a novel small-scale building integrated agriculture system was designed and constructed. In this research, the total energy and water consumption, annual CO_2 production, and the total cost of employing the novel system were analyzed from the building residents' and social points of view. Moreover, the results were compared with the total results of a building and a separate standard greenhouse with the same product. The results show that the total energy reduction because of using the novel system was 31.2%. According to the results, the novel system will cause approximately 3400 $kgCO_2$ emission reduction over a life cycle of 20 years. Moreover, yearly water consumption reduction was 19.2 L kg^{-1} of lettuce production. The payback period was approximately 5 years based on the cost analysis results comprising investment, operational, and social costs. Sensitivity and Scenarios analyses were conducted to better understand the effect of probable influential parameters and make the investment for the novel system secure and attractive.

Keywords: Energy modelling, Environmental analysis, Green Building, NPV, Vertical green system

Introduction

HVAC (Heating, Ventilation, and Air Conditioning) systems are responsible for 38% of the total energy consumption in residential sectors (González-Torres, Pérez-Lombard, Coronel, Maestre, & Yan, 2022). In this context, one of the key strategies to optimize energy usage is preventing energy waste (Kazemzadeh, Fuinhas, Koengkan, Osmani, & Silva, 2022). To address this, researchers have proposed various approaches, such as implementing Thermal Energy Storage (TES) technologies to minimize energy loss through building boundaries (Peker, Kocaman, & Kara, 2018). Phase Change Materials (PCMs) have gained significant attention in building construction due to their high thermal energy storage capacity (Tyagi *et al.*, 2021; Reyez-Araiza *et al.*, 2021). Approximately 50% of energy loss in buildings occurs through windows and doors. Therefore, smart window technology has been developed to intelligently regulate the amount of sunlight entering buildings (El-Deeb, Ismail, & Hassaan, 2020; Teixeira, Gomes, Rodrigues, & Pereira, 2020).

Numerous studies have explored the potential of vertical farming as an energy-efficient solution in buildings. In this context, the energy-saving potential of Vertical Green Systems (VGSs) has been thoroughly

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https://doi.org/10.22067/jam.2024.89307.1274

examined through both numerical (Šuklje, Medved, & Arkar, 2016; Pigliautile, Chàfer, Pisello, Pérez, & Cabeza, 2020) and experimental (Zheng, Dai, & Tang, 2020; Talaei, Mahdavinejad, Azari, Prieto, & Sangin, 2021) research across various climate regions globally. Sánchez-Reséndiz, Ruiz-García, Olivieri, and Ventura-Ramos (2018) analyzed the impact of installing living walls on the thermal performance of buildings in a semi-arid climate. They concluded that incorporating living walls on south-facing walls enhances the thermal efficiency of buildings. VGSs contribute to reducing building energy consumption in four key ways: by serving as a natural barrier against thermal sunlight, acting as an insulator (Lee & Jim, 2019), functioning as an evaporative cooler, and providing wind protection (Chen, Tsay, & Chiu, 2017).

In several research studies, the DesignBuilder software, a sophisticated and validated building energy simulation tool, has been utilized to model green systems. Alvarez-Sánchez, Leyva-Retureta, Portilla-Flores, and López-Velázquez (2014) conducted a numerical analysis of the thermal behavior of a greenhouse using DesignBuilder, finding the energy simulation results to be accurate and reliable. Karimi, Farrokhzad, Roshan, and Aghdasi (2022) explored both experimentally and numerically the impact of green walls as passive energy reducers in humid regions, using DesignBuilder for their simulations. They concluded that green walls effectively lowered the building's energy consumption, although the cooling capacity was influenced by plant type and building architecture. Wang and Iddio (2022) examined the energy performance of indoor farming with the EnergyPlus simulation software, reporting a 48.1% reduction in natural gas consumption due to the system. Additionally, Vox, Blanco, Convertino, and Schettini (2022) analyzed the effect of green façades on the winter HVAC system heating load, demonstrating that it decreases both conductive and radiative heat transfer, acting as a thermal barrier.

A comprehensive review of urban agriculture literature revealed that urban agriculture leads to reduced transportation needs for food procurement, thereby lowering transportation costs (Azunre, Amponsah, Peprah, Takyi, & Braimah, 2019). Additionally, a comparison between traditional soil-based vertical farming with natural lighting and indoor vertical farming suggested that vertical farming with natural lighting could be the most efficient urban farming system for producing large quantities of food in Singapore, considering resource usage and environmental impacts (Song *et al.*, 2022).

In addition to the building sector, the agricultural industry consumes 21% of the world's total energy, driven by the growing demand for high-quality and abundant agricultural products throughout the year (Benke & Tomkins, 2017). The increasing energy needs and the urgent concerns about climate change have led to a heightened interest in developing more sustainable agricultural systems. Nonetheless, a major challenge in adopting these systems is evaluating their financial viability. A comprehensive financial feasibility analysis is crucial to determine whether introducing new systems is practical. Regarding global food trade, the FAO (2020) reports that the monetary value of global food exports was approximately 1.38 trillion USD in 2018. This figure contrasts sharply with 380 billion USD in 2000, with vegetables and fruits making up the largest portion of these exports, accounting for 23%.

A range of case studies have focused on comparing the economic aspects of vertical farming in urban settings with traditional greenhouse methods (Pomoni, Koukou, Vrachopoulos, & Vasiliadis, 2023). Trimbo (2019) assessed the financial sustainability of vertical farming in indoor environments in São Paulo, finding that while such systems are more water-efficient and environmentally friendly, they involve a high initial capital expenditure. In contrast, the Interatomic Energy Agency (IEA) (2021) notes that achieving a low-carbon economy requires substantial investments in clean energy

technologies and infrastructure. Gumisiriza, Ndakidemi, Nalunga, and Mbega (2022) explored the economic viability of producing lettuce using an outdoor vertical farming system in Africa, and their findings indicated that these small-scale systems are economically viable, sustainable, and contribute to enhancing food security in urban areas. Avgoustaki and Xydis (2020) examined multiple scenarios to evaluate the financial benefits of vertical farming in Denmark, revealing that vertical farming is considerably more profitable than traditional greenhouse methods. Furthermore, Chamroon and Aungkurabrut (2019) investigated an automated hydroponic greenhouse designed for household use, determining that the payback period for lettuce production in this system was 3.3 years.

An examination of existing literature highlights that both the building sector and the agri-food industry are major consumers of energy. While Vertical Green Systems (VGS) have shown promise as a means to enhance energy efficiency in buildings, there remains a notable research and practical gap in developing a new integrated system that combines building structures with urban agriculture. Such a system would ideally be economically viable and promote the seamless interaction between buildings and agricultural practices, with the goal of reducing overall energy and water usage as well as minimizing annual CO_2 emissions.

This paper aims to provide a detailed assessment of the energy, environmental, and financial viability of a new integrated agricultural system within buildings and explore its potential for widespread adoption. The unique features and performance metrics of this innovative system, as well as the associated challenges and opportunities related to energy use, environmental impact, and financial considerations will be examined. The study will unfold in several phases: First, a new multipurpose system that integrates building functions with agricultural activities and conducts initial experiments to evaluate its feasibility will be proposed. Subsequently, a numerical simulation based on the experimental data and existing research will be developed. This simulation will analyze the annual performance of the combined building and agricultural system, focusing on total energy consumption and yearly CO_2 emissions. Finally, an economic analysis, assessing key financial indicators such as the Levelized Cost of Lettuce (LCOC), Payback Period (PP), and Net Present Value (NPV) will be carried out. Different parameters and scenarios that affect financial metrics to understand the economic implications of the proposed system will also be simulated.

Materials and Methods

Experimental site

This study was conducted in Mashhad, a city positioned at 36.31º North latitude and 59.53º East longitude, with an elevation of 1037 meters above sea level during 2023. Mashhad has a cold semi-arid climate (Köppen: BSk), marked by hot summers and cold winters. The experimental system was installed at Ferdowsi University of Mashhad.

System configuration

The design of the novel system integrates indoor vertical farming with outdoor vertical green systems to ensure continuous air circulation for the plants while maximizing the use of natural daylight. The system's dimensions are 2.1 meters in length, 0.55 meters in width, and 1.2 meters in height. It encompasses a comprehensive framework that includes plant cultivation areas, a displacement mechanism, irrigation and rainwater collection systems, as well as measurement and control subsystems. Figure 1 illustrates the detailed setup of the system. The plant cultivation area is organized into three mobile pipe bases, each featuring three rows of U-shaped PVC pipes arranged 30 cm apart. These pipes are filled with a hydroponic substrate comprising a mixture of cocopeat and perlite. Each pipe is equipped with a 1 mm fine steel mesh filter and a drainpipe designed to collect and transfer excess water to a central reservoir. The pipes contain four apertures, each with a

diameter of 0.06 meters and spaced 0.144 meters apart, intended for the insertion of hydroponic pots. The arrangement of the pipes on a stepped base prevents shading of lower rows by upper rows and ensures adequate sunlight exposure for all plants. Transparent components of the system are constructed from polycarbonate (PC) and Polymethyl Methacrylate (PMMA) sheets, with PC used for the side panels and a combination of PC and PMMA for the front panel. The displacement subsystem comprises two DC motors, a power supply, gear racks, and pinions. The recirculating irrigation subsystem includes three pumps, one air pump, and three water tanks. This subsystem operates in cycles of 20 seconds every 1.5 hours during daylight hours. The control subsystem manages irrigation timing, exposure durations, and the movement of the plant cultivation areas, ensuring optimized system performance.

The measurement and control system incorporated various devices such as thermocouples, a lux meter, digital timers, time counters, and data loggers. Temperatures of the indoor air in the rooms, the system's air temperature, and the ambient air temperature were recorded at five-minute intervals. Thermocouples of type K were employed to measure the indoor air temperatures, positioned at the same height in the center of each room and protected from direct sunlight. The accuracy of the experimental data was contingent upon the precision of the measuring instruments, with the overall uncertainty of the experiments calculated to be 2.34%. During the study, two types of lettuce—Batavia and Romaine—were grown within the system. The experiments were conducted over a period of 40 days, covering the entire growth cycle from planting to harvest, and were carried out in the spring.

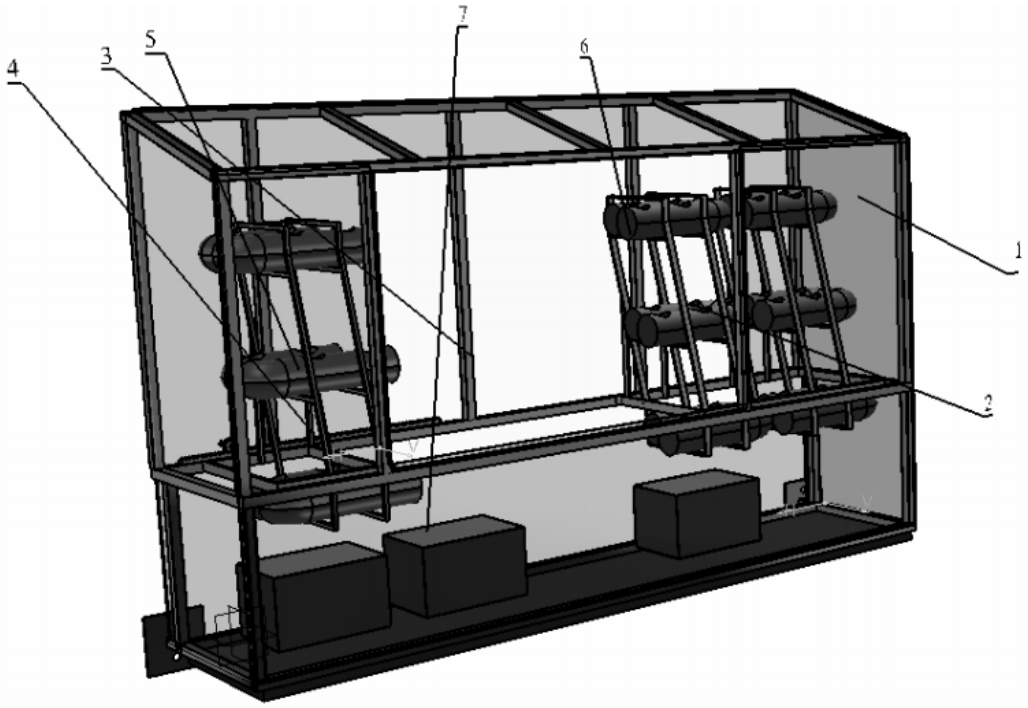


Fig. 1. System illustration: 1) Polycarbonate sheets, 2) Hydroponic pots, 3) Polymethyl Methacrylate (PMMA) sheet, 4) Pipe bases, 5) U-shaped PVC pipes, 6) The displacement subsystem, 7) Solution storage tank

Some key features of the novel system include:

- The system serves as a mobile natural canopy that can be positioned over windows.
- By being installed on the exterior surface of windows, the system occupies minimal interior space within living and working areas.

- As depicted in Figure 2, the system allows plants to move horizontally, optimizing natural light exposure within the room.
- The system can be set up independently from other units in the building or even within different rooms of the same apartment.
- Maintenance and plant cultivation are accessible solely through the building's window, which eliminates the need to enter the system. This design reduces the risk of contamination and prevents the introduction of pathogens via footwear.
- It supports the production of clean, organic food indoors, free from pesticides and chemical fertilizers.



Fig. 2. Horizontal plant mobility in the novel system

To evaluate the system's performance, two rooms were selected, each with identical dimensions of 3 meters by 1.7 meters by 2.5 meters. Both rooms were situated under the same conditions regarding orientation, sealing, and insulation. These rooms were located on the second floor of a building with a total height of 7 meters. Each room featured a south-facing window with dimensions of 1.2 meters by 0.9 meters, resulting in a window-to-wall ratio of 0.21. The novel system was installed prominently outside in front of the window in one of these rooms designated for plant growth.



Fig. 3. The experimental rooms

Computational model

To investigate the impact of plants on a building's energy consumption, it is crucial to first evaluate the energy performance of the plants themselves. This begins with analyzing the energy balance equation for plant leaves. The findings from this analysis are then incorporated into building energy simulation software to accurately simulate the interaction between the plants and the building. The steady-state energy balance equation for the plant tissue, assuming metabolic process energy losses are negligible (Jones, 2013), is given by equation (1).

$$\alpha_f I_s - C - Q_{rad} - L_f = 0 \quad (1)$$

where, the parameters include the solar absorptivity of the plants (α_f), the solar irradiance (I_s), convection heat transfer (Q_{rad}), radiation heat transfer (L_f), and latent heat. The system was modeled using DesignBuilder software, with the plants functioning as window shading elements (Larsen, Filippín, & Lesino, 2015). The fundamental properties of both the window and the shading are outlined in Table 1. To incorporate the latent heat effect from plant transpiration into the simulation, modifications were made to the window and shading properties (Larsen *et al.*, 2015). These adjustments, detailed in equations (2-4), were then input into the software for accurate simulation. It is important to note that the plants were not continuously positioned in front of the window throughout the year. The performance schedule for the positioning of the plants is provided in Table 2.

Table 1- The window shade properties

Property	Reference	Value	Unit
Solar transmittance	(Larsen *et al.*, 2015)	0.2	---
Solar reflectance	(Larsen *et al.*, 2015)	0.3	---
Visible transmittance	Experimental Data	0.08	---
Visible reflectance	(Larsen *et al.*, 2015)	0.09	---
Thermal emissivity	(Larsen *et al.*, 2015)	0.95	---
Thermal transmittance	(Larsen *et al.*, 2015)	0	---
Thickness	Experimental Data	0.001	m
Conductivity	(Larsen *et al.*, 2015)	0.59	W (m ºC)$^{-1}$
Shade to Glass Distance	Experimental Data	0.2	m

Table 2- Performance schedule of the system

January		**April**		**July**		**October**	
Until 06:00	1*	Until 05:00	1			Until 05:00	1
Until 17:00	0**	Until 21:00	0	Until 24:00	1	Until 18:00	0
Until 24:00	1	Until 24:00	1			Until 24:00	1
February		May		August		November	
Until 06:00	1			Until 05:00	0	Until 06:00	1
Until 17:00	0	Until 24:00	1	Until 22:00	1	Until 16:00	0
Until 24:00	1			Until 24:00	0	Until 24:00	1
March		June		September		December	
Until 07:00	1			Until 05:00	0	Until 06:00	1
Until 19:00	0	Until 24:00	1	Until 21:00	1	Until 17:00	0
Until 24:00	1			Until 24:00	0	Until 24:00	1

*It means the plants are placed in front of the window.
** It means the plants are not placed in front of the window.

Given that plants are three-dimensional objects, their shadows on both the sides and above are significant and affect the simulation. Therefore, in addition to modeling the front window shading, the simulation also included definitions for the upper and lateral shading

around the window. To avoid shading lower rows with the upper ones, the plant rows were arranged in a stepped configuration, resulting in variable distances from the window (see Fig. 4). In the simulation, multiple windows were defined along each side of the plants, and the distances between these windows and the shadings were adjusted in accordance with the variable distances from the plants' rows to the windows. To accurately assess the total plant coverage from the front view, the Plant Coverage Rate (PCR) was analyzed. A photograph of the plants was taken on the 20th day after planting, the midpoint of the growing period. The coverage rate was then calculated using MATLAB code.

Next, the schematic of the rooms in DesignBuilder is shown in Figure 5. The weather data were obtained from the Iran Meteorological Organization (IRIMO) database.

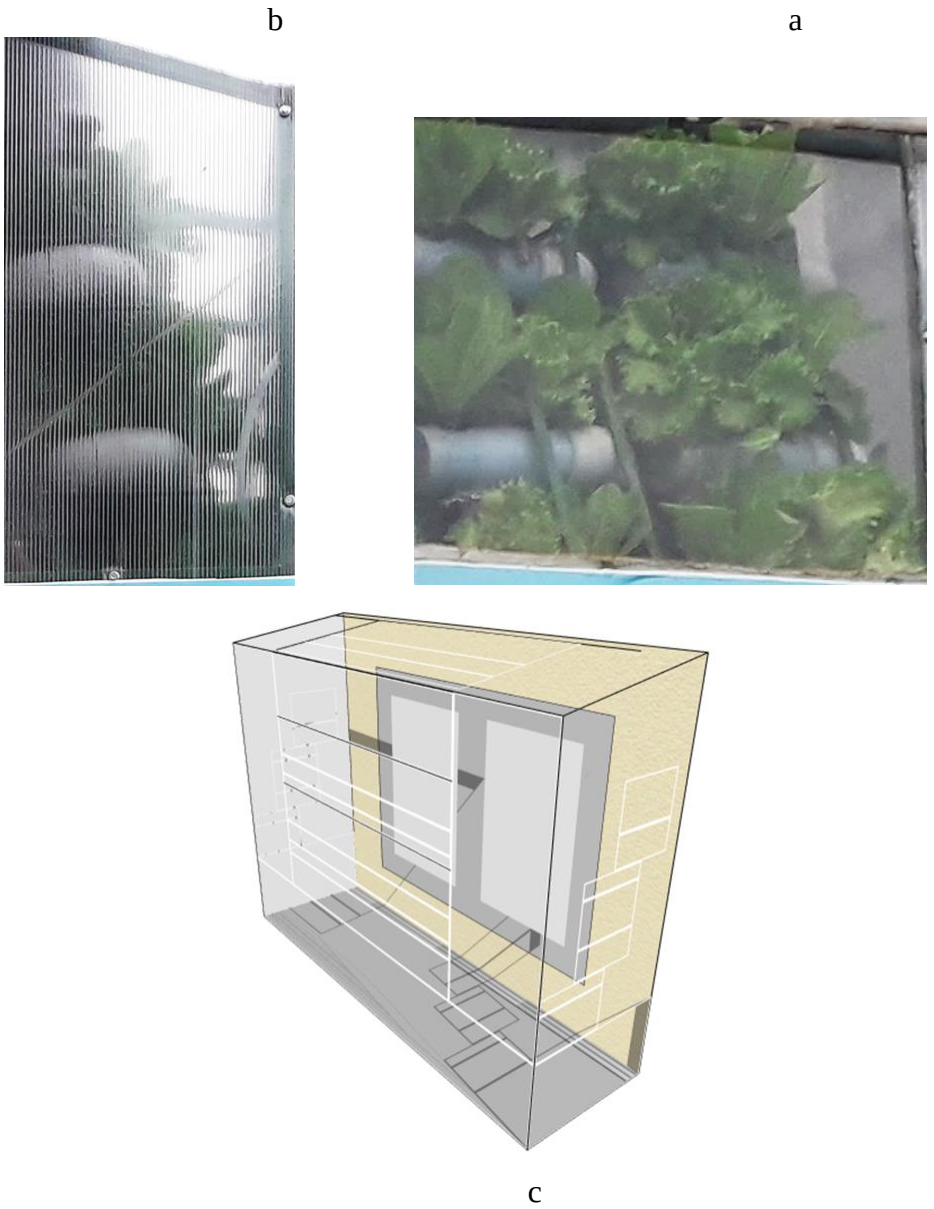


Fig. 4. Segmentation of the external cover of the novel system for precise positioning of window shadings in plant simulation: a) side view, b) front view, and c) 3D CAD

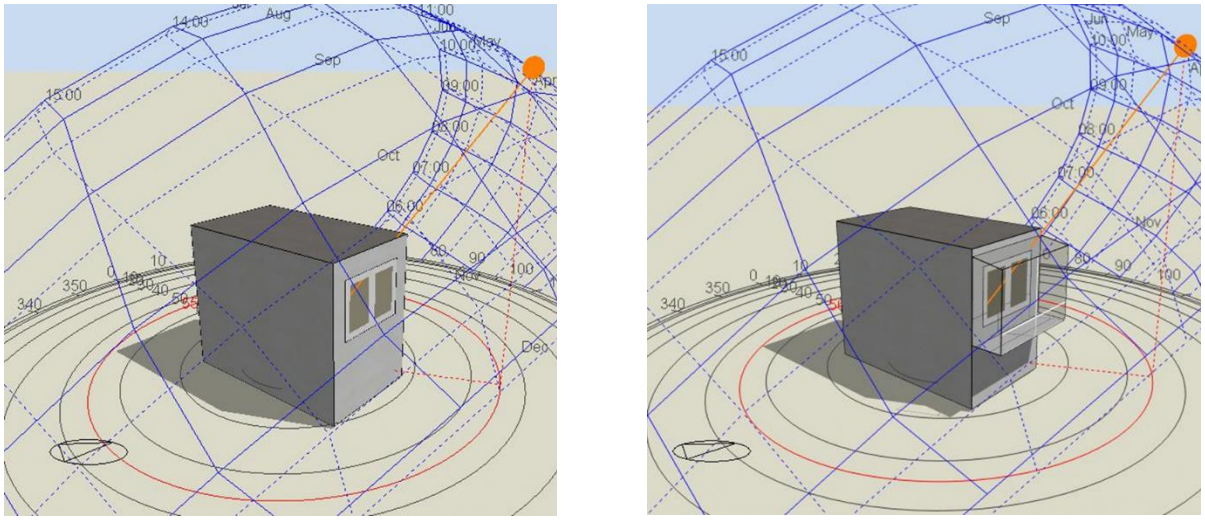


Fig. 5. The layout of the rooms as represented in the DesignBuilder software

Properties Modification

This section aligns with the study 'Solar Thermo-Visual Gain Optimization of a Building Using a Novel Proposed Nature-Based Green System' conducted and published by Naserian, Khodabakhshian, Kazemi, and Jozay (2024), with detailed information provided below:

"In contrast to blinds, the temperature of plants does not increase linearly with the amount of absorbed heat because some of this heat is transformed into latent heat. Consequently, both sensible and latent heat effects must be incorporated into the plant simulation simultaneously. While the impact of sensible heat can be addressed by incorporating window shading in the simulation, the effect of latent heat requires modifying certain parameters according to the equations outlined by Larsen *et al.* (2015). These modifications were applied using the specified equations."

$$\alpha_{mo} = \alpha_f (1-x) \tag{2}$$

$$\varepsilon_{mo} = \varepsilon_f (1-x) \tag{3}$$

$$\varepsilon_{w,mo} = \frac{\varepsilon_w (1-x)}{1-\varepsilon_w x} \tag{4}$$

where, α_f , ε_f , and ε_w represent the solar absorption and infrared emissivity of the plants and the room window glass, respectively. Additionally, x denotes the ratio of latent heat released by the plants to the total absorbed radiation, defined by the following equation.

$$x = \frac{\Lambda}{[\Lambda + \gamma(1 + r_s / r_a)]} \tag{5}$$

where, r_s and r_a denote the surface resistance of the natural canopy and the aerodynamic resistance, respectively. The methodology for calculating these resistances will be explained in the subsequent paragraph. Furthermore, γ represents the psychrometric constant, expressed in kPa/°C, while Λ is the slope of the saturation vapor pressure versus temperature curve, also measured in kPa/°C at the given air temperature. The air pressure (P) for the experimental region is 89,472 Pa.

$$\Lambda = \frac{4098\left[0.618 Exp\left(\frac{17.27 T_a}{T_a + 237.3}\right)\right]}{(T_a + 237.3)^2} \tag{6}$$

$$r_s = \frac{r_1}{LAI_{active}} \tag{7}$$

where, r_1 represents the stomatal resistance of the plant leaf, which is determined using equation (9) from Pollet, Bleyaert, and Lemeur (1998). The parameter LAI_{active} refers to the active leaf area index and is calculated as 0.5 times the leaf area index (LAI). The LAI is a key metric for evaluating the effectiveness of Vegetated Green Systems (VGSs) as passive

cooling solutions, as discussed by Pérez, Coma, Sol, and Cabeza (2017). To assess this, the photosynthetically active radiation (PAR) was measured at various locations within the system using a PAR meter. These measurements were then used in equation (8) to indirectly determine the LAI of the system, as outlined by Zhang (2019)

$$LAI = \frac{-\ln\left(\frac{PAR_{below}}{PAR_{above}}\right)}{0.9} \quad (8)$$

$$r_1 = 164\left(\frac{31.029 + I_s}{6.740 + I_s}\right)(1 + 0.011(D-3)^2)(1 + 0.016(T_a - 16.4)^2) \quad (9)$$

where D and T_a are the vapor pressure deficit and the air temperature, respectively. D was calculated from the following equation (Pollet *et al.*, 1998)

$$D = e_{s(T)} - e = (1.0007 + 3.46\times10^{-8}P)\left(611.21 + \exp\left((18.678 - (T_a/234.5))T_a/(257.14 + T_a)\right)\right)(1 - RH) \quad (10)$$

where $e_{s(T)}$ and e are the partial pressure of saturation and the actual vapor pressure, respectively.

The aerodynamic resistance of the canopy in s/m is defined as equation (11) (Zhang, 2019).

$$r_a = 840\left(\frac{d}{|T_s - T_a|}\right)^{0.25} \quad (11)$$

where, d represents the leaf characteristic length, which was measured experimentally on the 20th day after planting, marking the midpoint of the planting period. The term $T_s - T_a$ denotes the temperature difference between the plant leaves and the ambient air, calculated as the average of the temperature differences observed under two extreme conditions: when the leaf surfaces were completely dry and when they were fully wet. For the dry leaf surface, $T_s - T_a$ is given by the following equation

$$T_s - T_a = \frac{I_s r_{HR}}{\rho_a C_P} \quad (12)$$

where r_{HR} is the heat and radiative resistance of the leaf surface (Graamans, Baeza, Van Den Dobbelsteen, Tsafaras, & Stanghellini, 2018) and was calculated from the following equation:

$$r_{HR} = \frac{r_a r_R}{r_a + r_R} \quad (13)$$

where r_R is the leaf radiative transfer resistance given by

$$r_R = \frac{\rho C_P}{8\varepsilon_L \sigma T_a^3} \quad (14)$$

where $\sigma = 5.67\times10^{-8} Wm^{-2}K^{-1}$ is the Stefan–Boltzmann constant, and ρ is the density of air and was considered temperature dependent and calculated as a function of the mean air temperature from the following equation:

$$\rho = \frac{P}{RT_m} = \frac{P}{287T_m} \quad (15)$$

where $T_m = T_a + (T_s - T_a)_{ave}/2$. The average measured temperature difference (i.e. $(T_s - T_a)_{ave}$) used for initial air properties calculations, was 11°C. For the wet leaf surface $T_s - T_a$ given by

$$T_s - T_a = -\frac{D}{\gamma + \Lambda} \quad (16)$$

For more details on the above equations, refer to (Vox *et al.*, 2022) and (Larsen *et al.*, 2015).

Cost analysis methods

The economic feasibility of the novel system is as important as its energy-saving potential and environmental benefits. The consumer is more willing to buy a product when the purchase cost and the economic savings that the purchase of that product entails during a certain period are known. In the current study, three cost analysis techniques were used to investigate the

economic feasibility of the novel system:

Net present value (NPV)

The economic feasibility of the new system was assessed using the discounted cash flow method. Equation (17) was used to calculate the net present value of cost over the life span. *F* represents the future value of the payment.

$$NPV = \sum_{n=0}^{N} \frac{F}{(1+d)^n} - I, \quad F = AI - AC \tag{17}$$

where *N* is the project lifetime (20 years), *n* is the year, *d* refers to the discount rate (12%), *AI* is annual income, *AC* is the annual cost, and *I* is the investment cost (Lu & Yin, 2021).

Payback period (PP)

Recovering the initial investment for a project can take many years. The simple PP method determines the years it takes for the cash flow to be equal to the total investment. It considers the sum of the annual cash flows and the initial investment as the total investment cost.

Levelized cost of lettuce (LCOL)

It is defined to measure the average cost of a lettuce head concerning to the system lifetime. It describes the net present value of a lettuce head and is calculated from the following equation:

$$LCOL = \frac{\sum_{n=0}^{N} \frac{AC}{(1+d)^n} + I}{\sum_{n=0}^{N} \frac{YLP}{(1+d)^n}} \tag{18}$$

where *YLP* is the yearly lettuce head production of the system (Reichelstein & Rohlfing-Bastian, 2015).

Social costs

Social cost, or electricity external cost, is the hidden cost that is not included in consumer utility invoices. The climate change and human health problems, acid rain, and water pollution caused by emissions from fossil fuel power plants are some examples of this cost. Society must pay for these consequences (Watkiss & Hunt, 2012).

Results and Discussion

Based on equations (5-16), the average value calculated *x* was 0.53. This value was derived using the region's average ambient air temperature, solar irradiation, and relative humidity, which were 24.3°C, 465 W/m², and 50%, respectively. To account for the impact of fluctuating latent heat on the energy performance of the plants, these properties were adjusted according to equations (2-4). Subsequently, the modified values were applied in the DesignBuilder software.

In Figure 6, the experimental and simulated results for the same day are compared. The figure shows that the maximum difference between the results was around 0.7°C. Thus, Figure 6 serves as evidence of the accuracy of the simulation results generated by the DesignBuilder software.

Energy and environment investigation results

This section examines the impact of the novel system on energy and water consumption, as well as CO_2 production, from the perspectives of building residents and societal benefits. To achieve this, the annual energy simulation results are first presented in Table 3. On sunny days during hot seasons, the plants in the novel system function not only as canopies for windows but also as thermal barriers, maintaining air temperatures lower than the outside. During cold nights, the system's air is completely isolated from the external environment, acting as a thermal shield for the windows. Additionally, during the daytime in cold seasons, the plants increase the humidity of the system's air through transpiration, which in turn enhances the air's latent heat. The results show that the novel system can reduce the room's total energy consumption by up to 31.2%. The energy required for plant cultivation was 440.6 kWh, equivalent to 4.37 kWh per kilogram of lettuce produced (Lages Barbosa *et al.*, 2015). In comparison, the annual energy consumption for producing one kilogram of lettuce in a standard greenhouse under similar climatic conditions is approximately 6 kWh (Graamans *et al.*, 2018). Therefore, while the novel

system does increase the building's overall energy consumption, it significantly reduces the total energy usage associated with both building operations and vegetable production from a broader societal perspective. The detailed calculations are provided in Table 4.

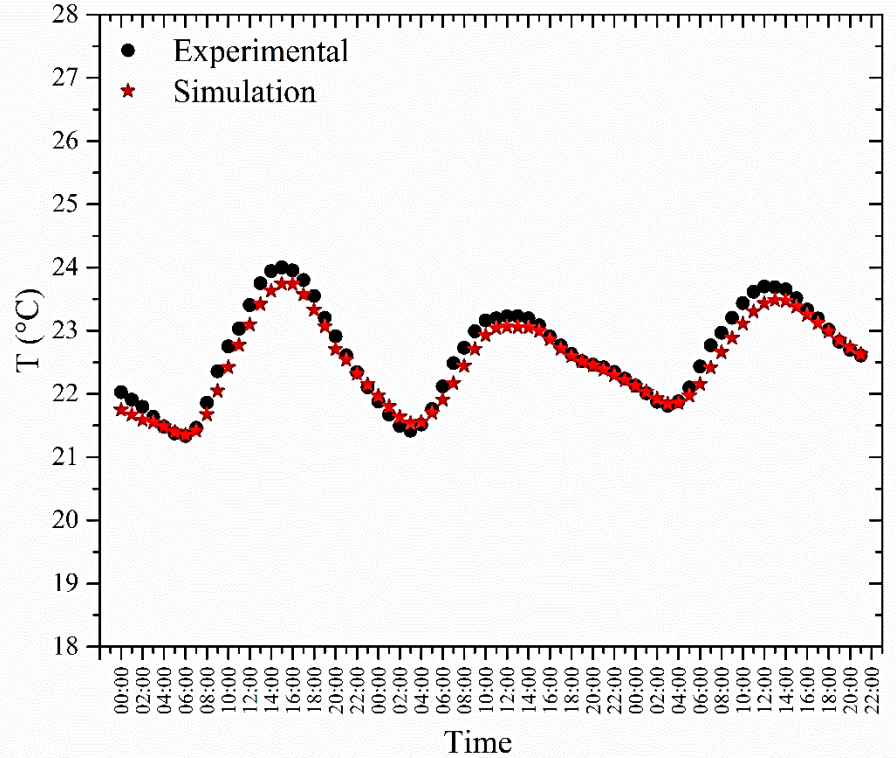


Fig. 6. Validation of the simulation

Table 3- The comparison of the energy performance of the rooms

Room	HVAC system	Lighting	Total
Plant	161.6 kWh	21.8 kWh	183.4 kWh
Control	253 kWh	13.8 kWh	266.8 kWh
Variation	-36.1 %	+65.21%	-31.2%

The results for electrical energy, water, and fuel consumption, as well as CO_2 production, are presented and compared in Table 4. In this analysis, the room equipped with the novel system was compared to the combined totals of a standard room and a separate greenhouse required to produce the same amount of lettuce, which in this case is 100.8 kg. The table shows that not only did the direct energy consumption for producing the crops decrease, but the indirect energy usage related to food miles and water extraction also saw a reduction.

Food miles refer to the distance between the farm and the final consumer, typically calculated by multiplying the distance by the mass of the food transported. To assess fuel consumption and the environmental impact of food miles, these distances are usually converted into vehicle fuel consumption related to food transportation (Smith, Watkiss, Tweddle, & McKinnon, 2005). In this study, food transportation was divided into two stages: from the farm to the food store (using diesel-fueled vehicles) and from the food store to the home (using gasoline-fueled vehicles) (Transportation and Energy Information of the Country, 2014). The findings align with the results of Gould and Caplow's (2012) study.

Table 4- The detail of the energy and environmental calculations

Resource	Content	Reference	Quantity (per year)
Energy (personal view)	The rooms HVAC and novel system	DesignBuilder software	(183.4-266.8) +440.6 = +357.2 kWh
Energy (social view)	The rooms HVAC, novel system, and standard greenhouse	DesignBuilder software, and Graamans *et al.* (2018)	(183.4-266.8) +440.6 (for the novel system) – 6*100.8 kWh kg^{-1} (for greenhouse) = -247.6kWh
Fuel (social view)	Transportation, and water extraction	Transportation and energy information of the country (2014); Iran Energy Balance Sheet (2020)	Diesel: -0.016 m^3*100.8 kg*0.104 L m^{-3} water (for water extraction) - 100.8 kg*0.046 L kg^{-1} (for transportation) = -4.84 L
Fuel (personal view)	Transportation	Transportation and energy information of the country (2014)	Gasoline: -0.06 L kg^{-1} *100.8 kg = -6.05 L
		Transportation and energy information of the country (2014)	Gasoline: -0.06 L kg^{-1} *100.8 kg = -6.05 L
Water (social view)	Agriculture and rain	Experimental Data, and Graamans *et al.* (2018)	-0.328m^3 (rain) + (252*0.42*20 L)/1000 (L m^{-3}) (for greenhouse) - 0.4 m^3 (for the novel system) = -2.04 m^3
Water (personal view)	Agriculture	Experimental data	+100.8 kg *0.004 L kg^{-1} = +0.40 m^3
Yearly CO_2 emission reduction (social view)	Energy reduction and transportation	Transportation and energy information of the country (2014); Iran Energy Balance Sheet (2020)	247.6 kWh *0.571 $kgCO_2$ kWh^{-1} + (4.84+6.05) L fuel*2.63 $kgCO_2$ L^{-1} fuel = 170.02 $kgCO_2$

The novel system offers significant environmental benefits by enabling food production within buildings, which drastically cuts down on transportation-related emissions compared to traditional farming methods. The results indicate that, over a 20-year life cycle, this system could lead to a reduction of approximately 3400 kg of CO_2 emissions.

The details of the fuel consumption data for food transportation, along with other environmental data used in Table 4, are presented in Table 5. These data were sourced from verified governmental resources, including the "Transportation and Energy Information of the Country" (2014) and the "Iran Energy Balance Sheet" (2020).

Cost analysis results

This section covers the capital expenditure required for constructing and setting up the novel system, along with the annual variable costs. Additionally, sensitivity analysis was used to identify the key parameters that could significantly impact the costs. Lastly, various cost scenarios are outlined and examined in detail. Table 6 details the total capital expenditure required for the novel system. The table indicates that an annual cost of $457 is necessary to produce 252 heads of lettuce. The system is designed to function for up to 20 years, provided it receives regular maintenance. Table 7 outlines the annual operational costs and revenue associated with the system. In this study, it is assumed that both the price of lettuce and annual operational costs will increase in line with inflation. To calculate the return on investment from the consumer's perspective, an intermediate electricity tariff of $0.011 per kWh (applicable to other uses) was used. From a societal perspective, the economic benefits were evaluated based on the cost of electricity production without subsidies. This cost was estimated using the price of crude oil, which was $51.50 per barrel at the time of the study. Given that each barrel of crude oil is equivalent to 1699.1 kWh, the cost per kWh of electricity was initially calculated as $0.030.

However, accounting for a power plant efficiency of 36.8% (Iran Energy Balance Sheet, 2020), the adjusted cost of electricity per kWh was determined to be \$0.0824.

Table 5- The details of the data used in resources analysis

Reason	Resource	Unit	Reference
Fuel consumption from farm to store	Diesel	0.046 L kg^{-1} Food	Transportation and energy information of the country (2014); Iran Energy Balance Sheet (2020)
Fuel consumption from store to house	Gasoline	0.06 L kg^{-1} Food	Iran Energy Balance Sheet (2020)
Emissions due to fuel combustion	CO_2	2.63 kg L^{-1} Fuel	Transportation and energy information of the country (2014)
Emission due to electricity production in power plants	CO_2	0.571 kg kWh^{-1} Electricity	Noorpoor and Kudahi (2015)
Energy consumption in a typical greenhouse	Electricity	6 kWh kg^{-1} Lettuce	Graamans *et al.* (2018)
Water consumption in a typical greenhouse	Water	20 L kg^{-1} Lettuce	Graamans *et al.* (2018)
Fuel consumption for water extraction	Diesel	0.104 L m^{-3} water	Iran Energy Balance Sheet (2020)
Captured CO_2 due to the lettuce photosynthesis	CO_2	0.1 kg kg^{-1} Lettuce	Carvajal (2010)
Gasoline to electrical energy conversion	Gasoline	1.76 kWh L^{-1} Gasoline	Iran Energy Balance Sheet (2020) (considering 20% efficiency)
Diesel to electrical energy conversion	Diesel	3.69 kWh L^{-1} Diesel	Iran Energy Balance Sheet (2020) (considering 35% efficiency)

Table 6- The detail of the total capital cost of the novel system

Commodity	Unit cost	Quantity	Cost
Galvanized rectangular pipe	1 \$ kg^{-1}	60 kg	\$60
LED	4 \$ $block^{-1}$	9	\$36
Wire	0.2 \$ m^{-1}	10 m	\$2
18AWG cable	\$7	1	\$7
PC sheet	8 \$ m^{-2}	6 m^2	\$48
PVC pipe +fittings	5 \$ m^{-1}	6 m	\$30
Substrate	2 \$ kg^{-1}	5kg	\$10
Seedlings grow tray	\$4	1	\$4
PE pipe + fittings	1 \$ m^{-1}	8 m	\$8
PMMA sheet	15 \$ m^{-2}	0.8 m^2	\$12
Electrical motor	\$12	2	\$24
Switching power supply	\$12	1	\$12
Thermostat + Contactor	\$25	1	\$25
Timer	\$12	2	\$24
Water pump	\$8	3	\$24
Water tank	\$4	3	\$12
Air pump	\$10	1	\$10
Elastomeric insulation	4 \$ m^{-2}	1.25 m^2	\$5
Gear + pinion	7.5 \$ m^{-1}	2	\$15
Rail	\$7	4	\$28
Manufacture + Installation	\$80	1	\$80
Total investment cost			\$476

Table 7- The details of annual operational cost and income of the novel system

Output	View point	Unit price	Quantity	Cost	Income
Water use	Personal	0.1 \$ m^{-3} (Mohammadi, Naderi, & Saghafifar, 2018)	0.4 m^3	\$0.04	0
Energy use (plants)	Personal	0.011 \$ kWh^{-1} (Mohammadi *et al.*, 2018)	440.6 kWh	\$4.85	0
Maintenance cost	Personal	2.5% capital cost	-	\$11.9	0
Seeds + fertilizer	Personal	20\$	1	\$20	0
Energy consumption reduction	Personal	0.016 \$ kWh^{-1} (Iran Energy Balance Sheet, 2020)	(-183.4 +266.8) kWh = 83.4 kWh	0	\$1.33
	Social	0.0824 \$ kWh^{-1}	247.6 kWh	0	\$20.40
Energy Subsidy payment reduction	Social	(0.0824-0.016) \$ kWh^{-1}	247.6 kWh	0	\$16.44
Fuel consumption reduction	Social	0.5 \$ L^{-1} gasoline 0.47 \$ L^{-1} diesel	6.05 L diesel + 4.84 L gasoline	0	\$5.26
	Personal	0.1 \$ L^{-1} gasoline	4.84 L gasoline	0	\$0.48
Fuel Subsidy payment reduction	Social	0.4 \$ L^{-1} gasoline 0.37 \$ L^{-1} diesel	6.05 L diesel + 4.84 L gasoline	0	\$4.17
Water reduction	Social	0.5 \$ m^{-3}	2.04 m^3	0	\$1.02
CO_2 reduction (excluding power production)	Social	0.024 \$ kg^{-1} (Ahmadi, Dincer, & Rosen, 2012)	10.89*2.63 = 28.64 kg	0	\$0.68
Lettuce production	Personal	0.6 \$ $head^{-1}$	252*0.96 = 242 heads (considering 4% poor quality product)	0	\$145.20
Social cost (due to power production)	Social	0.054 \$ kWh^{-1} (Karimzadegan, Rahmatian, Farsiabi, & Meiboudi, 2015)	247.6kWh	0	\$13.37
Total	Personal view point annual cost and income			\$36.8	\$147.01
	Social view point annual cost and income			0	\$61.34

The results presented in the table indicate that the annual societal income generated by the novel system amounted to \$61.34, translating to \$0.25 per head of lettuce. Based on the Net Present Value (NPV) analysis, the payback period for the system is approximately five years.

The table highlights several areas of cost savings from different perspectives. For building residents, these savings stem from lower costs for plant lighting at night due to reduced tariffs, decreased electricity usage during peak tariff periods, minimized urban transportation expenses for purchasing lettuce, and more cost-effective lettuce production. From a societal perspective, the cost savings include reductions in overall energy consumption, lower CO_2 emissions, and decreased social costs associated with energy and transportation.

The income derived from building energy savings is calculated based on the peak daily electricity prices, reflecting the reduction in energy consumption during periods of high demand. In contrast, the majority of the novel system's energy use occurs at night, when grid electricity consumption is at its lowest and electricity prices are reduced.

Sensitivity analysis

Sensitivity analysis involves examining how changes in one or more input variables

impact the output of a model. It is a method for determining which input variables have the most significant effect on the output and understanding how variations in these inputs influence the results. This technique is often used in financial modeling to identify key variables that drive financial outcomes and assist decision-makers in focusing on these critical factors. In engineering design, sensitivity analysis helps evaluate how adjustments in materials or design choices affect the performance of a system, considering both cost and technical feasibility constraints.

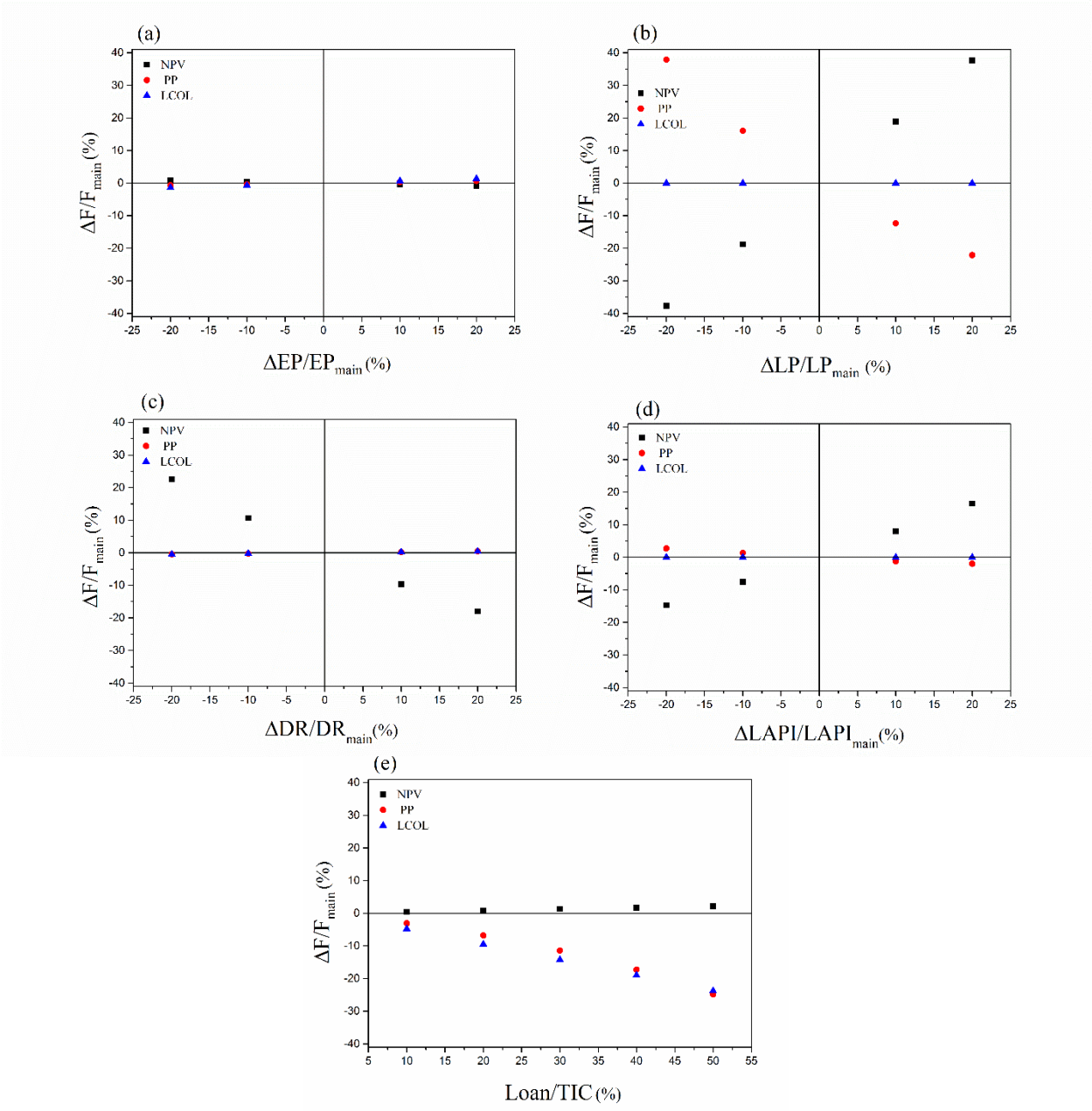


Fig. 7. Sensitivity analysis of the NPV, PP, and LCOL based on (a) EP, (b) LP, (c) DR, (d) LAPI, and (e) Loan/TIC (True Interest Cost) (%)

In this study, sensitivity analysis focused on several key parameters that are likely to influence the Net Present Value (NPV), payback period (PP), and levelized cost of lettuce (LCOL). These parameters include electricity price (EP), lettuce price (LP), discount rate (DR), and the annual increment in lettuce price (LAPI).

Figure 7 illustrates the results of the sensitivity analysis. It shows that the lettuce price (LP) is the most critical input parameter, while the electricity price (EP) is the least critical. Due to the substantial energy subsidies in Iran, the cost of electricity is relatively low (as noted in Table 7). Consequently, changes in EP have a minimal impact on economic calculations, making this finding consistent with expectations. The sensitivity of EP may vary in countries with higher electricity prices, and further investigation would be required in such contexts. Additionally, with the exception of EP and Loan/TIC (%), the Net Present Value (NPV) and Levelized Cost of Lettuce (LCOL) are notably sensitive to changes in input parameters. The annual rate of increase in lettuce prices significantly affects both NPV and payback period (PP). For instance, if lettuce prices do not increase annually, the payback period could extend to 5.72 years.

Analyzing the effect of varying the Loan/TIC (%), where the loan interest rate matches the inflation rate—on the performance metrics reveals that an increase in this parameter leads to a nearly proportional decrease in both the payback period (PP) and the levelized cost of lettuce (LCOL). However, once the Loan/TIC (%) exceeds 30%, the rate of decrease in the payback period accelerates with further increases in this parameter. Figure 7e demonstrates that government support in the form of loans can enhance the attractiveness of investment in this sector. The findings from the sensitivity analysis offer valuable insights for decision-makers, allowing them to develop informed strategies by understanding how changes in input variables affect the outcomes.

Scenario analysis

Investigating different scenarios for the financial support of a system is a crucial step towards achieving investment security and sustainability.

In this section, the results of investigating different scenarios for financial support of the novel system are evaluated. Through these results, policymakers, researchers, and stakeholders can identify the best financing models for the novel system to ensure the achievement of broader economic, social, and environmental objectives. Table 8 provides the results of different financial scenarios. According to the table, some of the results can be obtained:

1- Financial support is necessary for the development and implementation of novel systems. From the payback period point of view, the best supporting scenario is a direct payment of the annual income of society to the investors as subsidies. Granting 50% of the required capital in the form of a loan to the investor, with an interest rate equal to both the inflation rate and the discount rate, will be prioritized and executed concurrently. However, if the electricity subsidy is removed, the investment payback period will increase to 6.53 years, the worst scenario analyzed. Therefore, paying a subsidy for electricity would be a supportive tool for promoting such productive systems, so that if it is removed, the payback period will increase by 32.58%.

2- The indirect payment of subsidy scenario has a uniform constructive effect on all the examined parameters. Indirect payment of subsidy to the investors by supplying necessary consumables, such as seeds and fertilizer, would decrease the payback period from 4.93 to 4.12 years. Moreover, this scenario will lead to the lowest LCOL.

Table 8- Different considered financial scenarios

Scenario	0	1	2	3	4	5
Description / Parameter	Main	Direct annual payment	No subsidy for electricity	Free seeds and fertilizer	50% loan with 5% interest rate with 5 years repayment period	50% loan with 8% interest rate with 5 years repayment period
Annual subsidy ($)	0	61.34	0	0	0	0
Electricity price ($ kWh^{-1})	0.011	0.011	0.0824	0.011	0.011	0.011
Lettuce price ($ $head^{-1}$)	0.60	0.60	0.60	0.60	0.60	0.60
Lettuce annual price increment	5%	5%	5%	5%	5%	5%
Discount rate	8%	8%	8%	8%	8%	8%
Inflation rate	5%	5%	5%	5%	5%	5%
NPV ($)	1106.5	2118.9	734.5	1393.8	1145	1131
Payback period (years)	4.93	3	6.53	4.12	3.52	3.68
LCOL ($)	0.42	0.41	0.61	0.30	0.32	0.32
NPV variation (%)	0	+91.48	-33.63	+25.96	+3.54	+2.18
Period payback variation (%)	0	38.91	+32.58	-16.27	-28.49	-25.19
LCOL variation (%)	0	-1.87	+45.0	-28.59	-23.89	-23.89

Conclusion

In the current study, first a novel, economically feasible system that enables the constructive interaction of the building and urban agriculture sectors was proposed to reduce total energy and water consumption and annual CO_2 production. After that, a numerical simulation was developed based on the experimental results and previous related research works; then, the yearly simulation of a room equipped with the novel system was performed, and the total energy and annual CO_2 production results were obtained. The results were compared with the total results of a control room and a separate standard greenhouse with the same product. Finally, an economic study based on the analysis of the financial indicators, such as LCOC, PP, and NPV, was carried out, and the sensitivity of different parameters and scenarios was examined. The main conclusions of this study are as follows:

- The total energy consumption reduction from using the novel system was 31.2 %.
- The novel system will cause approximately 3400 $kgCO_2$ emissions reduction over a 20-year life cycle.
- The payback period was approximately five years based on the NPV results.
- Financial support is necessary for the development and implementation of the novel system.
- From the payback period point of view, the best supporting scenario is the direct payment of annual income of society to the investors as subsidies
- Indirect payment of subsidies to the investors by providing the system annual consumable material such as seeds and fertilizer would have a uniform and constructive effect on all the examined economic parameters.
- Paying a subsidy for electricity would be a supportive tool for promoting such productive systems.
- The society's income from the novel system was calculated to be approximately $0.25 per lettuce head.

Acknowledgment

The authors would like to thank the Ferdowsi University of Mashhad for providing the laboratory facilities and financial support through the project.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

M. M. Naserian: Simulation, Validation, Visualization, Data pre and post processing, Writing.

R. Khodabakhshian: Supervision, Methodology, Data pre and post processing, Statically analysis, Conceptualization, Review & editing, Funding acquisition.

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مقاله پژوهشی
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ٤۱۸-۳۹۷

تحلیل انرژی، محیط‌زیستی و اقتصادی سامانه نوین سبز یکپارچه با ساختمان: دیدگاه ساکنان و جنبه‌های اجتماعی

محمد مهدی ناصریان[۱]، رسول خدابخشیان کارگر[۱*]

تاریخ دریافت: ۱۴۰۳/۰۵/۲۰
تاریخ پذیرش: ۱۴۰۳/۰۸/۰۵

چکیده

بخش ساختمان و بخش کشاورزی-غذایی به‌ترتیب تقریباً ۴۰٪ و ۲۱٪ از کل انرژی جهان را مصرف می‌کنند. این پژوهش با هدف ترکیب این دو بخش پرمصرف انرژی برای کاهش مصرف انرژی کل جامعه انجام شده است. برای این منظور، یک سیستم کشاورزی یکپارچه کوچک‌مقیاس با ساختمان طراحی و ساخته شد. در این پژوهش، مصرف کل انرژی و آب، تولید سالانه دی‌اکسید کربن و هزینه کل استفاده از سیستم نوین از دیدگاه ساکنان ساختمان (شخصی) و جنبه‌های اجتماعی مورد تحلیل قرار گرفت. علاوه بر این، نتایج با نتایج کلی یک ساختمان و یک گلخانه استاندارد جداگانه با همان محصول مقایسه شد. نتایج نشان داد که کاهش کل انرژی به دلیل استفاده از سیستم نوین ۳۱/۲٪ بوده است. بر اساس نتایج، سیستم نوین موجب کاهش حدود ۳۴۰۰ کیلوگرم دی‌اکسید کربن در طول یک دوره عمر ۲۰ ساله خواهد شد. همچنین، کاهش مصرف آب سالانه به میزان ۱۹/۲ لیتر بر کیلوگرم تولید کاهو به‌دست آمد. دوره بازگشت سرمایه بر اساس نتایج تحلیل هزینه که شامل هزینه‌های سرمایه‌گذاری، عملیاتی و اجتماعی می‌شود، حدود ۵ سال بود. تحلیل های حساسیت و سناریوها نیز به‌منظور درک بهتر تأثیر پارامترهای مؤثر احتمالی انجام گردید تا سرمایه‌گذاری برای این سامانه نوین را مطمئن و جذاب نماید.

واژه‌های کلیدی: آنالیز محیطزیست، ساختمان سبز، سیستم سبز عمودی، مدلسازی انرژی، NPV

۱- گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران
(*- نویسنده مسئول: Email: Khodabakhshian@um.ac.ir)

https://doi.org/10.22067/jam.2024.89307.1274

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Review Article
Vol. 15, No. 3, 2025, p. 419-434

Prospects of Mechanization in Direct Seeded Rice: A Comprehensive Review

S. Manoj Kumar[1], R. Karthikeyan[2*], K. Thirukumaran[1], A. Senthil[3], P. Dhananchezhiyan[4]

1- Department of Agronomy, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
2- Directorate of Crop Management, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
3- Department of Crop Physiology, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
4- Department of Farm Machinery and Power Engineering, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
(*- Corresponding Author Email: karthikeyan.r@tnau.ac.in)

Received: 11 May 2024
Revised: 31 August 2024
Accepted: 07 September 2024
Available Online: 02 June 2025

How to cite this article:
Manoj Kumar, S., Karthikeyan, R., Thirukumaran, K., Senthil, A., & Dhananchezhiyan, P. (2025). Prospects of Mechanization in Direct Seeded Rice: A Comprehensive Review. *Journal of Agricultural Machinery*, *15*(3), 419-434. https://doi.org/10.22067/jam.2024.87897.1247

Abstract

The traditional method of transplanting rice seedlings is labor-intensive, prompting a shift towards direct seeding of rice as an alternative crop establishment method. Direct seeding offers several advantages, including reduced labor requirements, timely sowing, and water conservation. Innovations in machinery have significantly enhanced the efficiency of direct-seeded rice cultivation, spanning advancements from land preparation to harvest. Techniques such as no-till methods and laser leveling promote efficient resource utilization and water conservation while minimizing soil disturbance. Specialized seeders and precision seed meters ensure accurate seed placement and uniform germination. Power-operated seeders and hand-held rotary dibblers further improve sowing efficiency. Modern irrigation systems, including drip irrigation, alternate wetting and drying, and automated soil moisture sensing, optimize water productivity. Weed management has advanced with mechanical, solar-powered, and autonomous weeding technologies. Additionally, crop mapping, variable rate technology, and unmanned aerial vehicles enable precise and site-specific weed control. Overall, modern machinery has transformed direct-seeded rice cultivation, resulting in increased input use efficiency, reduced labor demands, higher crop yields, and improved sustainability. Continued innovation offers significant potential for optimizing plant establishment, minimizing post-harvest losses, enhancing profitability, and conserving natural resources. This review article examines these advancements and their implications for the future of direct-seeded rice cultivation.

Keywords: Dibbler, Direct Seeded Rice (DSR), Drum Seeder, Mechanization

Bibliometric analysis

A bibliometric analysis of the provided references reveals a comprehensive and diverse range of research topics related to agricultural technologies, particularly focusing on rice cultivation, spanning from 2007 to 2024. This period shows a continued interest in modern and traditional farming techniques, including irrigation, water management, precision agriculture, laser land leveling, direct seeding, and transplanting methods. It also highlights strategies for weed management using UAVs and AI, alongside a focus on agricultural mechanization and environmental sustainability. The majority of studies are concentrated in Asia, specifically in countries like Nepal, India, Bangladesh, China, and Malaysia, emphasizing the regional significance of rice cultivation. In addition,

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https://doi.org/10.22067/jam.2024.87897.1247

contributions from Africa and Europe indicate a global interest in these technologies. The research is disseminated through various reputable journals and conferences, including "Journal of Agriculture and Natural Resources," "Advances in Agricultural and Food Research Journal," "Agronomy," "Agriculture," "Indian Journal of Ecology," "Irrigation Science," and presentations at IOP Conference Series and IEEE Global Humanitarian Technology Conference. Technological advancements highlighted in the references include the development and evaluation of agricultural machines like paddy seeder, drum seeder, power weeder, transplanter, precision farming tools such as laser-guided and drone-based technologies, and data-driven models for forecasting and improving agricultural outcomes. This analysis underscores the rapid evolution and diversification of agricultural practices aimed at enhancing efficiency, sustainability, and productivity in rice cultivation, reflecting the dynamic nature of research and innovation in this critical sector.

Introduction

Rice is a vital staple food for over half of the world's population, particularly in South and Southeast Asia and Latin America (De Nardi, Carnevale, Raccagni, & Sangiorgi, 2024). Rice cultivation is crucial in ensuring food security and sustainable agriculture (Rao, Johnson, Sivaprasad, Ladha, & Mortimer, 2007). It is cultivated in approximately 60 million hectares of land in South Asia, with India alone accounting for about 43.5 million hectares (Kemparaju, 2023). The traditional method of establishing rice crops is through transplanting seedlings from a nursery, which can be labor-intensive and time-consuming. However, in recent years, direct seeding of rice has gained popularity as an alternative method of crop establishment (Liu *et al*., 2014). Direct seeding of rice refers to the practice of sowing rice seeds directly in the field, eliminating the need for nursery preparation and transplanting. There are several advantages associated with direct seeding of rice. Firstly, direct seeding of rice saves labor as it eliminates the need for nursery preparation and the subsequent transplanting of seedlings (Kumar & Ladha, 2011). This is particularly beneficial in countries like India, where increased economic growth has led to reduced availability of labor for agriculture. Secondly, direct seeding of rice allows for faster and easier planting, enabling farmers to sow their crops on time. This is especially important in regions with unpredictable weather patterns (Farooq *et al*., 2011). Additionally, direct seeding of rice requires less water compared to the traditional method of transplanting. This is crucial in areas where water resources are being depleted and more water is required for urbanization (McDonald *et al*., 2014).

In recent years, there have been several advancements in machinery for direct sown rice cultivation, from land preparation to harvesting (Kumar, Dogra, Narang, Singh, & Mehan, 2021). These advancements have greatly improved the efficiency and productivity of rice cultivation, making it more cost-effective and sustainable. One of the significant advancements in direct seeded rice cultivation machinery is the development of specialized equipment for land preparation (Pitoyo & Idkham, 2021). This includes the use of no-till approaches, plows, and disks. These advancements have allowed for more efficient soil preparation, reducing the need for manual labor and increasing the accuracy and uniformity of seedbed preparation (Kumar *et al*., 2021).

Another significant advancement in direct seeded rice cultivation machinery is the development of equipment for crop establishment. This includes the use of direct sowing machines, which allows for the precise placement of seeds in the field (Rajamanickam, Uvaraja, Selvamuthukumaran, & Surya, 2021). These advancements have streamlined the entire process, from land preparation to yield, resulting in increased efficiency, higher yields, and reduced labor requirements (Yu, Zhang, & You, 2021). Overall, the advancements in

machinery for direct sown rice cultivation have transformed the industry and contributed to its success (Muazu, Yahya, Ishak, & Khairunniza-Bejo, 2014). They have allowed for more precise and efficient land preparation, resulting in improved soil health and reduced soil compaction. Additionally, direct seeding of rice offers savings in the cost of nursery raising and leads to significant labor and time savings. The use of machines in sowing also eases intercultivation practices, which enhances aeration to the roots, promoting better plant health and growth.

Innovation Techniques in Land Preparation for Rice Cultivation

Innovative land preparation techniques have been developed to achieve optimal productivity in rice cultivation (Rao & Naidu, 2019). These techniques aim to make the most efficient use of resources, decrease labor requirements, and encourage water conservation. One innovative approach is the implementation of no-till or conservation tillage practices. These methods involve minimizing soil disturbance by avoiding intensive plowing or using disks (Pittelkow *et al*., 2015). This helps to retain moisture, reduce soil erosion, and maintain the natural structure of the soil. Additionally, no-till practices also promote the retention of crop residue on the soil surface, which helps to improve soil fertility and organic matter content. Furthermore, innovative machinery has revolutionized land preparation for rice cultivation. The innovation in land preparation for rice cultivation is essential for sustainable and efficient rice cultivation. These innovations not only improve productivity but also contribute to the conservation of natural resources and reduction of labor requirements, ultimately benefiting farmers and the environment. Innovation in land preparation for paddy cultivation, including techniques such as no-till methods and the use of mechanized rice transplanters, is revolutionizing the way rice is cultivated (Regalado & Cruz, 2010). According to a recent study by Hassan *et al*. (2021), the use of mechanization and precision agriculture technologies plays a vital role in achieving this goal. Sustainable and efficient rice production is of utmost importance in today's rapidly changing world, as highlighted by Zhang *et al*. (2013).

Power tillers and tractors offer greater versatility in terms of their attachments and applications (Hassan *et al*., 2021). They can be used for plowing, harrowing, leveling, and even transplanting or seeding. This versatility allows farmers to adapt to different soil conditions and cultivation techniques, further enhancing efficiency. Moreover, power tillers and tractors enable farmers to cover larger areas of land in a shorter period of time. This helps to ensure proper seed placement, spacing, and depth, resulting in uniform crop emergence and higher yields (Miah & Haque, 2015). It is important to note that the choice of tillage practices should be based on various factors, such as soil type, climate, and crop variety (Quayum & Ali, 2012). In comparison to manual labor and traditional tillage methods, the use of power tillers and tractors in rice cultivation has been found to significantly improve efficiency, productivity, and cost-effectiveness (Paman, Wahyudy, & Bahri, 2019).

Efficiency of Laser Land Leveler in Preparing Fields for Direct Seeded Rice Cultivation

The laser land leveler is a modern technology that has gained popularity in preparing fields for direct seeded rice cultivation. It offers several advantages compared to traditional methods such as plows or disks (Yaligar *et al*., 2017). Firstly, the laser land leveler provides a higher level of precision and accuracy in leveling the field. This ensures an even distribution of water across the field, which is crucial for optimal rice growth and yield. Additionally, the laser land leveler is highly efficient, allowing for faster field preparation compared to manual labor or conventional machinery. Furthermore, the laser land leveler helps to reduce soil compaction and improve soil health. This is achieved through its ability to precisely control the depth and intensity of field leveling, minimizing unnecessary soil disturbance

(Hoque & Hannan, 2014). The reduced labor requirements not only save on costs but also address the challenges of labor availability during peak farming seasons. Moreover, the use of laser land levelers contributes to environmental sustainability by minimizing the environmental impact of traditional land preparation methods (Maqsood & Khalil, 2013). The precision and accuracy of the laser leveler result in minimal soil erosion and disturbance, maintaining the ecological balance of the farmland. The adoption of laser land levelers in direct seeded rice cultivation not only enhances overall agricultural productivity but also aligns with sustainable farming practices, making it an important technological advancement for modern farming operations (Kumar, Karaliya, & Chaudhary, 2017). Thus, the laser land leveler is an efficient tool for preparing fields for direct seeded rice cultivation. Its precision and ability to optimize seed placement, reduce labor and water requirements, and minimize soil disturbance make it an asset for farmers (Manandhar, Zhu, Ozkan, & Shah, 2020). Hu *et al.* (2020) conducted a leveling verification test on a 0.36 ha paddy field, and field flatness was measured using a mesh method before and after the operation. It showed that the standard deviation of the relative elevations of the field decreased from 5.97 to 1.59 cm and work efficiency was 8.7 mu h^{-1} (1 mu = 0.67 ha.), which means that the proposed leveler worked effectively and more efficiently than the rotary leveler.

In Direct Seeded Rice (DSR) experiment conducted during Kharif (June to october) 2014-15 and 2015-16 at the Agricultural Research Station, Karnataka, India. The total irrigation water applied showed a significant reduction of 23.2% for laser-leveled lands and 18.1% for traditionally leveled lands compared to the control treatment. The net returns and benefit-cost ratio were highest in the DSR treatment on laser-leveled land, amounting to ₹80,972 ha^{-1} and 3.11, respectively. Conversely, the lowest net returns and benefit-cost ratio were observed in the pre-transplanted rice (PTR) treatment on traditional-leveled land, with ₹62,618 ha^{-1} of net returns and a benefit-cost ratio of 2.4 (Rajkumar *et al.*, 2017). The variable cost per acre demonstrated a decrease in laser land-leveled farms in comparison to non-adopter farms. Furthermore, owing to enhanced productivity, adopter farms yielded higher gross returns, amounting to ₹43,518, compared to ₹40,739 in non-adopter farms. The returns over variable costs were also notably higher in laser land-leveled fields, reaching ₹32,966 per acre, while non-adopter farms only witnessed returns of ₹30,034 per acre. Consequently, the utilization of laser land leveling technology resulted in an increase in profit, reaching ₹2,932 per acre in rice crop (Sandhu, Singh, Kaur, & Singh, 2019).

Enhancements in Sowing Equipment for Direct Seeded Rice

Direct seeded rice cultivation, also known as dry sowing or direct drilling, is an innovative method that involves sowing rice seeds directly into the fields without the need for transplanting seedlings (Zeng *et al.*, 2011). This method not only saves labor and time, but also reduces the risk of transplanting shock and allows for better utilization of resources such as water and fertilizers. To improve the efficiency and effectiveness of direct seeded rice cultivation, there have been several advancements in sowing equipment. These advancements aim to address the challenges and limitations associated with traditional broadcasting methods, such as uneven seed distribution, poor seed-to-soil contact, and increased susceptibility to weed competition. Some of the enhancements in sowing equipment for direct seeded rice cultivation include:

(i) Improved seed drills

Modern seed drills have been designed to ensure accurate and consistent seed placement, allowing for better seed-to-soil contact and optimal germination rates (Ningthoujam, Haribhushan, Langpoklakpam, & Bhattacharjya, 2020).

(ii) Seed rate adjustment mechanisms

Some sowing equipment is now available with built-in mechanisms that allow farmers to easily adjust the seed rate according to their specific requirements, thus optimizing seed usage and reducing wastage.

(iii) Automatic depth control

Advanced sowing equipment now includes automatic depth control mechanisms that ensure consistent and precise seed placement at the desired depth, promoting uniform germination and plant growth (Kumar *et al*., 2021).

(iv) Precision seed meters

These seed meters have been developed to accurately measure and distribute the seeds at a consistent rate, ensuring uniformity in seed spacing and reducing seed wastage.

Power Operated Direct Seeded Rice Cultivation

Power-operated direct seeded rice cultivation is a method that aims to mechanize the process of sowing paddy seeds directly into the soil. Several sources highlight the importance of precision in seed distribution to achieve optimum plant population and yield (Yu *et al*., 2021). Additionally, the use of power-operated machines for direct seeding in rice fields can significantly reduce labor needs and increase efficiency. By analyzing the agronomic requirements of film-covering direct seeding in rice fields and considering the characteristics of operating conditions, a machine has been designed to ensure the efficient and effective distribution of paddy seeds, while also minimizing resistance and maintaining excellent trafficability in rice fields (Pitoyo & Idkham, 2021). This machine, powered by a high-speed rice transplanter, incorporates a suspension structure to enhance its maneuverability across various soil conditions.

Hand-held rotary Dibbler for Direct Seeded Rice Cultivation

A major drawback of direct-seeded cultivation of rice is the uneven distribution of pre-germinated seeds on wet puddled soil, leading to lower yields. To overcome this challenge, researchers at South China Agricultural University have developed a precision rice hill-drop drilling technology with synchronous furrowing and ridging. This technology allows for the uniform hill-dropping of pre-germinated seeds in the desired positions on puddled soil (Zeng *et al*., 2011). This precision seeding method significantly improves crop growth and effectively reduces disease and pest infestations caused by irregular and uneven seed distribution. To further enhance the efficiency and ease of direct seeding cultivation, a hand-held rotary dibbler has been designed. This hand-held rotary dibbler ensures accurate and controlled placement of rice seeds at the correct spacing and depth, resulting in optimum plant population (Pitoyo & Idkham, 2021). The hand-held rotary dibbler is lightweight and easy to use, making it suitable for small-scale farmers. Its adjustable depth and spacing settings offer flexibility to accommodate different seed varieties and spacing requirements. This tool helps farmers achieve uniform seed placement, which is essential for improving crop establishment and maximizing yields. Additionally, the ease of use and affordability of this tool make it a practical solution for smallholder farmers looking to enhance their rice cultivation methods (Nageswar Bandi, Mathew, & Patil, 2020). To evaluate the performance of a hand-held rotary dibbler for direct-seeded paddy cultivation, various parameters were considered. These parameters included the theoretical and effective field capacity, field efficiency, and missing hill percentage (Ratnayake & Balasoriya, 2013). The theoretical field capacity of the hand-held rotary dibbler was observed to be 0.22 ha h^{-1}, with an effective field capacity of 0.18 ha h^{-1}. The field efficiency was found to be 81%, indicating the effectiveness of the rotary dibbler in terms of its ability to effectively sow rice seeds directly in the field.



Fig. 1. Hand-held rotary dibbler

Performance of Drum Seeder

The mechanization of direct seeding rice cultivation has been achieved using a manually operated mechanical drum seeder. However, it has its drawbacks, such as uneven distribution of seeds and lower yield (Rao & Naidu, 2019). To address these challenges, a redesigned manually operated mechanical drum seeder was developed. Known as the conical drum seeder, it was evaluated in paddy fields against traditional methods such as manual broadcasting (Ratnayake & Balasoriya, 2013). The conical drum seeder showed higher field capacity, field efficiency, and accuracy in seed placement compared to manual broadcasting. These results indicate that the conical drum seeder technology holds great potential for direct seeded rice cultivation, offering increased productivity and cost savings while maintaining optimal plant population and yield. The use of precision hill seeders, such as the conical drum seeder, in direct seeded rice cultivation offers numerous benefits (Nageswar Bandi *et al*., 2020). These include improved distribution uniformity, increased yield, seed conservation, labor and time savings, and overall efficiency. Direct sowing using a drum seeder not only diminishes the expenses associated with nursery establishment and transplanting but also elevates yield by 12.7 percent, concurrently abbreviating crop duration and cultivation expenses. The adoption of this method led to a reduction in cultivation costs by 19.5 percent and amplified net returns by 34.3 percent (Kumari & Sudheer, 2015).

Rao, Patil, Rao, & Reddy (2014) evaluated the performance of a manually operated paddy drum seeder inAndhra Pradesh, India, over three years. Complete mechanization in paddy (drum seeder, cono weeder, and paddy thresher) (T_1), with Reclamation of soil by Dhaincha + complete mechanization in paddy (drum seeder, cono weeder, and paddy thresher) (T_2), which resulted in a 10% and 14% increase, respectively, in the average grain yield compared to conventional farming practices. In treatment T_2, where a green manure crop (Dhaincha) was cultivated and incorporated into the soil using traditional plowing methods before sowing the seeds in paddy, the average cost of cultivation decreased by 25%. Additionally, the adoption of mechanized cultivation techniques led to the crop reaching maturity eight to ten days earlier than with traditional farming methods. This study demonstrated the potential for improving the socio-economic status of farmers by transitioning towards mechanized and organic paddy cultivation strategies.

On comparison of drum seeding with transplanting of rice, it was revealed that direct

seeding using a drum seeder was identified as the most economically viable option, yielding higher grain output and resulting in a shorter crop duration and consuming less water, leading to increased water-use efficiency compared to the transplanting approach (Kumar, Singh, Sagar, & Maurya, 2018).

Sangeetha, Balakrishnan, Sathya Priya, and Maheswari (2009) evaluated the influence of seeding methods and weed management practices on direct seeded rice at Tamil Nadu Agricultural University, Coimbatore, India. The results revealed that the drum seeding combined with green manure technique led to a significant increase in leaf area index (LAI), higher number of tillers per square meter, enhanced dry matter production (measured in kg per hectare), and superior grain yield, outperforming the broadcasting method.

Komatineni *et al*. (2023) reported that Bluetooth based remote controlled battery powered drum seeder exhibited a field capacity of 0.023 ha h^{-1} and a field efficiency of 82%, whereas the manual drum seeder had a field capacity of 0.017 ha h^{-1} and a field efficiency of 62%. Compared to the manual drum seeder, the developed seeder reduced the physical strain by 64%, as evidenced by the operator's heart rate and energy expenditure rate; the operational cost of the developed seeder was reduced by ₹230 per hectare compared to the manual drum seeder.

Mir *et al*. (2023) opined that four times of mechanized cono-weeding operation was found promising for improving productivity and efficient weed control in direct drum-seeded rice in temperate conditions of Kashmir, India.

Kumar and Chinnamuthu (2022) evaluate the effect of time and method of sowing of wet direct seeded rice at Tamil Nadu Agricultural University, Coimbatore, India during the first fortnight of July using the Paddy + Dhaincha drum seeder method and recorded a higher grain yield of 5707 kg ha^{-1} which resulted in 33 percent higher yield than that achieved with thebroadcasting method. Table 1 presents the sowing equipment along with their corresponding field capacities.



Fig. 2. Drum seeder

Table 1- Sowing equipment and field capacity

Sowing Equipment	Field Capacity (ha h^{-1})	Reference
Drum Seeder	0.12 – 0.18	Pradhan, Nayak, Mohanty, and Behera (2014)
Power-Operated Direct Seeder	0.168 – 0.114	Dhruw and Verma (2018)
Hand-held Rotary Dibbler	0.02 – 0.04	Sahoo, Sahu, and Rout (2012)

Enhancements in irrigation technologies for Direct Seeded Rice

Water Productivity (WP) and Water Use Efficiency (WUE) are crucial for sustainable agricultural water management, ensuring the conservation of resources (Luo *et al*., 2022). Drip irrigation, though not widely adopted in rice farming, is advocated for its potential to enhance productivity while minimizing water usage (Kilemo, 2022). Recent advancements in automated irrigation systems, utilizing soil moisture sensing through Internet of Things (IoT) technology, offer significant water and labor-saving benefits (Arouna, Dzomeku, Shaibu, & Nurudeen, 2023). Integration of smart irrigation systems across various cropping scenarios, with decreasing costs, shows promise for more efficient and sustainable water management practices in agriculture, potentially reducing global water consumption and alleviating labor burdens associated with frequent irrigation (Conesa, Conejero, Vera, & Ruiz-Sánchez, 2021).

The efficacy of Alternate Wetting and Drying (AWD) in conserving water and enhancing productivity exhibits remarkable superiority within the Direct Dry Seeded Rice (DDSR) system when contrasted with AWD in the Transplanting Rice (TPR) system (Ishfaq, Akbar, Anjum, & Anwar-Ijl-Haq, 2020). Additionally, drip irrigation combined with direct seeded rice managed at 20% Cumulative Pan Evaporation (CPE) with 1-day intervals, showcased superior performance in growth parameters, as well as grain and straw yields, achieving statistically higher grain yield (8076 kg ha^{-1}) and straw yield (8651 kg ha^{-1}) compared to conventional transplanted rice. Furthermore, when scrutinizing water use efficiency between direct-seeded rice and puddled transplanted rice, the former demonstrates greater efficiency without compromising growth, yield, and other yield characteristics (Kumawat, Sepat, Kumar, Jinger, & Kaur, 2017).

Enhancements in Weed Management Technologies for Direct Seeded Rice

Weeds, as unwanted plants, threaten crop yields by competing for vital resources such as water, nutrients, light, and space, highlighting the necessity for effective weed management in agriculture to meet future food demands. Mechanical weeding, recognized for its eco-friendly and sustainable attributes, has gained traction in recent years due to its cost reduction, labor efficiency, and suitability for organic farming, particularly in rice cultivation. A solar-powered sprayer was engineered for herbicide application, harnessing solar energy as its primary power source. Weighing in at 15 kg, the sprayer operates at a speed of 2.5 km h^{-1}. Upon evaluation, the theoretical field capacity, effective field capacity, and field efficiency of the developed solar-operated sprayer were determined to be 0.6 ha h^{-1}, 0.5 ha h^{-1}, and 83.33 percent, respectively. This innovation not only diminishes laborious tasks but also proves to be economically viable and environmentally friendly, utilizing readily available solar energy, which is accessible to farmers at an affordable cost (Basavaraj, Ajaykumar, & Swathi, 2020). Ongoing research focuses on enhancing mechanical weed control methods (Barbaś, Sawicka, Marczak, & Pszczółkowski, 2020). Crop and weed mapping aids in site-specific herbicide applications and optimizing management strategies, while precision agriculture, employing technologies like Variable Rate Technology (VRT) and remote sensing, enables precise and efficient weed management. Advancements in autonomous driving technology have led to the development of intelligent paddy weeding machines, incorporating satellite navigation and automatic control systems for precise intra-row and inter-row weeding (Daponte *et al*., 2019). Additionally, Unmanned Aerial Vehicles (UAVs) are increasingly utilized for their ability to swiftly monitor and manage weed patches, particularly in navigating between crop rows, thus contributing to effective weed control in agriculture (Radoglou-Grammatikis, Sarigiannidis, Lagkas, & Moscholios, 2020).

Ragesh, Jogdand, and Victor (2018) reported that the modified Paddy power weeder stands out as the superior choice for weed management compared to the Ambika paddy weeder, boasting higher weeding efficiency at 20 and 45 days after sowing (DAS). While both the Paddy power weeder and Ambika paddy weeder exhibit comparable field efficiency, a notable distinction arises in operational cost, where thePaddy power weeder proves to be significantly more feasible than its Ambika counterpart.

Utilizing drones for the application of pretilachlor followed by bispyribac sodium herbicide proves to be a highly effective strategy for weed management in direct seeded rice. This approach not only demonstrates superior efficacy but also offers advantages in terms of energy utilization and profitability (Paul, Arthanari, Pazhanivelan, Kavitha, & Djanaguiraman, 2023).

Unmanned aerial vehicles (UAVs) are predominantly employed for tasks such as nutrient application and pesticide spraying, especially among smallholder farmers and in various industries. The incorporation of artificial intelligence (AI), which encompasses UAVs along with a range of sensors including hyperspectral, multispectral, and RGB cameras, as well as thermal and odor sensors, for early weed detection methods holds promise for more effective weed management outcomes. And the use of UAVs and AI technologies for the detection and control of weeds in rice crops (Ahmad *et al*., 2023).

Kishore Kumar (2018) studied the effect of different wet seeding methods and weed management practices on grain yield of unpuddled rice in Tamirabarani command area of Tamil Nadu, India and the results revealed that rice established through drum seeder along with the pre emergence application of pyrazosulfuron ethyl at 20 g a.i ha^{-1} on 8 DAS followed by post emergence (POE) bispyribac sodium at 25 g a.i ha^{-1} at 30 DAS not only significantly reduced density and dry weight of weeds but also increased the grain yield of rice and benefit-cost ratio.

Arivukodi and Velayutham (2017) evaluated the evolving suitable weed management practices for direct sown drum seeded rice in the Thamirabarani command area of Tamil Nadu, India, and the results revealed that the application of pretilachlor @ 750 g a.i. ha^{-1} on 8 DAS as PE + bispyribac sodium @ 25 g a.i. ha^{-1} on 30 DAS as POE not only significantly reduced density and dry weight of weeds but also increased the grain yield of rice.

The Impact of Modern Mechanization on Yield and Efficiency

Modern machinery had a significant impact on rice yield and efficiency in rice production. By utilizing advanced technologies and machinery, farmers can improve various stages of rice production, leading to increased yield and higher efficiency levels (Paman *et al*., 2019). Furthermore, the availability of machine power, such as hand tractors, irrigation pumps, power threshers, and rice milling units, has increased significantly in recent years. This increased availability of machine power has contributed to the overall mechanization of rice production, leading to improved productivity and higher rice yields (Haryono, Hudoyo, & Mayasari, 2021). Furthermore, the intensification approach, which includes the use of good seeds and a mechanization approach, has also played a crucial role in increasing rice production and yield. In summary, modern machinery has revolutionized the paddy rice production system, allowing for more efficient and productive farming practices. Modern machinery has revolutionized rice production, leading to increased yield and efficiency. Overall, the impact of modern machinery on rice yield and efficiency in rice production has been significant (Acharya, Regmi, Gauchan, KC, & KC, 2020). Modern machinery has revolutionized rice production, leading to increased yield and efficiency. By employing modern machinery in rice production, farmers can streamline and optimize various stages of the process, resulting in higher yields and improved efficiency in the field. The use of modern machinery in rice production has

greatly increased threshing and winnowing capacity, leading to higher yields in rice farming (Ningthoujam *et al*., 2020). Table 2 and Table 3 present the rice sowing methods along with the grain yields obtained (kg ha^{-1}), as well as the sowing and weeding equipment utilized, along with their respective efficiencies (%).

Table 2- Type of sowing and yield (kg ha^{-1})

Types of sowing	Yield (kg ha^{-1})	Reference
Manual Broadcasting	5518	Ratnayake and Balasoriya (2013)
Drum seeder	7553	Ratnayake and Balasoriya (2013)
Transplanter	5680	Rao, PB, and Chandrayudu (2020)

Table 3- Sowing and weeding equipment and efficiency

Equipment	Efficiency (%)	Reference
Drum Seeder	65 – 75	Pradhan *et al*. (2014)
Power-operated Direct Seeder	68 – 78	Dhruw and Verma (2018)
Hand-held Rotary Dibbler	60 – 70	Sahoo *et al*. (2012)
Power-operated Weeder	70 – 80	Kumar and Mohankumar (2019)

Future Prospects of Machinery in Direct Seeded Rice Cultivation

The prospects of machinery in direct seeded rice cultivation hold tremendous potential for improving efficiency, productivity, and sustainability in the agricultural sector. With advancements in technology and the development of specialized machinery, farmers can expect to see significant benefits in various aspects of rice cultivation (Haryono *et al*., 2021). For instance, the availability and utilization of power-intensive machines for land preparation, threshing, and milling have already contributed to increased capacity in rice mechanization in some regions (Paman *et al*., 2012). Furthermore, the implementation of sustainable agricultural mechanization programs has resulted in the distribution of combine harvesters and four-wheel tractors to farmer groups, further enhancing the mechanization of rice farming (Haryono *et al*., 2021). These developments in machinery offer several advantages for direct seeded rice cultivation. Firstly, the use of machinery can greatly reduce manual labor and physical exertion required in various farm operations (Paman *et al*., 2012). This not only alleviates the burden on farmers but also saves time and increases overall efficiency, enabling timely completion of farm operations. Additionally, mechanized farming schemes provide the opportunity to optimize plant establishment methods, such as direct sowing or transplanting, as well as different harvesting techniques. This can lead to improved crop yield, reduced post-harvest losses, and increased profitability for farmers. Overall, the prospects of machinery in direct seeding rice cultivation are promising and hold the potential to revolutionize the agriculture industry.

Conclusion

The evolution of machinery in direct-seeded rice cultivation marks a transformative shift towards efficiency, sustainability, and productivity in agriculture. From innovative land preparation techniques to precision sowing equipment, irrigation advancements, and weed management technologies, each aspect of modern machinery contributes to streamlined operations and improved outcomes for farmers. These technological advancements not only alleviate labor burdens but also optimize resource utilization, conserve water, enhance soil health, and mitigate environmental impacts. Looking forward, the future of machinery in rice cultivation holds significant promise for further innovations, which are poised to elevate efficiency, productivity, and sustainability in the agricultural landscape, ultimately ensuring a more resilient future for farmers and the global food supply chain.

Acknowledgments

The authors have nothing to acknowledge, and this research has received no external funding.

Funding

This research was not supported by a specific grant from any private, public, or non-profit organization.

Conflicts of Interest

The authors declare that they have no conflict of interest.

Data Availability

The article contains the statistical data used to substantiate the findings of the study.

Authors Contribution

S. Manoj Kumar: Conceptualization, Data collection, Writing the manuscript.

R. Karthikeyan: Supervision, Visualization, Correction.

K. Thirukumaran: Supervision, Visualization, Correction.

A. Senthil: Technical advice

P. Dhananchezhiyan: Visualization, Technical advice

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مقاله مروری
جلد ۱۵، شماره ۳، پاییز ۱۴۰۴، ص ۴۳۴-۴۱۹

چشم‌انداز مکانیزاسیون کشت مستقیم بذر برنج: مروری جامع

اس. مانوج کومار[۱]، آر. کارتیکین[۲*]، کا. تیروکوماران[۱]، ای. سنتیل[۳]، پی. دهانان‌چژیان[۴]

تاریخ دریافت: ۱۴۰۳/۰۲/۲۲
تاریخ پذیرش: ۱۴۰۳/۰۶/۱۷

چکیده

روش سنتی نشاکاری برنج نیاز به نیروی انسانی زیادی دارد و منجر به تغییر به سمت کاشت مستقیم بذر برنج برای کشت برنج شده است. از جمله مزایای کاشت مستقیم بذر می‌توان به کاهش نیاز به نیروی کار، کاشت به‌موقع و صرفه‌جویی در آب اشاره کرد. نوآوری در ماشین‌آلات کشاورزی کارایی کشت مستقیم بذر برنج را به‌طور قابل‌توجهی بهبود بخشیده است و این پیشرفت تمام مراحل از آماده‌سازی زمین تا برداشت را در برمی‌گیرد. تکنیک‌هایی مانند روش‌های بدون خاک‌ورزی و تسطیح لیزری، استفاده کارآمد از منابع و حفظ منابع آب را تضمین می‌کند و در عین حال اختلالات خاک را به حداقل می‌رساند. امکان قرارگیری دقیق بذر و جوانه‌زنی یکنواخت با استفاده از بذرکارهای اختصاصی و دستگاه‌های سنجش دقیق بذر فراهم شده است. استفاده از بذرکارهای پشت‌تراکتوری و کارنده‌های دستی گردان راندمان کاشت را بیشتر افزایش می‌دهند. روش‌های آبیاری مدرن مانند آبیاری قطره‌ای، آبیاری تناوبی، و سنجش خودکار رطوبت خاک، بهره‌وری آب را بهینه می‌کنند. مدیریت علف‌های هرز با فناوری‌های وجین‌کن‌های مکانیکی از طریق انرژی خورشیدی و خودران تکامل یافته است. نقشه‌برداری‌های مختلف زمین و عملکرد محصول، فناوری نرخ متغیر و وسایل نقلیه هوایی بدون سرنشین (پهپاد) امکان کنترل دقیق علف‌های هرز بر اساس مدیریت مکانی خاص را فراهم می‌کنند. به‌طور کلی، ماشین‌آلات مدرن انقلابی در کشت مستقیم بذر برنج ایجاد کرده‌اند که منجر به افزایش عملکرد، کارایی بالاتر در استفاده از نهاده‌ها، کاهش نیاز به نیروی کار، افزایش عملکرد محصول و بهبود پایداری تولید شده است. تداوم نوآوری، چشم‌انداز وسیعی برای بهینه‌سازی استقرار گیاه در خاک، به حداقل رساندن تلفات پس از برداشت و افزایش سودآوری و در عین حال حفظ منابع طبیعی دارد. این مقاله مروری به بررسی این پیشرفت‌ها و پیامدهای آن‌ها برای آینده کشت مستقیم بذر برنج می‌پردازد.

واژه‌های کلیدی: بذرکار، بذرکارهای استوانه‌ای، دیبلر، کشت مستقیم برنج، مکانیزاسیون

۱- دانشکده زراعت، دانشگاه کشاورزی تامیل نادو، کوایمباتور، ایالت تامیل نادو، هند
۲- معاونت مدیریت محصولات زراعی، دانشگاه کشاورزی تامیل نادو، کوایمباتور، ایالت تامیل نادو، هند
۳- دانشکده فیزیولوژی گیاهی، دانشگاه کشاورزی تامیل نادو، کوایمباتور، ایالت تامیل نادو، هند
۴- دانشکده مهندسی ماشین‌آلات کشاورزی و قدرت، دانشگاه کشاورزی تامیل نادو، کوایمباتور، ایالت تامیل نادو، هند
(*- نویسنده مسئول: Email: karthikeyan.r@tnau.ac.in)

https://doi.org/10.22067/jam.2024.87897.1247

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Review Article
Vol. 15, No. 3, 2025, p. 435-458

Developing a Methodological Framework for Agricultural Cooperatives Studies: A PRISMA Systematic Review

M. Bamdad[1], M. Zangeneh[1*], S. H. Peyman[1]

1- Department of Biosystems Engineering, Faculty of Agricultural Sciences, University of Guilan, Rasht, Iran
(*- Corresponding Author Email: zanganeh@guilan.ac.ir)

Received: 09 August 2024
Revised: 22 September 2024
Accepted: 13 October 2024
Available Online: 02 June 2025

How to cite this article:
Bamdad, M., Zangeneh, M., & Peyman, S. H. (2025). Developing a Methodological Framework for Agricultural Cooperatives Studies: A PRISMA Systematic Review. *Journal of Agricultural Machinery*, *15*(3), 435-458. https://doi.org/10.22067/jam.2024.89290.1273

Abstract

Agricultural cooperatives (ACs) play a vital role in the global agricultural sector, yet their success in food production and supply varies significantly across countries. This study presents a comprehensive review of existing literature on ACs using the PRISMA methodology and proposes a methodological framework to guide future research. Each selected study was analyzed based on four key dimensions: purpose, methodology, factors examined, and key findings. These variables were then categorized to enable a more robust comparative analysis. The review highlights that the success of ACs is driven by effective management, strong marketing strategies, and a dedicated workforce. Education emerges as a critical factor, irrespective of age or gender. However, strategies for success differ among cooperatives, underscoring the need for context-specific research to accurately assess the status and needs of ACs in various regions.

Keywords: Agricultural cooperative, Agricultural services, Cooperative, Member participation, Performance evaluation

Introduction

The rationale of the review

Cooperation is the collaborative effort of individuals or groups working towards a common goal. It has played a crucial role in the survival of our ancestors and has significantly contributed to the formation of modern society. Additionally, cooperation has the potential to facilitate success in the contemporary economic landscape of the 21st century. Agricultural cooperatives (ACs) are widely acknowledged as significant institutions in the global agricultural sector. Despite the various forms of linkages among farmers, scholarly literature indicates that ACs represent the most viable form of linkage (Van Phuong, Thi Thu Huong, & Hong Quy, 2020). Research on ACs has been conducted in numerous countries, employing diverse methodologies to explore comparable factors. The success of agricultural cooperatives in producing and delivering food to consumers varies among countries. While some studies have reported high success rates of ACs in certain countries (Iliopoulosa, Värnikb, Filippic, Võllib, & Laaneväli-Vinokurovd, 2019), others have shown less success. Research by Van Phuong *et al.* (2020) has identified factors contributing to success and failure in both developed and developing nations. The commitment of members tends to

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https://doi.org/10.22067/jam.2024.89290.1273

decrease as agricultural cooperatives grow in size. The increasing complexity of an organization and the diversity of its membership pose sustainability challenges, as highlighted by Bareille, Bonnet-Beaugrand, and Duvaleix-Tréguer (2017). Financial audits and other management deficiencies can jeopardize the long-term viability and profitability of these entities, as noted by Benson (2014). The effectiveness of agricultural cooperatives depends on their business objectives, which have been defined in various ways in the literature. Studies can be classified into two categories based on their assumptions: those assuming a singular objective and those assuming multiple objectives, as suggested by Soboh, Lansink, Giesen, and van Dijk (2009). Various analytical tools, such as the efficiency-profitability matrix (Xaba, Marwa, & Mathur-Helm, 2018), and traditional indicators (Lauermann, Moreira, Souza, & Piccoli, 2020), have been utilized to assess cooperative performance. Previous research on cooperative performance has predominantly focused on financial accounting measures. Limited empirical research has been conducted to evaluate the sustainable performance of agricultural cooperatives' operations (Marcis, de Lima, & Da Costa, 2019). According to Marcis, Bortoluzzi, de Lima, and Da Costa (2018), most sustainability assessment models for cooperatives lack an integrated approach to address the three dimensions of sustainability. Therefore, it is crucial to adopt a comprehensive approach that considers various dimensions of collaborative performance, as advocated by Franken and Cook (2015).

The aim of the current study is to provide a thorough examination of the extant literature on audit committees (AC). This review seeks to explore different facets associated with AC, including their objectives, determinants, outcomes, and research approaches. Furthermore, the study intends to put forward a methodological framework that can offer direction for future investigations in this domain.

Objectives

As indicated in the existing literature, the predominant focus of research in this field has been on various dimensions including performance, ownership, governance, finance, and member attitudes (Grashuis & Su, 2019). In cases where the variables are non-parametric, a group of similar variables is outlined in the objectives section, along with the factors and outcomes. Subsequently, a comparison is conducted among each group to identify frequently occurring variables that are considered significant within each respective category. This underscores the study's concentration on a specific subject. Potential sources of bias will be meticulously examined, and studies with a high probability of bias will be pinpointed. Following this, the key findings of these studies will be analyzed for any potential implications. The current study seeks to illustrate the relationship between objectives, contributing factors, and the success of cooperatives through the application of Vensim modeling software. The primary objective of this study is to establish a methodological framework that can be applied in future research endeavors. The framework will be presented at the culmination of the study.

Methods

Protocol of the Review

The current investigation utilized the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to conduct an exhaustive review of studies pertaining to agricultural cooperatives (AC). The PRISMA guidelines constitute a meticulously developed and evidence-based collection of essential elements for reporting systematic reviews and meta-analyses. While the primary emphasis of the PRISMA guidelines is on reporting reviews that evaluate the impacts of interventions, they can also provide a framework for reporting systematic reviews with objectives other than intervention assessment, such as examining etiology,

prevalence, diagnosis, or prognosis (Page, McKenzie, *et al.*, 2020). Initially, relevant keywords were employed to identify studies related to AC. Key terms in this context encompass cooperation, cooperative, cooperative model, cooperative organization, agriculture, farm, agricultural cooperative, farmer cooperative, producer cooperative, agricultural service cooperative, family farming, performance, performance assessment, agricultural services, service design, agricultural service design, supply chain, agricultural supply chain, agricultural service supply chain, and associated terminology. The systematic review protocol is delineated in Figure 1.

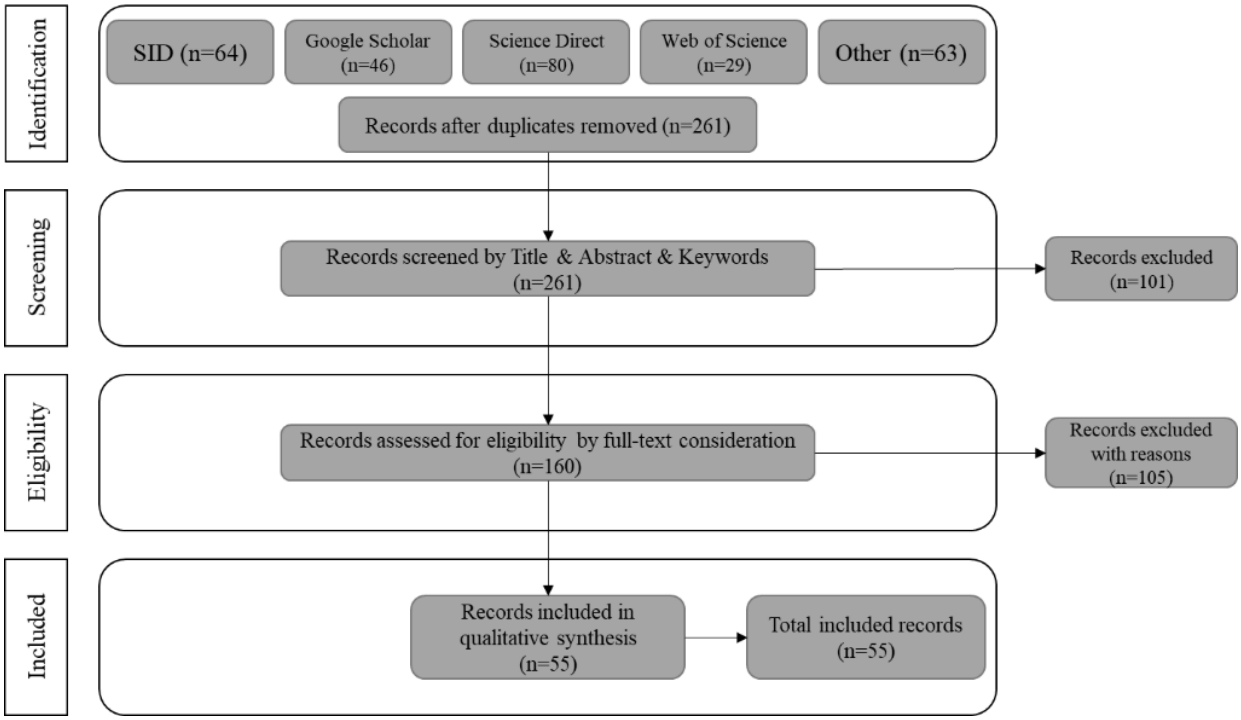


Fig. 1. Systematic review process

Eligibility Criteria

The primary criterion utilized to select relevant studies for this review was their pertinence. The evaluation of relevance involved screening the title and keywords, with further scrutiny of the abstract during the review process. The second criterion considered the publication year, with inclusion criteria specifying studies published after 2010. The third criterion focused on studies' objectives, variables studied, methodologies, and main findings. Throughout this process, separate categories were created for each aspect of the reviewed studies, which are detailed in the Results section. Studies that did not provide evidence of factors contributing to success or failure were excluded from the analysis.

Study Selection

Following an extensive search of databases, a total of 282 studies were identified based on the relevance of their keywords in titles and abstracts. Among these, 64 were sourced from the Scientific Information Database (SID), 80 from ScienceDirect, 29 from the Web of Science (WOS) database, 46 from Google Scholar, and 63 from miscellaneous sources. Subsequent to a meticulous examination, 21 duplicate studies were detected and subsequently removed. A screening process was then conducted on the initial pool of 261 studies to evaluate their relevance based on titles, abstracts, and keywords, resulting in the exclusion of 97 studies. Upon a thorough examination of the complete text of the

remaining 164 studies, 105 were excluded due to their lack of relevance to the study's purpose, factors, methods, and findings classifications. Studies published before 2010 were also excluded from the analysis. Ultimately, 55 studies met the criteria for inclusion in this systematic review. Additionally, certain book chapters were omitted during this process. A comprehensive analysis of the 164 studies led to the establishment of categories for the four main sections of a research study, which encompass primary objectives, factors under investigation, methodologies employed, and significant findings. These categories were designed to offer a comprehensive overview of various aspects of AC, facilitating the inclusion of a broader range of research variables. The frequency of each variable in the studies was considered to achieve this objective. Identical variables within each section were initially identified and categorized into respective classes, followed by the allocation of similar variables to these pre-defined classes. The purposes of the studies were classified into performance evaluation, assessing cooperative membership, identifying the main problems of cooperatives, and investigating the development and success of cooperatives. The factors studied were categorized into seven groups: structural, financial, demographic, operational, governmental, social, and environmental factors. Findings were classified into efficiency and performance, membership, advisory and suggestions, and policy-related matters. The frequency of each category was determined for each part and utilized in the analysis. To offer a comprehensive analysis of the current state of research on AC, this study considered four key indicators within each study: purposes, factors, methods, and key findings. One of the primary factors contributing to bias in research studies is an inaccurate sample size, which can lead to unreliable findings. To identify potential biases, a thorough examination of the data collection methods, including sample size (Cochran method, Morgan table), and sampling methods (simple or stratified random sampling), was conducted. An assessment was also carried out regarding the quality of the participants involved in the data extraction. The data obtained from the studies were analyzed to demonstrate diversity across categories using various charts. In order to assess potential bias among studies, we conducted a comparative analysis of the sources and methodologies employed to extract factors, the data extraction procedures utilized, and whether the studies relied on secondary research and statistical analysis or primary field research to obtain their data.

Risk of Bias Across the Studies

The majority of the studies included in this analysis gathered data through field research and interviews with various stakeholders, including AC members, managers, householders, and experts. For example, 31 studies, such as those conducted by Mozaffari (2016), utilized these methods for data collection. Other studies used different methodologies, such as literature reviews, official reports, and statistical analyses. The research in this field has employed a variety of methodologies. Some studies have used statistical analysis, reports, and academic research to explore different topics (e.g., Li and Li, 2010). In contrast, other studies have relied on academic libraries to investigate common subjects and similar themes (e.g., Benson, 2014), thereby contributing to the existing knowledge base. The data collection methods varied among the studies, with questionnaires being the most frequently used approach (39 studies, such as Shen and Shen (2018) and Brandão and Breitenbach (2019)), followed by library research (10 studies, such as Wolz, Möllers, *et al.* (2019)), and field research (5 studies, such as Marcis, de Lima *et al.* (2019)). Some studies did not specify the data extraction method used. To identify potential biases in the studies, we conducted a comparative analysis of their findings, considering the specific topics of interest being investigated. The results of the bias analysis are presented in Table 2.

Various factors can contribute to an

increased risk of bias in survey research findings. In studies utilizing questionnaires, biases can arise from the sample size and the diversity of individuals included in the sample. Therefore, it is advisable to ensure that the initial sample size is adequate. Employing a random sampling technique is essential to ensure a diverse representation of the statistical population in the sample. Furthermore, extraneous questions that are not directly related to the main research topic but can influence respondents' answers can introduce bias. The phrasing and structure of questions may inadvertently direct respondents' attention to specific issues. The sequencing of questions is another critical factor that can impact responses, particularly if it changes during the survey administration. These factors, along with others that may affect the accuracy and reliability of data collected through questionnaire-based survey studies, can be mitigated through meticulous attention and adherence to appropriate research methodologies.

Table 3 provides a comprehensive overview of the empirical literature on agricultural cooperatives (ACs), summarizing key aspects such as research purposes, methods, studied factors, and findings. The table highlights the diversity of methodologies employed, including statistical tests like T-tests and regression analysis, as well as qualitative approaches such as the Delphi method and SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis. The studied factors span economic, managerial, social, and environmental dimensions, reflecting the multifaceted nature of AC performance. Key findings often emphasize the importance of education, strategic planning, and member participation in driving cooperative success, while also identifying challenges like financial constraints and management deficiencies. This synthesis underscores the need for a holistic approach to evaluating ACs, integrating financial, operational, and social metrics to better understand their performance and sustainability. The table serves as a valuable resource for researchers aiming to identify gaps in the literature and design future studies with robust methodological frameworks.

Results

Study Selection

A total of 55 studies were selected for inclusion in this research. During this procedure, certain book chapters were excluded.

Study Characteristics

Several studies have been published within the last decade, specifically between 2010 and 2020. The studies typically had a regional scope and a sample size ranging from 100 to 1000 ACs.

Risk of Bias within Studies

The current review has identified that the studies analyzed utilized four main techniques to determine the appropriate sample size. These methods comprised the Cochran method (16 studies), the Morgan table (3 studies), the Snowball method (3 studies), and the Neyman-Pearson method (1 study). Among the 21 studies examined, it was observed that some studies did not specify the methodology used to establish the sample size. The sampling methods employed were Simple Random Sampling (13 studies), Stratified Random Sampling (6 studies), Purposive Sampling (6 studies), Multistage Sampling (2 studies), and Complete Enumeration (2 studies). From the findings of the reviewed studies, it was evident that 9 of them had insufficient sample sizes and sampling methods. The studies that demonstrate a potential for bias based on the assessed bias factors is presented in Table 1. The data collection process in the studies delineates the quality of participants into three levels. The highest level (A) is attained when the participants are experts, followed by the next level (B) when the participants are cooperative managers, and the third level (C) when the participants are cooperative members.

Table 1- Factors influencing research bias based on participant type: (A) experts, (B) cooperative managers, or (C) cooperative members (with A > B > C in influence)

	Data Extraction	Data Collection Method	Sample size method	Sampling method	Participants		Reference(s)
					Quantity	Quality	
1	Self-dependent	Questionnaire	Cochran	Simple Random Sampling (RS)	165	C	(Donyaei, Yaghoubi, & Rajaei, 2010)
2	Self-dependent	Questionnaire	Cochran	Simple RS	212	A	(Baseri, Sadeghi, & Khaksar, 2010)
3	From different studies	Library Research	Not mentioned	-	10	C	(Li & Li, 2010)
4	Self-dependent	Questionnaire	Cochran	Stratified RS	250	C	(Ghiasvand Ghiasy & F.Hosseini, 2011)
5	From similar studies	Questionnaire	Cochran	Stratified RS	209	C	(Solouki, Malekmohammadi, & Chizari, 2011)
6	Self-dependent	Questionnaire	Not mentioned	-	50	B	(Mahazril'Aini, Hafizah, & Zuraini, 2012)
7	From similar studies	Library Research	Not mentioned	-	11	C	(Benson, 2014)
8	Self-dependent	Questionnaire	Not mentioned	-	1000	C	(Franken & Cook, 2015)
9	From similar studies	Questionnaire	Cochran	Simple RS	168	A	(Savari, Dorrani, & Shabanali Fami, 2015)
10	From similar studies	Questionnaire	Not mentioned	-	20	C	(Hosseini & Mahdizadeh, 2015)
11	Self-dependent	Field Research	Not mentioned	-	-	-	(Tsymbalista, 2016)
12	Self-dependent	Questionnaire	Cochran	Simple RS	49	B	(Mozaffari, 2016)
13	From similar studies	Questionnaire	Cochran	Simple RS	133	C	(Rasouliazar, Kivanifar, & Rashiedpour, 2016)
14	Self-dependent	Field Research	Not mentioned		3205	C	(Bareille *et al.*, 2017)
15	Self-dependent	Field Research	Not mentioned	-	487	A	(Gao, Zhang, Wu, Yin, & Lu, 2017)
16	Self-dependent	Field Research	Not mentioned	-	128	C	(Shamsuddin, Ismail, Mahmood, & Abdullah, 2017)
17	Self-dependent	Questionnaire	Not mentioned	-	30	B	(Kurakin & Visser, 2017)
18	From different studies	Questionnaire	Not mentioned	-	12	C	(Shen & Shen, 2018)
19	From different studies	Library Research	Not mentioned	-	15	C	(Anzilago, Panhoca, Bezerra, Beuren, & Kassai, 2018)
20	From similar studies	Library Research	Not mentioned	-	-	-	(Iliopoulos & Valentinov, 2018)
21	Self-dependent	Field Research	Not mentioned	Purposive S	17	C	(Marcis *et al.*, 2019)
22	From similar studies	Questionnaire	Not mentioned	Simple RS	10	B	(Brandão & Breitenbach, 2019)
23	Self-dependent	Questionnaire	Not mentioned	-	8	C	(De Rosa, McElwee, & Smith, 2019)
24	NA	Questionnaire	Not mentioned	-	280	C	(Piwoni-Krzeszowska, 2019)
25	Self-dependent	Questionnaire	Not mentioned	-	7	B	(Ribašauskienė *et al.*, 2019)
26	From different studies	Questionnaire	Not mentioned	-	-	-	(Wolz *et al.*, 2019)
27	From similar studies	Library Research	Not mentioned	-	-	C	(Bijman, 2020)
28	Self-dependent	Questionnaire	Not mentioned	-	162	C	(Fawen & Cheng, 2020)

Results of Individual Studies

The objective of this study was to gain a comprehensive understanding of the research framework pertaining to AC. We have opted to explicate the principal components of each study based on these criteria. Accordingly, the studies were deconstructed into four distinct components, namely research purposes, studied factors, methods, and findings

Synthesis of Results

Purpose's classification

The research purposes were classified into four distinct categories: performance evaluation, assessment of cooperative membership, identification of cooperative main problems, and investigation of the development and success of cooperatives. The frequency distribution of each category observed in the reviewed studies is depicted in Figure 2.

Table 2- Findings bias across studies

Topic	Studied Factor(s)	Key Finding(s)	Sample Size Validity	Reference(s)
Member Participation	General attributes, Market information, Decision making, Form of management	Low participation of members in cooperative decisions points to deficient management	Not valid	(Brandão & Breitenbach, 2019)
	Member participation, social capital Common beliefs, Awareness of the principles of cooperation	Studied factors can explain 39 percent of the variance in member participation	Valid	(Ansari, Jourablou, Pourafkari, & Hashemianfar, 2015)
	Economic factors, Member's features Organizational factors, Socio-cultural factors, Educational factors, Management factors, Political factors	Economic factors had the biggest impact on cooperative development, while members' features and political factors had no impact	Valid	(Pirouz & Gholipoor, 2018)
	Strategic planning, Member participation	Strategic planning and member participation are effective on cooperatives' overall success and performance	-	(Mahazril'Aini *et al.*, 2012)
	Heterogeneity factors	Solutions based on member loyalty and commitment not only failed but also resulted in unfortunate side effects	-	(Iliopoulos & Valentinov, 2018)
	Creativity and innovation, Free and optional membership, Economic participation of members, Independence of cooperatives, Cooperation between cooperatives	Studied factors affect member participation and cooperative success	-	(Hosseini & Mahdizadeh, 2015)

Table 3- General overview of the empirical literature on AC

Purpose(s)	Method(s)	Studied factor(s)	Key finding(s)	Reference(s)
Identifying and investigating the causes of the failure of AC	T-test	High fees for bank facilities, Insufficient market demand, High cost of raw materials, lack of specialized staff, High cost of hiring, Insufficient company capital, Weak marketing services	Studied factors had an important role in the cooperative's lack of success	(Khafaie, 2010)
Investigating and identifying the effective factors for strengthening and developing entrepreneurship in agricultural production cooperatives	Pearson correlation coefficient, ANOVA test	Board education level, Age and education of the CEO, Total number of members	Education and success are related	(Donyaei *et al.*, 2010)
Identifying and analyzing the role of production cooperatives on rural development	Chi-Square method, T-test	Average membership income, Production performance, Area under cultivation, Return on investment, Land and labor, Migration rate, Participation in productive and social affairs, Job satisfaction level	Cooperation has changed the traditional way of looking at agriculture into the commercial way	(Baseri *et al.*, 2010)
Investigating the factors affecting the success of production cooperatives	Wilcoxon signed-rank test	Sociocultural, Personality, Managerial Educational, Economic	Because knowledge, insight, skill, and ability are adventitious; education plays an important role in providing solutions	(Karami & Agahi, 2010)
Evaluating the level of performance of agricultural leading enterprises	BP neural network model, AHP (Analytic Hierarchy Process) method	Sustainability factors	A reasonable performance evaluation system can effectively improve operational efficiency	(Li & Li, 2010)
Analysis of barriers and limitations of employment development in agricultural production cooperatives	Delphi method	Technical, Financial, Structural, Marketing and sales, Managerial, Legal	Studied factors show a 76.5 percent impact on development barriers	(Ghiasvand Ghiasy & F.Hosseini, 2011)

Investigating the effectiveness of extension training activities in improving the activities of agricultural production cooperatives	Spearman's rank correlation coefficient, Regression analysis	Age, education, Total annual income, Cooperative revenue, Area under cultivation, Consulting with experts	Education was 53.8 percent effective on farmer knowledge	(Solouki *et al.*, 2011)
Identifying the problems of marketing agricultural products of production cooperatives	Delphi method, AHP (Analytic Hierarchy Process) method	Economic, Managerial, Operational, Market, Structural	The lack of marketing plans and not using experts are the most important bottlenecks	(Ghadiri Moghaddam & Nemati, 2011)
Examining the factors influencing a cooperative's performance through strategic planning and members' participation.	Pearson's correlation coefficient	Strategic planning, Member participation	Strategic planning and member participation are effective on cooperatives' overall success and performance	(Mahazril'Aini *et al.*, 2012)
Case study of inactive cooperatives to identify the reasons for their inactivity	Delphi method	The inefficiency of the banking system, Lack of efficient labor, Procrastination and delegating responsibilities to each other, High cost of providing inputs	Problems inside the cooperatives had a big impact on their failure	(Hazrati & Babaei Fini, 2012)
Assessing whether cooperative membership increases the likelihood of the adoption of fertilizers, improved seeds, and pesticides	PSM (Propensity Score Matching) method	Age, Gender, Education, Household size, Leadership position, Wealth	Cooperative membership improves the mean fertilizer adoption rate by about 9–10 percentage	(Abebaw & Haile, 2013)
Performance evaluation of AC	T-test	Social items, Economic items, Environmental items	From member's perspective cooperatives were successful but from the agency's point of view they were not economicly successful	(Portaheri, Papoli, & Fallahi, 2013)
Determining the economic efficiency of agricultural production cooperatives and the factors affecting their economic efficiency	Chi-Square method, T-test	Variety of activities, Current value of capital, Value of initial capital, The amount of managerial knowledge, The value of other activities	Manager's education is important in the cooperative success	(Shajari, Barikani, & Amjadi, 2013)
Identifying options for financial auditing system for agricultural cooperatives	-	Agricultural cooperative auditing	Commercially viable cooperatives will require regular financial audits as part of the standard management practices	(Benson, 2014)
Identifying the effective factors in improving the level of economic efficiency of agricultural production cooperatives	DEA (Data Envelopment Analysis) method	Number of members, Marginal profit, The current value of capital, Managerial knowledge	Managerial knowledge, experience, and education can improve cooperative performance	(Sepehrdoost & Yosefi, 2014)
Examining the impact of strategic planning on firm performance in the agribusiness sector	Spearman's correlation coefficient	Overall profitability, Competitive position in your industry, Member satisfaction, Ability to achieve the vision, Overall performance	cooperatives make sacrificing one performance attribute for better performance on another	(Franken & Cook, 2015)
Investigating the social factors affecting the participation of members of agricultural cooperatives	Pearson correlation coefficient, T-test, Multiple regression analysis	Member participation, Social capital, Common beliefs, Awareness of the principles of cooperation	Studied factors can explain 39 percent of the variance in member participation	(Ansari *et al.*, 2015)
Investigating the role of agricultural production cooperatives in achieving sustainable development in the agricultural sector	the interval of standard deviation from the mean (ISDM), Bartlett's test, KMO (Kaiser-Meyer-Olkin) test, Varimax rotation	Personal and professional characteristics, Study towards sustainable development, the role of production cooperatives in achieving sustainable development	Member's lack of knowledge of sustainable development is proved	(Savari *et al.*, 2015)

Investigating the relationship between entrepreneurial spirit and adherence to cooperative principles	Spearman's rank correlation coefficient	Creativity and innovation, Internal control, Free and optional membership, Economic participation of members, Self-government and independence of cooperatives, Cooperation between cooperatives	Studied factors affect member participation and cooperative success	(Hosseini & Mahdizadeh, 2015)
Identifying performance evaluation indicators of AC; Quantitative and qualitative improvement of these organizations; Identity successful AC	Delphi method	Social, Economic, Individual, Legal, Educational, Environmental	Profitability with 89.3 percent and education with 86.2 percent are the most important factors of success	(Heydari, Naderi Mahdei, Yaeghoubi Farani, & Heydari, 2015)
Investigating the effect of cultural capital and demographic variables on the performance of agricultural cooperatives	Bartlett's test, KMO(Kaiser-Meyer-Olkin) test, Regression analysis	Membership, Customer Orientation, Cultural capital, Consumption of cultural goods, Cultural behavior and practices, Non-financial performance	Consumption of cultural goods and Cultural behavior and practices was 33.6 percent effective on cooperative performance	(Mirfardi, Ahmadi, Sadeqnia, & Rostami, 2015)
Identifying the weaknesses, strengths, opportunities, and threats of agricultural production cooperatives	Bartlett's test, SWOT (Strengths, Weaknesses, Opportunities, and Threats) matrix	Strengths, Weaknesses, Opportunities, Threats	Cooperatives have a good chance of success only if they use good approaches	(Ohadi & Kurki Nejad, 2015)
Understanding the views of those involved in agricultural production cooperatives on economic issues	Coefficient of variation, Multiple regression analysis	Personal and professional characteristics, Activities and goals, Economic issues, Problems, and obstacles to achieving goals	Preparation and distribution of agricultural inputs is one of the key factors in achieving the goals of cooperatives	(Paloj & Teymori, 2015)
Identifying the factors of family farms' reluctance to entrepreneurship	-	Economic pushing and pulling factors, Ideological pushing and pulling factors	farmer advise and support must of necessity be tailored to individual farm circumstances	(Aisling, Seamus, & Mary, 2016)
Identifying the main problems of developing the services of agricultural cooperatives	-	Development problems	low activity of rural population in participating in cooperatives, lack of funds to finance the fixed assets purchase	(Tsymbalista, 2016)
Determining the economic efficiency of AC and prioritizing the problems they face in the management process and marketing system	AHP (Analytic Hierarchy Process) method	Quantitative and qualitative characteristics of cooperatives and managers, Socio-economic characteristics, Problems, and obstacles	Conducting location studies before establishing cooperatives is crucial for cooperative success	(Mozaffari, 2016)
Analysis of obstacles to the progress of agricultural production cooperatives	Exploratory Factor Analysis	Social, Economic, Administrative and legal, Information and marketing barriers, Capital barriers	Studied factors had a 69 percent effect on cooperatives	(Rasouliazar *et al.*, 2016)
Identifying the factors affecting the success of agricultural production cooperatives	Multiple regression analysis	Sociocultural, Educational, Managerial, Economic, Operational, Environmental, Structural, Age, Job experience	Studied factors are 52.5 percent effective in cooperative success	(Ahmadpor, Mokhtari, & Porsaeed, 2016)
Assessing the determinants of member commitment	Probit model	Economic involvement, Innovation, Training, Supply services, Total Sales	Studied factors have an impact on member commitment	(Bareille *et al.*, 2017)
Enriching international literature on exploring family farm growth in China; expanding dimension constitution of resource-based theory	hierarchical linear model, entropy method	Material capital resources, Human capital resources, Organizational capital, Financial capital resources, Social ecology, Economic ecology, Natural ecology, Financial index, Profit potential	Studied factors such as education and improvement of production equipment had positive effects on the growth of family farm	(Gao *et al.*, 2017)
Investigating the economic performance of AC	Regression analysis, Breusch-Pagan LM test, Hausman test	The current ratio, Leverage, Net fixed asset Turnover, Investment, Dividend, Cooperative size, Return on equity, Return on total assets	Studied factors are significant indicators of cooperative financial performance	(Shamsuddin *et al.*, 2017)
Weaknesses and strengths of top-down cooperatives	interviews and observations	Top-down cooperatives problems	Top-down cooperatives and not member-controlled cooperatives do not show success	(Kurakin & Visser, 2017)

Identifying and prioritizing marketing barriers for agricultural production cooperatives	T-test	Economic, Managerial, Human, Market, Structural, Operational	Economic barriers and the presence of the fixers had the most impact on cooperative marketing	(Feizabadi & Javadi, 2017)
Accurate evaluation of the performance of agricultural cooperatives	Fuzzy Delphi method	Economic, Social, Managerial, Legal, Educational, Individual	Studied factors can be considered the most important factors affecting cooperative performance	(Heydari, Naderi Mahdei, Yaghoubi Farani, & Heidary, 2017)
Analysis of components affecting the sustainable development of agricultural cooperatives	Factor analysis, Chi-Square method	Social, Economic, Environmental, Institutional	Studied factors have a 63 percent impact on the sustainable development of cooperatives	(Haji, Chizari, & Chobchian, 2017)
Examining the impact of agricultural cooperative membership on the technical efficiency (TE) of apple farmers	SPF (Strategic Prevention Framework) model	Age, Gender, Education, Household size, Orchard size, Off-farm work, Access to credit, Farming vehicle	Cooperative members have better efficiency than non-members; Factors affecting productivity are different for members and non-members	(Ma, Renwick, Yuan, Ratna, 2018)
Examining the comparative performance of agro-industrial cooperatives considering the economic-financial and socioeconomic dimensions	Spearman's correlation coefficient, Walk method	Growth and development of cooperative members, Financial results, Assistance/satisfaction of cooperative members, Economic and financial stability, Capacity of facing a crisis, Credibility and soundness, Quality management	cooperatives with better relative economic-financial performance are not listed among those that best promote the well-being of their members	(Lauermann *et al.*, 2020)
Construct and analyze the research landscape on the sustainability performance evaluation of agricultural cooperatives' operations	ProKnow-C Method	Sustainability factors, Performance evaluation	Most evaluation models are for decision making	(Marcis *et al.*, 2018)
Investigating the development of cooperatives and family farms	Semi-structured interviews	Family farm and Cooperatives programs	The incoherence and distrust among farmers undermine their ability to form a genuine cooperative for mutual benefits	(Shen & Shen, 2018)
Examining the level of commitment to cooperative principles	Multiple correspondence analysis, Chi-square method	Capital manufactured, Social capital and relationship, Human capital, Natural capital, Intellectual capital, Financial capital, Postage	there is a narrow understanding of GRI G4 principles among cooperatives' employees that could be addressed with educational activities	(Anzilago *et al.*, 2018)
Performance evaluation of agricultural cooperatives	Delphi method, Judgment matrix method	Economic Performance, Non-economic performance	The evaluation results can more realistically show the actual development of cooperation and have a positive guiding effect on the future development	(Shao, Xu, & Ma, 2018)
Investigating the effect of tacit knowledge exchange on marketing performance in agricultural production cooperatives	Partial Least Squares method	Senior executives support, Trust among employees, Social opportunities, Coordination of functional parts, Quality of communication, Size of the company, Experience, Environmental instabilities	Studied factors can improve cooperative marketing	(Baghbani Arani, Maghsoudi Ganjeh, Ariyapour, Sotudeh Arani, & Mehtari Arani, 2018)
Identifying the factors affecting the development of agricultural cooperatives	T-test, Factor analysis	Economic factors, Member's features, Organizational factors, Sociocultural factors, Educational factors, Management factors, Political factors	Economic factors had the biggest impact on cooperative development, while members' features and political factors had no impact	(Pirouz & Gholipoor, 2018)
Investigating the sustainability of agricultural cooperatives	-	Heterogeneity factors	Solutions based on member loyalty and commitment not only failed but also resulted in unfortunate side effects	(Iliopoulos & Valentinov, 2018)

Performance evaluation through return and profitability analysis	DEA (Data Envelopment Analysis) method	Efficiency, profitability	Efficiency does not always translate to profitability, there is a need for managers to continuously measure performance and investigate areas of improvement	(Xaba *et al.*, 2018)
Assessing the adherence to a set sustainability performance indicator to form an assessment model for agricultural cooperatives' operations	SAAC (Sustainability Assessment of Agricultural Cooperatives) method	Sustainability factors, Commercial relations, Specific indicators of the cooperatives	Studied indicators were adequate to the sustainability practices in the operations of agricultural cooperatives	(Marcis *et al.*, 2019)
Identifying the main problems encountered in the management of agricultural cooperatives	semi-structured questionnaire	General attributes, Market information, Decision making, Form of management	Low participation of members in cooperative decisions points to deficient management	(Brandão & Breitenbach, 2019)
examining the role of serendipity on the entrepreneurial process of diversification	face-to-face semi-structured interviews	Business characteristics, Business activities, and processes, Personal characteristics of the farmer, Entrepreneurial skills of the farmer	A clear division of labor between older and younger generations and between male and female farmers can be used to manage the various categories of skills	(De Rosa *et al.*, 2019)
Investigating the financial situation of Czech and Polish AC	T-test, U-Mann-Whitney test	Total assets, Fixed assets, Total liabilities, Net profit	Most of the commonly used financial measures give an incomplete picture of a cooperative's performance	(Piwoni-Krzeszowska *et al.*, 2019)
Analysis of barriers and incentives for the development of AC	Semi-structured survey method	Policy factors	Policy measures mostly promote or have a neutral impact on the development of cooperatives, institutional environment focuses on the traditional concept of the cooperatives	(Ribašauskienė *et al.*, 2019)
Identifying barriers to stunted growth of agricultural service cooperatives	-	Historical obstacles, Mental obstacles, Structural obstacles, Political and institutional obstacles	Members who are pioneering cooperative development in an environment of low trust, share common characteristics	(Wolz *et al.*, 2019)
understanding family farm succession dynamics in extensive livestock farming of two marginal areas in Spain	Axial coding	Potentiality, Willingness, Effectiveness	Successor willingness is a key step in succession and less attention is paid to this step by policymakers	(Bertolozzi-Caredio, Bardaji, Coopmans, Soriano, & Garrido, 2020)
Investigating large organizational differences and performance characteristics of cooperatives	-	Heterogeneity factors	Only when researchers obtain a good understanding of the organizational and functional characteristics of the cooperatives they are studying, their research will generate unambiguous insights	(Bijman, 2020)
Investigating the supply chain of agricultural cooperative services	Variance analysis	Pre-and post-production supply services, financing services	the level of education significantly positively affects the supply of cooperative services	(Fawen & Cheng, 2020)

The results reveal that the investigation of the development and success of agricultural cooperatives (AC) attracted significant interest during the early years of the previous decade but experienced a decline in attention by 2012. Subsequently, research focus shifted towards performance evaluation, which has remained a primary area of interest since 2012. Moreover, published studies have increasingly incorporated the assessment of AC membership as a research objective since 2014. The identification of the main problems

faced by AC since 2015 has been the subject of several studies published by Feizabadi and Javadi (2017) and Brandão and Breitenbach (2019).

A diagram illustrating the objects contained within each category is presented in Figure 3. In order to maintain diagrammatic simplicity, we have limited the inclusion of objects to a maximum of three.

Factor's classification

The research being examined encompasses seven distinct categories of factors: structural, financial, demographic, operational, governmental, social, and environmental factors. The distribution frequency of each category within the sample under analysis is visually depicted in Figure 4.

The predominant focus of research has been on financial aspects within the context of agricultural cooperatives. While evaluating the success of a cooperative based on its financial returns for members may appear logical, it is essential to acknowledge that efficiency does not always translate to profitability. Relying exclusively on financial metrics for assessing the performance of an agricultural cooperative may lead to a limited comprehension of the diverse factors influencing its success, including regional marketing policies that vary across different areas. Therefore, a more holistic approach to performance evaluation is imperative to gain a deeper insight into the elements contributing to the prosperity of an agricultural cooperative. Structural factors constitute a significant area of study alongside financial considerations. While fundamental concepts of agricultural cooperatives are crucial, the level of emphasis on this subject may be considered excessive. Operational and social factors hold substantial importance, yet they often receive comparatively less attention than financial factors. Operational factors, such as management and performance, serve as critical indicators of success. Social factors exert both direct and indirect influences on nearly every aspect of cooperative existence, with member participation standing out as a prominent tangible factor.

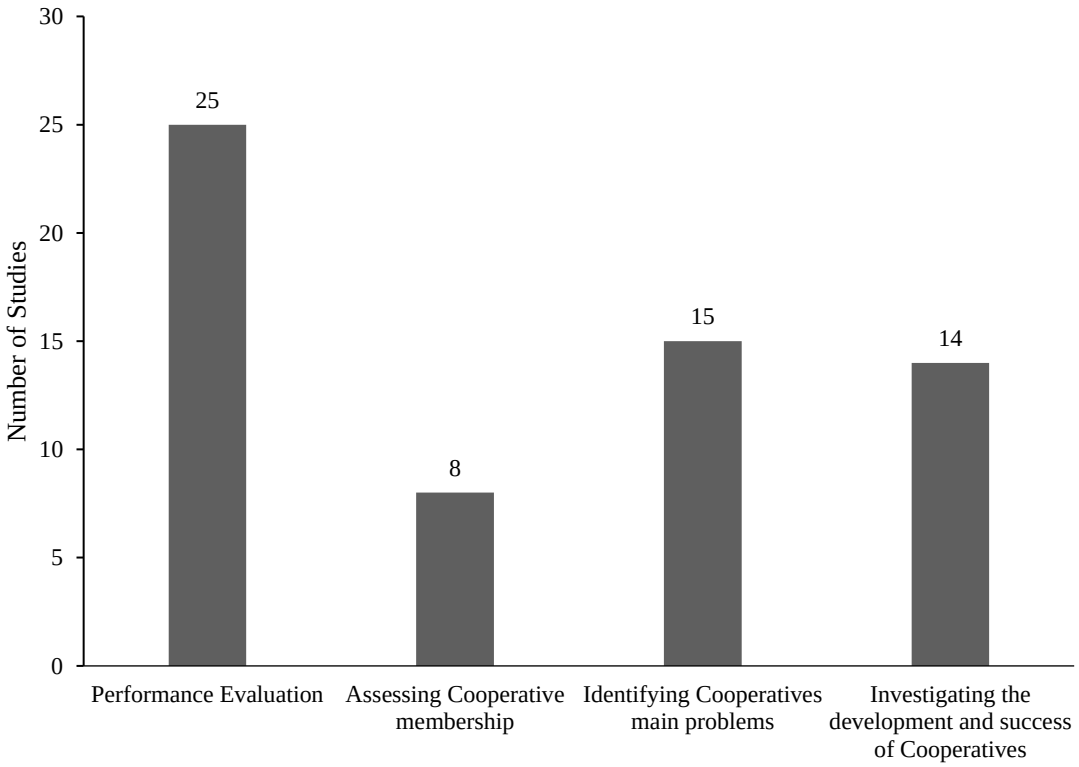


Fig. 2. Frequency of purpose classification

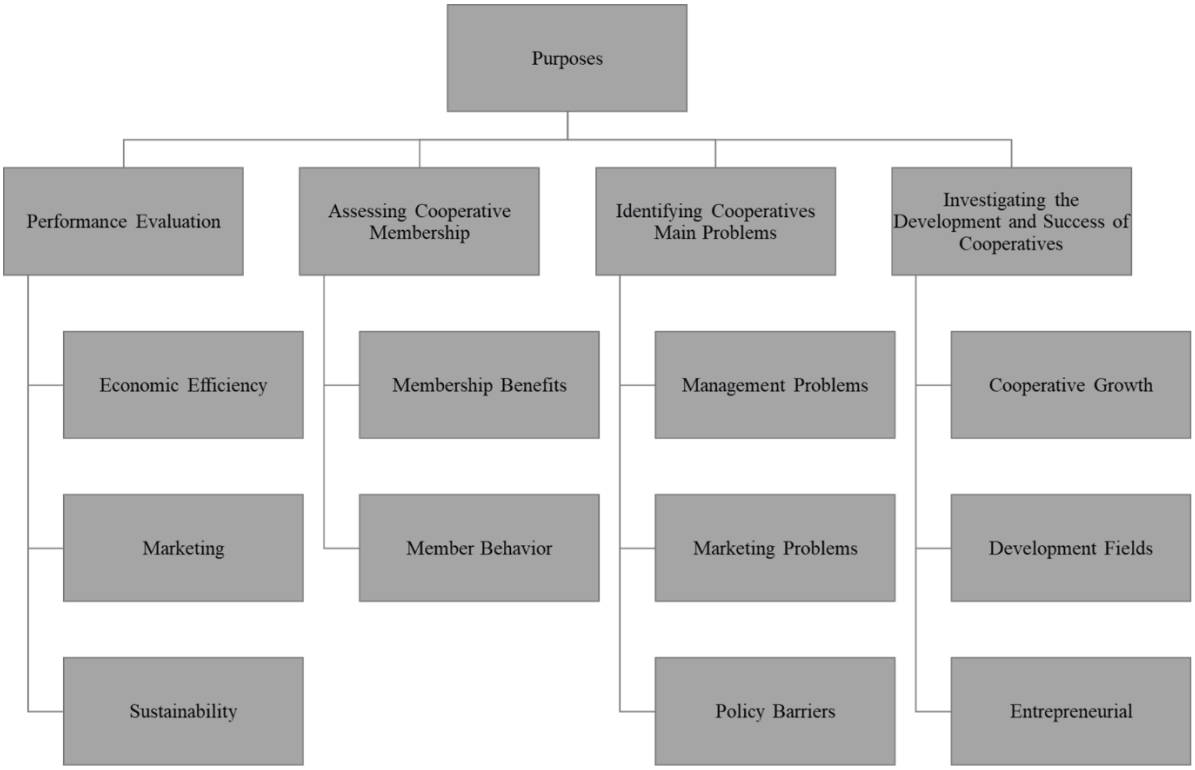


Fig. 3. Diagram of purposes

The significance of governmental policies cannot be overstated; however, it may not be advisable to allocate extensive research resources to this area. Demographic variables like age and gender do not seem to have a significant impact on the success of agricultural cooperatives. Nevertheless, the level of education has been identified as a potentially influential factor. Despite the importance of environmental factors, they are frequently accorded low priority in the context of agricultural cooperatives. Nonetheless, it is crucial to monitor indicators such as input consumption and pollution, and regulate them appropriately to ensure sustainable and environmentally responsible practices within agricultural cooperatives. In conclusion, it is recommended that forthcoming studies prioritize the examination of financial, operational, and social factors while also considering potential environmental impacts.

Figure 5 depicts a diagram of the factors that were studied, including the associated objects. Similar to the diagram of purposes, each branch is limited to a maximum of three objects.

Methods

The utilization of data analysis methods in the selected studies is depicted in Figure 6. Both parametric and non-parametric tests are commonly used in statistical analysis. The T-test, Regression analysis, and Delphi method are frequently employed statistical techniques in research. The T-test is utilized to determine the statistical significance of a hypothesis concerning the subject under study (Feizabadi & Javadi, 2017). Regression analysis is a robust statistical technique that aids in identifying variables that significantly impact a topic of interest. It enables the identification of significant factors, exclusion of irrelevant ones, and assessment of their interrelationships with confidence (Aldrich, 2005). Ansari *et al.* (2015) and Mirfardi *et al.* (2015) utilized regression analysis in their studies. The Delphi method, as applied by Heydari *et al.* (2017) and Shao *et al.* (2018), is a systematic approach used to achieve consensus or decision-making among a group of experts

through surveys and feedback iterations. The method involves gathering responses from experts through multiple rounds of questionnaires, which are then compiled and shared with the group.

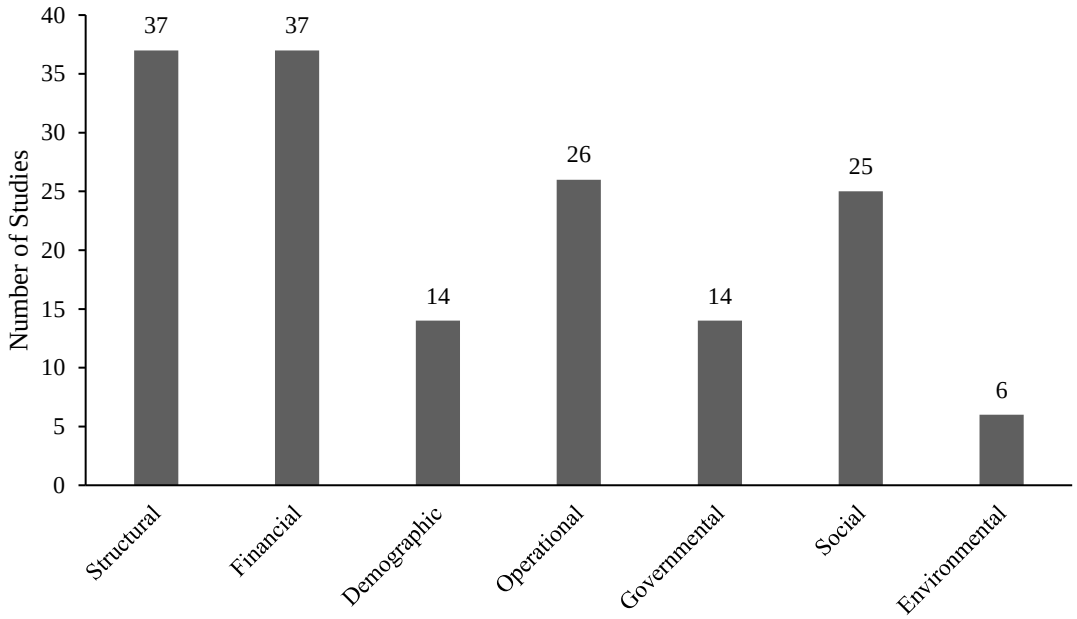


Fig. 4. Frequency of studied factors classification

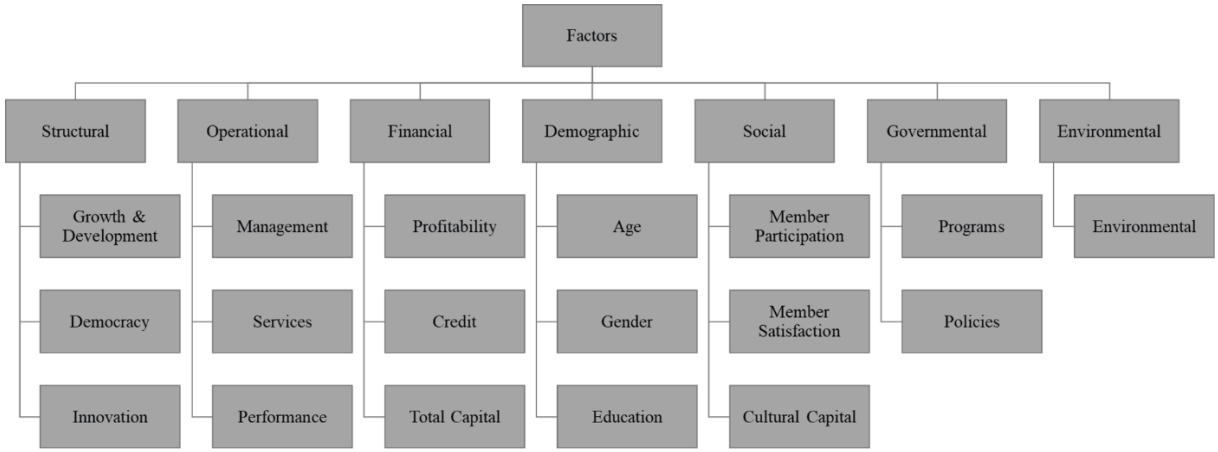


Fig. 5. Diagram of the studied factors

Despite criticisms for its lack of clear methodological guidelines, the Delphi method requires continued commitment from participants who may be asked the same question multiple times, and lacks evidence regarding its reliability. The Analytic Hierarchy Process (AHP) is a precise methodology for determining the relative importance of decision criteria through weight quantification. The magnitudes of factors are estimated through pair-wise comparisons based on the experiences of individual experts. Respondents use a specifically designed questionnaire (Mozaffari, 2016) to compare the relative significance of each pair of items. This methodology is also supported by Ghadiri Moghaddam and Nemati (2011). A drawback of the Analytic Hierarchy Process (AHP) is the subjective nature of decision-making, often influenced by obscure human emotions

(Forman & Gass, 2001). The Bartlett and KMO tests were used to validate the factors under study by Savari *et al.* (2015) and Ohadi & Kurki Nejad (2015). The prevalent approach for data collection and evaluation in the field of AC research over the past decade appears to be the utilization of the T-test in conjunction with the Delphi technique or Analytic Hierarchy Process (AHP).

Findings

The outcomes should align with the research objectives and the variables being studied. Therefore, we classified the significant findings of the examined studies into four specific categories. These identified categories include efficiency and performance, membership, advisory and suggestions, and policy-related results. The distribution frequency of each category is illustrated in Figure 7.

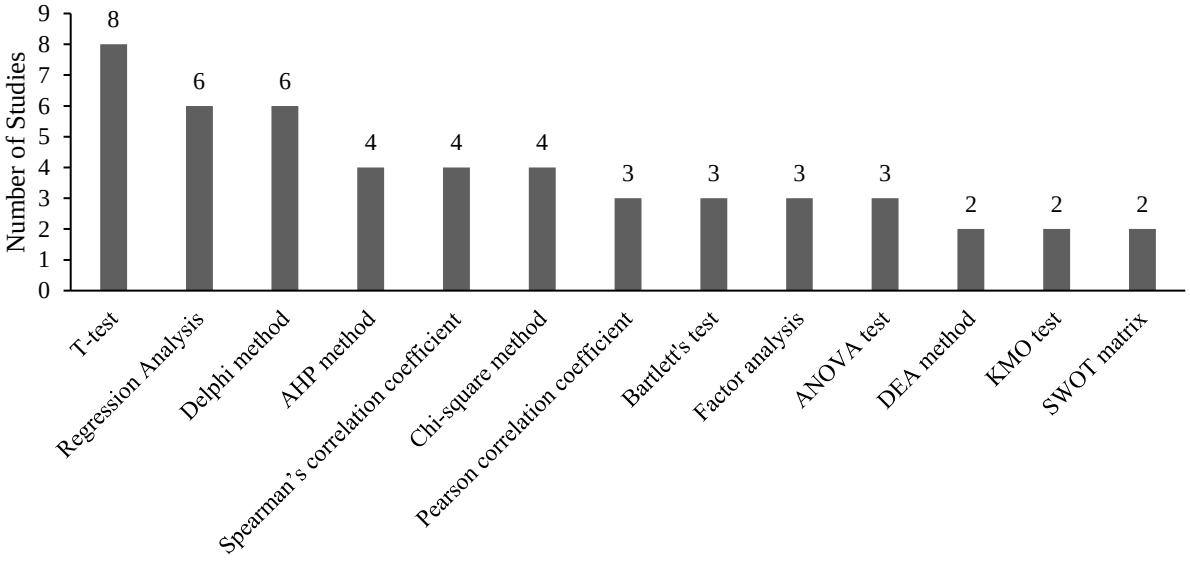


Fig. 6. Frequency of methods used in selected studies

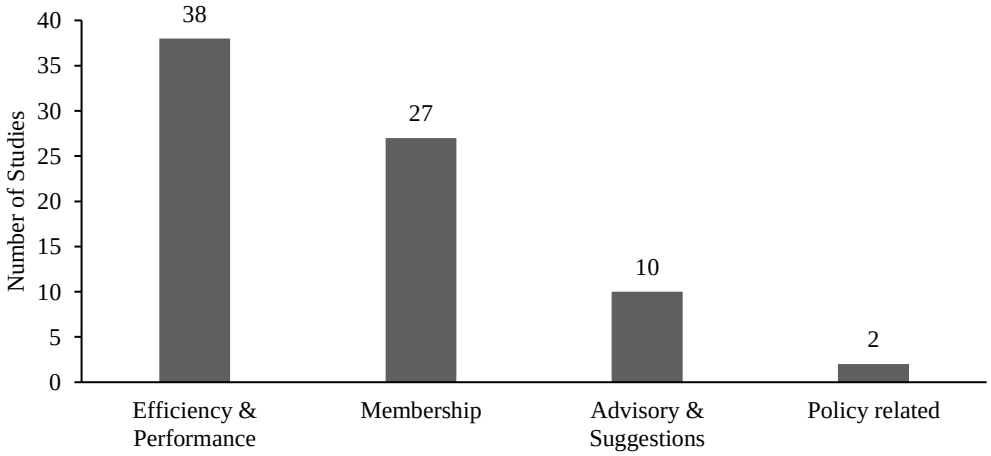


Fig. 7. Frequency of key findings classification

Various studies conducted by different researchers have explored the factors influencing the success and challenges faced by cooperatives. Donyaei *et al.* (2010) and Karami & Agahi (2010) highlighted the significant role of education in fostering

cooperation. Ghadiri Moghaddam and Nemati (2011) identified the absence of marketing strategies and the failure to involve experts as key hindrances to the advancement of air conditioning systems. Mahazril'Aini *et al.* (2012) and Hazrati and Babaei Fini (2012) emphasized the impact of membership on cooperative sustainability. Specifically, Mahazril'Aini *et al.* (2012) underscored the importance of member engagement in determining cooperative success, while Hazrati and Babaei Fini (2012) pointed out that internal disagreements among members can lead to failure. Shajari *et al.* (2013) stressed the essential role of effective AC management in achieving success, noting that managers with higher educational qualifications tend to have more successful careers. Sepehrdoost and Yosefi (2014) conducted a study that corroborated previous findings, indicating that managerial knowledge, experience, and education can enhance cooperative performance. Franken and Cook (2015) observed that cooperatives often make trade-offs between different performance attributes to improve overall performance. Mozaffari (2016) highlighted the importance of conducting location studies before establishing cooperatives to ensure their success. Kurakin and Visser (2017) reported that top-down cooperatives, in contrast to member-controlled cooperatives, were not successful in Russia. Iliopoulos and Valentinov (2018) found that strategies focusing on member loyalty and commitment to achieve cooperative sustainability were ineffective and led to unintended consequences. Piwoni-Krzeszowska *et al.* (2019) noted that conventional financial measures may not offer a comprehensive assessment of cooperative performance. Additionally, Bijman (2020) determined that a higher level of education positively influences the provision of cooperative services.

The categories illustrated in Figure 7 have been expanded upon in a diagram. Figure 8 presents the objects that belong to each category.

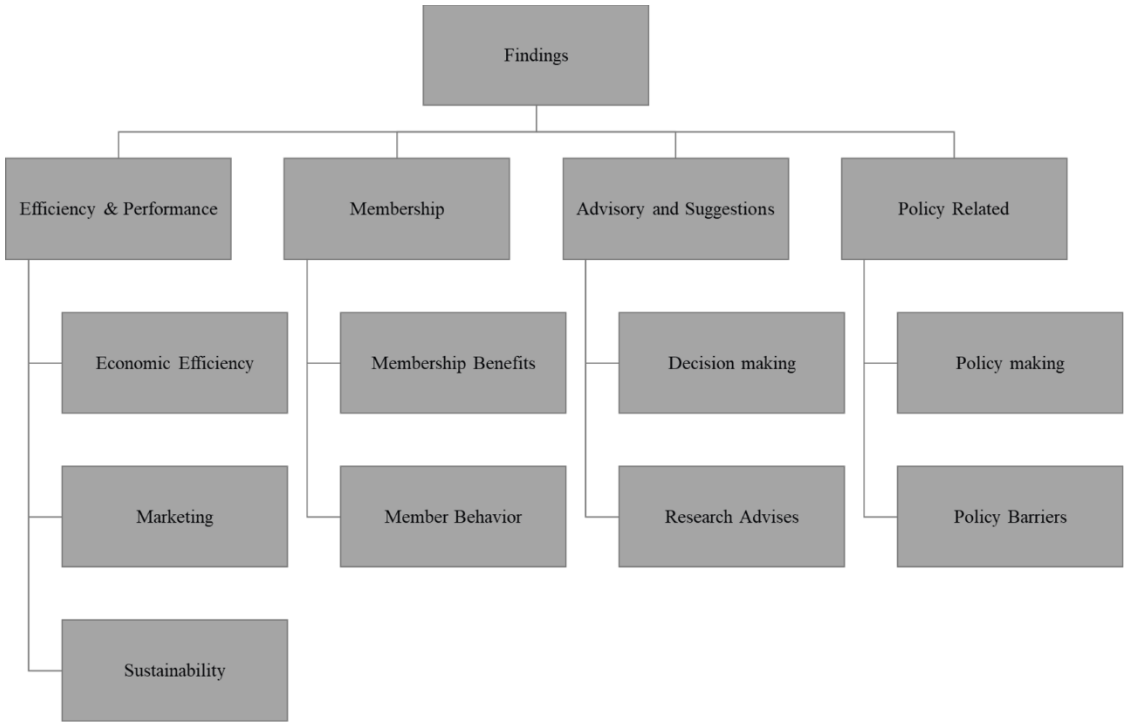


Fig. 8. Key findings of selected studies

Path analysis

The relationship between the factors analyzed and their influence on the success of cooperation is visually represented in Figure 9,

drawing upon the conclusions of pertinent research. The size of each circle in the figure corresponds to its perceived significance as indicated by the study. Arrows in the figure signify the impact of one element on another, with the object at the arrow's origin affecting the object at its endpoint. These impacts were identified through a thorough examination of selected studies, revealing instances of reciprocal interactions among certain elements. The results suggest that a majority of the variables investigated have a notable effect on the effectiveness, performance, and membership status of agricultural cooperatives, reflecting the researcher's specific focus on these objectives. The illustration presented was created using version 7.3.5 of Vensim PLE.

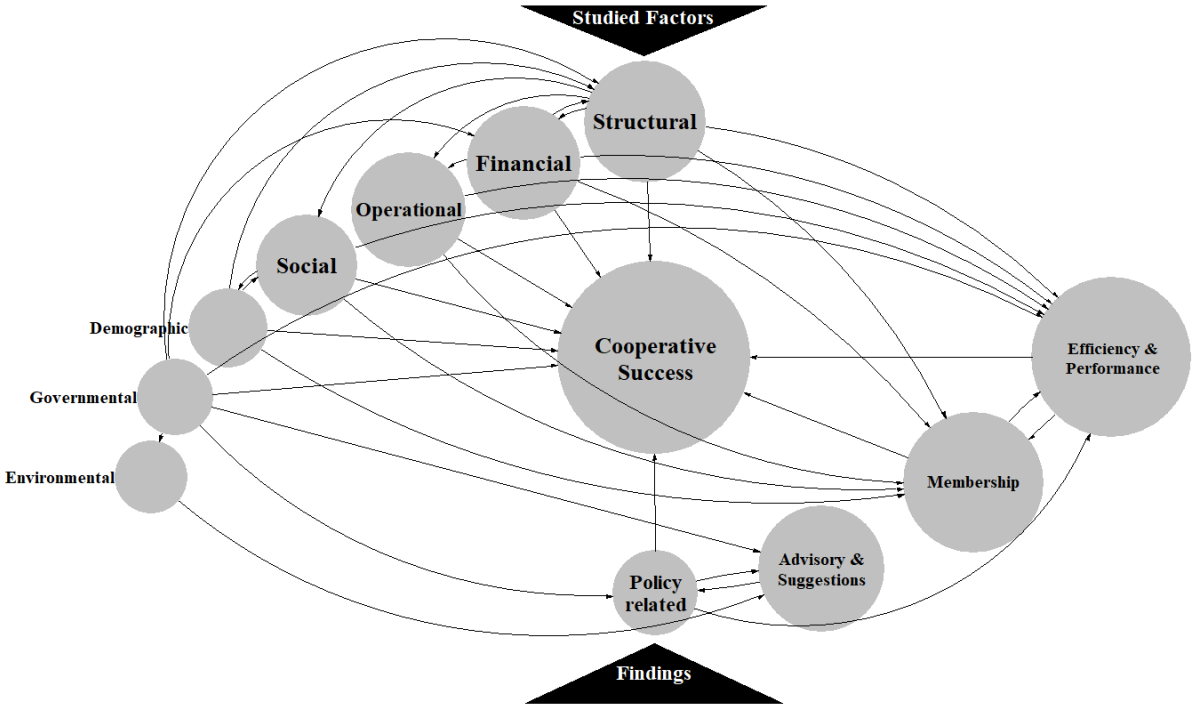


Fig. 9. The relation between studied factors and key findings of studies

Discussion

Summary of evidence

The concept of Agricultural Cooperatives (AC) involves a group of agricultural workers forming a union to work collaboratively. This allows individuals to access benefits provided by governmental bodies, often associated with socialist governments, to enhance their market influence. These associations may have the capacity to impact the market or government policies positively or negatively. In contemporary times, cooperatives are more focused on economic objectives, diminishing the historical significance of cooperatives. Research has explored the factors contributing to successful cooperation, revealing that effective management, successful marketing, and committed members are crucial for AC's success. Education is deemed essential regardless of age or gender. Similar to other businesses, AC must prioritize operational efficiency to attain financial viability. The study analyzed 55 publications on AC from 2010 to 2020, with Figure 10 illustrating the distribution of studies over the years examined.

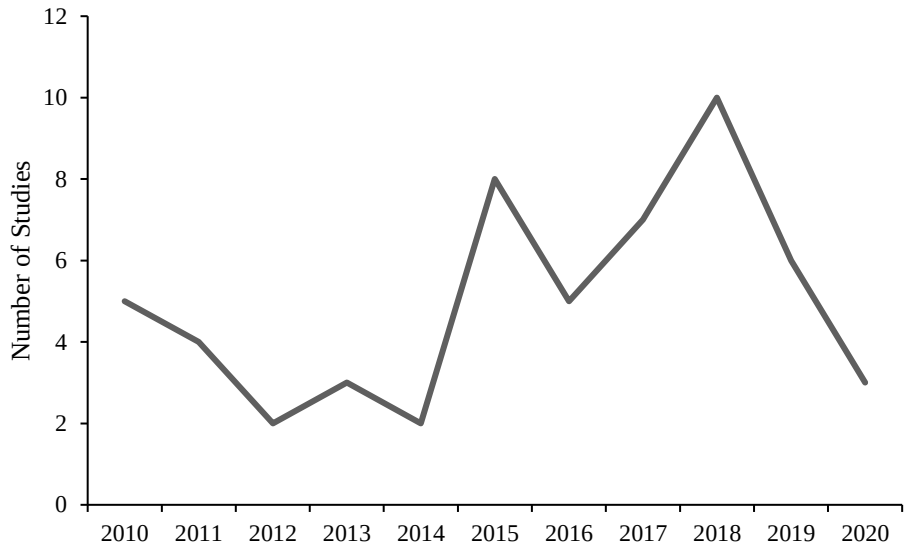


Fig. 10. Distribution of studies from 2010 to 2020

It is visible that there are more papers in the year 2018 followed by the year 2015.

Limitations

The constraints associated with these studies pertain to the identification and choice of research variables, modification of literature review variables to suit the geographical context of the study, and ensuring a sufficient sample size to obtain dependable outcomes.

Conclusion

This study presents a comprehensive overview of the current academic literature on the subject of Agricultural Cooperatives (AC). Out of the 261 studies initially reviewed, only 55 studies met the predetermined selection criteria. The data extracted from each study is typically categorized into four main groups, including research objectives, factors under investigation, methodologies employed for data collection and analysis, and key findings. Given the non-parametric nature of the variables in this field, there is a wide range of variables with diverse nomenclature. Similar factors were grouped into distinct clusters within each section. The reviewed studies were categorized into four main themes: performance evaluation, membership evaluation in cooperatives, identification of primary challenges faced by cooperatives, and examination of the progress and success of cooperatives. The analysis revealed that in the past decade, scholars have predominantly focused on evaluating the effectiveness, operational efficiency, and financial performance of AC. The factors related to AC were classified into seven groups: structural, financial, demographic, operational, governmental, social, and environmental. The studies primarily examined the structural and financial factors influencing AC presence, with additional attention to social and operational factors. Key findings were grouped into four categories: efficiency and performance, membership, advisory and recommendations, and policy-oriented. As research in this field primarily centers on assessing AC efficiency and performance, the majority of results also focus on performance. Each study contributes to a deeper understanding of cooperative practices among farmers. However, inconsistencies were noted in the objectives and variables examined, leading to a wide range of proposed solutions. Readers are advised to consider specific contexts for the applicability and endorsement of these solutions. Conducting dedicated research that accounts for various influencing variables is recommended to obtain accurate information on the status of AC in a particular region. The methodological framework proposed by this research is illustrated in Figure 11.

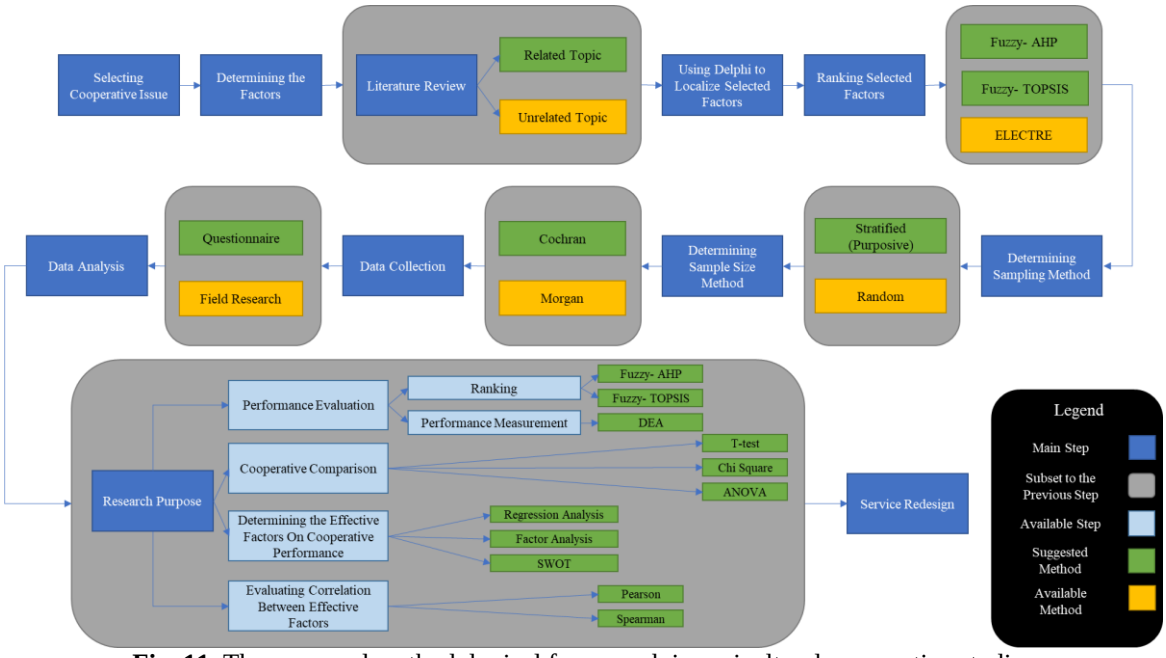


Fig. 11. The proposed methodological framework in agricultural cooperative studies

Funding

This work was financially supported by the University of Guilan and the Organization of Cooperatives, Labor, and Social Welfare of Guilan Province, Iran [grant number 7614].

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

M. Zangeneh: Supervision, Conceptualization, Methodology, Revision.

M. Bamdad: Drafting, Validation, Visualization, Text Mining.

S. H. Peyman: Supervision and Technical Advice.

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جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ٤٥۸-٤۳٥

تدوین چارچوب روش‌شناختی برای مطالعات تعاونی‌های کشاورزی- مروری نظام‌مند توسط پریسما

مهدی بامداد[۱]، مرتضی زنگنه[۱*]، سیدحسین پیمان[۱]

تاریخ دریافت: ۱۴۰۳/۰٥/۱۹
تاریخ پذیرش: ۱۴۰۳/۰۷/۲۲

چکیده

تعاونی‌های کشاورزی به‌طور گسترده در جهان به‌عنوان یک نهاد برجسته در بخش کشاورزی شناخته می‌شوند. موفقیت تعاونی‌های کشاورزی در تولید و عرضه مواد غذایی تفاوت قابل‌توجهی را در کشورهای مختلف نشان می‌دهد. هدف این تحقیق بررسی جامع مطالعات موجود درباره تعاونی‌های کشاورزی با استفاده از روش پریسما است. یک چارچوب روش‌شناختی نیز برای هدایت تحقیقات آینده پیشنهاد شده است. در ابتدا، تجزیه و تحلیلی کامل از چهار بخش از هر مطالعه، از جمله اهداف، روش‌شناسی، عوامل مورد مطالعه و یافته‌های کلیدی انجام شد. متعاقب آن، متغیرهای درون هر بخش برای تسهیل تحلیل مقایسه‌ای جامع‌تر، طبقه‌بندی شدند. بررسی‌ها نشان داد که موفقیت تعاونی‌های کشاورزی منوط به مدیریت مؤثر، استراتژی‌های بازاریابی موفق و اعضای متعهد است. آموزش صرف‌نظر از سن یا جنسیت افراد از اهمیت بالایی برخوردار است. در نهایت، استراتژی‌های دستیابی به موفقیت ممکن است در میان تعاونی‌های مختلف متفاوت باشد. توصیه می‌شود که برای به‌دست‌آوردن اطلاعات دقیق در مورد وضعیت یک تعاونی کشاورزی در یک منطقه خاص یا در شرایط خاص تحقیقات هدفمند انجام شود.

واژه‌های کلیدی: ارزیابی عملکرد، تعاونی، تعاونی کشاورزی، خدمات کشاورزی، مشارکت اعضا

۱- گروه مهندسی بیوسیستم، دانشکده علوم کشاورزی، دانشگاه گیلان، رشت، ایران
(*- نویسنده مسئول: Email: zanganeh@guilan.ac.ir)

https://doi.org/10.22067/jam.2024.89290.1273

Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Review Article
Vol. 15, No. 3, 2025, p. 459-490

Potential and Pitfalls of Using Drone Technology in Sustainable Agriculture: An Overview

S. Rishikesavan[1], P. Kannan[2*], S. Pazhanivelan[2], R. Kumaraperumal[1], N. Sritharan[3], D. Muthumanickam[1], M. Mohamed Roshan Abu Firnass[4], B. Venkatesh[5]

1- Department of Remote Sensing and GIS, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
2- Centre for Agricultural Nanotechnology, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
3- Department of Rice, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
4- Department of Soil Science & Agricultural Chemistry, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India
5- Department of Civil Engineering, Alagappa Chettiar Government College of Engineering and Technology, Karaikudi, Tamil Nadu, India
(*- Corresponding Author Email: kannan.p@tnau.ac.in)

Received: 11 August 2024
Revised: 07 December 2024
Accepted: 11 December 2024
Available Online: 22 June 2025

How to cite this article:
Rishikesavan, S., Kannan, P., Pazhanivelan, S., Kumaraperumal, R., Sritharan, N., Muthumanickam, D., Mohamed Roshan Abu Firnass, M., & Venkatesh, B. (2025). Potential and Pitfalls of Using Drone Technology in Sustainable Agriculture: An Overview. *Journal of Agricultural Machinery, 15*(3), 459-490. https://doi.org/10.22067/jam.2024.89334.1276

Abstract

Drones have emerged as a promising technology in precision agriculture, supporting Sustainable Development Goals (SDGs) by enhancing sustainable farming practices, improving food security, and reducing environmental impact. This review article is intended to meticulously analyze the multiple applications of drone technology in agriculture, such as crop health monitoring, pesticide and fertilizer spraying, weed control, and data-driven decision-making for farm optimization. It emphasizes the role of drones in precision spraying, promoting targeted interventions, and minimizing environmental impact compared to conventional methods. Drones play a vital role in weed management and crop health assessment. The paper focuses on the importance of data collected by drones to acquire the necessary information for decision-making concerning irrigation, fertilization, and overall farm management. However, using Unmanned Aerial Vehicles (UAVs) in agriculture faces challenges caused by batteries and their life, flight time, and connectivity issues, particularly in remote areas. There are legal challenges whereby regulatory frameworks and restrictions are present in different regions that affect the operation of drones. With the help of continuous research and development initiatives, the challenges depicted above could be solved, and the fullest potential of drones can be tapped for achieving Sustainable Agriculture.

Keywords: Crop monitoring, Data-driven decision making, Precision agriculture, Resource optimization, Unmanned Aerial Vehicles (UAVs)

Introduction

Drones were initially created for military purposes and are also called Unmanned Aerial Vehicles (UAVs) (Zhang *et al.*, 2020), miniature pilotless aircraft, or mini flying robots (Hafeez *et al.*, 2022). UAVs are remotely controlled aircraft equipped with Global Positioning System (GPS) and specialized equipment such as thermal and multispectral sensors. The modern use of drone technology is in military affairs, search and rescue operations, agriculture, surveying

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https://doi.org/10.22067/jam.2024.89334.1276

and mapping, documenting archaeological sites and artifacts, and forest and wildlife protection (Rejeb, Abdollahi, Rejeb, & Treiblmaier, 2022). In the agriculture sector, conventional practices suffer from challenges including high use of chemicals, lack of farm labor, uneven distribution of sprays, environmental pollution, and an inability to reach many farms. These conventional methods burn more cash on pesticide application and are less effective in managing pests and diseases (Hafeez *et al.*, 2022). However, the recent infusion of cutting-edge technologies into agricultural paradigms has inaugurated a paradigm shift characterized by innovation and heightened efficiency in recent years (Puri, Nayyar, & Raja, 2017). The application of mechanistic methods and Artificial Intelligence in farming has ignited an increased rate of innovation and efficiency much earlier than expected (Puri *et al.*, 2017). Among such incipient innovations, Unmanned Aerial Vehicles (UAVs), also known as drones, have emerged as a powerful tool in revolutionizing the agricultural field. According to Nhamo *et al.* (2020), in that regard, drones are capable of capturing accurate and high-resolution images, sending and supplying multiple feeds simultaneously with real-time results, and undertaking numerous operations in agricultural fields. UAVs have the potential to transform traditional remote sensing (RS) systems in which plant monitoring and growth, weed discrimination, crop water stress, disease, and crop yield assessment, and systematic approaches to pest and nutrient management are converted into one real-time or at any given conditional strategy. The equipment depends on the intended use of drones; These include, among other things, cameras, sensors, and control devices.

The use of UAVs in small-scale agriculture, especially in water-stressed areas, is of great value as they provide valuable information for operational decisions at the farm level. It is useful for risk mitigation against crop failure and low yields (Nhamo, Mabhaudhi, & Modi, 2019). Drone data collection is useful to farmers as it can manage pests, decide on resource inputs, and maximise harvests (Olson & Anderson, 2021). Continuous monitoring of crops is to detect small changes that may not be easily visible by the human eye (Delavarpour, Koparan, Nowatzki, Bajwa, & Sun, 2021; Pongnumkul, Chaovalit, & Surasvadi, 2015). UAVs equipped with high-resolution multispectral cameras enable precise monitoring of individual plants, ideal for smallholder farms (Barbedo, 2019). With the help of multispectral images, Normalized Difference Vegetation (NDVI) and Normalized Difference Red Edge (NDRE) indices are developed, offering valuable insights into crop health by assessing solar radiation absorption intensity and other critical factors (Ishihara, Inoue, Ono, Shimizu, & Matsuura, 2015). Besides, thermal cameras add value to UAVs' abilities to measure evapotranspiration and identify water stress (Hoffmann *et al.*, 2016). The spread of UAV use in agriculture is made possible by the reduced cost, with many models now priced affordably, despite additional operational expenses (Barbedo, 2019; Mulero-Pázmány, Stolper, Van Essen, Negro, & Sassen, 2014).

Policies are progressively becoming more balanced, particularly in rural areas where safety and privacy concerns are less pronounced (Barbedo & Koenigkan, 2018). UAVs enable rapid reconnaissance of large rural estates, complementing ground-based sensors and surpassing the resolution limitations of satellite imagery (Barbedo, 2019; Gabriel *et al.*, 2017). Advancements in imaging sensors enable high-resolution aerial images even at high altitudes, making it easier to detect problems early (Barbedo, 2019). In addition, the use of UAVs is becoming more and more convenient as automated flight missions and offline planning are possible. Drones play a critical role in assessing risks and damage in disaster-affected agricultural areas and providing timely information for efficient response and recovery efforts (Dileep, Navaneeth, Ullagaddi, & Danti, 2020; Ren, Zhang, Cai, Sun, & Cao, 2020). Even when monitoring the impacts of climate change on

agriculture, drones provide valuable data for adaptive resource management and crop selection, thereby increasing resilience to future challenges (Ukhurebor *et al.*, 2022).

Drones are a practical, rapid, and affordable technology that can gather information on crop emergence, inform decisions about replanting, and assist in predicting yield by combining high-resolution data with algorithms for machine learning. This system generates output with 97% accuracy using data acquired through drones and photogrammetry. Drones equipped with LiDAR sensors make it possible to estimate biomass changes in tree and crop biomass through differential height measurements.

Drone applications for agriculture correspond with multiple Sustainable Development Goals (SDGs). Improving crop monitoring and yield forecasts helps achieve SDG 2: Zero Hunger, by boosting food security. SDG 12: Responsible Consumption and Production is supported by precision spraying and data-driven interventions, since they minimize environmental effects using less pesticide and fertilizer. Additionally, by maintaining crop health and optimizing resource use, drones assist SDG 13: Climate Action, through climate-smart agriculture. SDG 15: Life on Land is related to the work in enhancing land management and protecting ecosystems, and SDG 9: Industry, Innovation, and Infrastructure is related to the promotion of agricultural innovation. Collectively, these technologies support sustainable farming methods that help achieve several SDGs.

The structure of this review is meticulously framed to offer a comprehensive understanding of the usage of drones in sustainable agriculture. The articles relevant to our study were identified using appropriate keywords from Google Scholar, and the same research literature was collected from the corresponding journal website. The main goal of this review article is to examine the inherent potentials and pitfalls associated with the use of drone technology to support sustainable agricultural practices. The aim is to reveal the latent benefits and limitations of the use of drones in agroecosystems by analyzing and evaluating the potential of unmanned aerial vehicle technology in various agricultural environments and functions, including crop monitoring, pest control, precision agriculture, and sustainable land management. Additionally, we have conducted an in-depth analysis of the technical and regulatory dynamics that govern the adoption and use of drone technology in agriculture, providing insights into the myriad opportunities and obstacles that chart the path to fully realizing its transformative potential.

Types of drones used in agriculture

In the field of agriculture, three primary classifications of Unmanned Aerial Vehicles (UAVs) are prevalent: Fixed-wing, Helicopter, and Multi-copter, plus hybrid drones (Fig. 1) (Velusamy *et al.*, 2022). This implies a need to consider factors such as the type of UAV model that will suit a given application and the financial resources available. For example, blimps comprise huge useful characteristics, including hovering capabilities, vertical flight, and lifting power. However, their utility is hampered by inherent limitations such as reduced speed and compromised stability in adverse weather conditions, which can impede accurate data acquisition (Liebisch, Kirchgessner, Schneider, Walter, & Hund, 2015).

Fixed-wing drones have immobile wings shaped like airfoils, generating lift as the vehicle attains a specific velocity (Marinello, Pezzuolo, Chiumenti, & Sartori, 2016). These UAVs are distinguished by their high-speed flight capabilities and prolonged endurance in the air (Herwitz *et al.*, 2004). Typically capable of achieving velocities ranging between 25-45 mph, fixed-wing drones exhibit a significant coverage capacity, spanning from 500 to 750 acres per hour, contingent upon battery specifications (Puri *et al.*, 2017).

Helicopters, on the other hand, are rotorcraft with a single set of spinning rotor blades attached to a central mast, creating lift, and often incorporating a tail or counter-central rotor for yaw control. Unmanned

helicopters possess the capability of vertical takeoff and landing, sideways flight, and hovering. They boast a larger payload capacity compared to multi-rotor UAVs, enabling them to accommodate sizable sensors like LiDAR (Chapman *et al.*, 2014). Multi-copters, alternatively, are rotorcraft equipped with multiple rotor blades, typically between 4 to 8, facilitating enhanced control over movements encompassing yaw, roll, and pitch (Marinello *et al.*, 2016). This configuration grants multi-copters heightened agility and maneuverability, making them particularly well-suited for applications demanding intricate aerial operations within confined spaces or complex environments.

Multi-copters UAVs provide advantages such as cost-effectiveness, hover capability, and minimal requirements for take-off and landing, rendering them extensively utilized for Field-Based Photography (FBP). However, they are accompanied by notable drawbacks, including limited flight duration, diminished payload capacity, and vulnerability to adverse weather conditions (Peña, Torres-Sánchez, de Castro, Kelly, & López-Granados, 2013).

Hybrid drones combine the beneficial features of both multirotor and fixed-wing models. They can take off and land vertically, like multirotor drones, while also featuring fixed wings that enable efficient gliding and coverage over extensive areas. This versatile design makes hybrid drones ideal for a wide range of agricultural applications (Garg, 2022). The advantages, disadvantages, and applications of fixed-wing drones, helicopters, and multi-copters are delineated in Table 1.

Crop-specific Standard Operating Procedures (SOPs) for drone applications

Standard Operating Procedures (SOPs) tailored to specific crops and environmental conditions are crucial for maximizing agricultural productivity and ensuring sustainable practices. The Ministry of Agriculture and Farmer's Welfare, supported by the Government of India (GOI), has taken progressive measures to promote the use of drones in agriculture. As part of these efforts, GOI has developed Standard Operating Procedures (SOPs) for drone spraying in agriculture. Crops are grown in various environments, so SOPs must be developed to address ecological factors like temperature, humidity, wind speed, terrain, and other environmental factors. These SOPs are focused on drone specifications such as flying speed and height above the crop canopy, sprayer factors including the type of nozzle, spray width, crop factors, volume of the canopy and growth stage, water and pesticide rates, and the best time to spray. Furthermore, they also consider the weather of the particular region and the climate zone where the chemicals will be used, to obtain the best efficiency of pesticides and to minimize the negative impact on crops. The flying height of the drone over the crop canopy depends on aspects like the total mass of the drone, the downforce impact over the crop canopy, and the type of sprayer.



Fixed-wing Helicopter (Zhang *et al.*,2020) Multi-copter

Fig. 1. Primary types of UAVs

Table 1- Benefits, drawbacks, and applications of fixed-wing drones, helicopters, and multi-copters

Drone type	Payload & applications in agriculture	Benefits	Drawbacks	Reference
Fixed wing	1. Large-scale spraying 2. Monitoring extensive areas 3. Crop growth assessment 4. Crop health status 5. Fertilizer and pesticide spraying	1. Streamlined architecture 2. Simplified maintenance 3. Increased flight speed 4. Enhanced energy efficiency 5. Superior survivability	1. Restricted accessibility 2. Reduced wind resistance 3. Challenges in launching and landing 4. Required more training 5. High initial and maintenance costs	(Hafeez *et al.*, 2022)
Helicopters	1. Spraying capacity (5 to 30 L) 2. Pesticide spray 3. Estimation of crop height 4. Soil and field analysis 5. Crop classification	1. Longer flying time 2. Increased speed 3. Robust durability 4. Accessibility to remote locations and operating on petrol 5. Vertical take-off, landing, hovering, forward, and backward	1. Incomplete coverage during spraying 2. Increased weight 3. Expensive setup 4. Stability issues 5. High initial and maintenance costs	(Hafeez *et al.*, 2022; Sinha, 2020)
Multi-copter	1. Spraying capacity (up to 100 L) 2. Local field requirements and crop stress, targeted pesticide spraying 3. Monitoring small fields, estimating crop height 4. Conducting soil and field analysis 5. Integral aspects of the overall agricultural approach	1. Tailored site management 2. Low-altitude flight and improved stability 3. Stable flight, increased payload, and slow capability 4. Vertical take-off and UAV swarms 5. Pre-programmed flight plans and improved accessibility	1.Limited by slow speed 2.Payload weight capacity 3.Complex architecture and challenging maintenance procedures 4.Limited flight capabilities 5.Unstable in windy weather	(Hafeez *et al.*, 2022; Ferraz, Santiago, Bruzi, & Vilela; 2024; Sinha, 2020)
Hybrid drone	1. Spraying capacity (10 to 100 L) 2. Field mapping and monitoring 3. Long-range missions 4. Monitoring crop conditions, detecting pests, diseases, and nutrient deficiencies through aerial surveys 5. Assessing soil health by capturing data on moisture levels, organic matter, and overall soil conditions	1. Longer time in flying 2. large-area coverage, precise and flexible 3. Adaptable for diverse farming tasks 4. Provides detailed imagery and data for informed decision-making	1. High initial and maintenance costs 2. Required more training 3. More complex and require frequent maintenance 4. Gasoline-powered hybrid drones can cause noise and air pollution when powered	(Hoffmann *et al.*, 2016; Kalaiselvi *et al.*, 2024)

To ensure operational efficiency and safety concerns, the drone is programmed to work at

the optimal level below the crop canopy to avoid drift when spraying. Nevertheless, it is indispensable to keep the vertical clearance above the crop because the thrust of the drone may be detrimental to the crop. Hence, the choice of the appropriate height for operation has been highlighted in the SOPs. Likewise, the speed of the flying of the drone is associated with the pattern of the spray distribution and it should also be optimized. Several experiments have been conducted to standardize the drone application among different crops, delineated in Table 2.

Rice

Rice is the most important staple crop and has been cultivated in a large area in Asia and as well as on other continents. It requires an SOP for drone application to achieve the fullest potential of drones in rice crop monitoring. Hence, Tamil Nadu Agricultural University in Coimbatore, India conducted a pioneering study on using drones for pesticide spraying in rice fields. They utilized a hexacopter drone with specific parameters, including a payload of 16 L and a fuel capacity of 3.5 L. Through this study, they established a standard operational protocol for drone-enabled pesticide application, determining that a flight height of 1.5-2.0 m, a flight speed of 5 m s^{-1}, coverage area of 4 min $acre^{-1}$, and wind speed below 5 km h^{-1} were optimal conditions for effective pesticide spraying (Subramanian, Pazhanivelan, Srinivasan, Santhi, & Sathiah, 2021). Similarly, research carried out in the rice fields of China explored miniaturized UAVs for efficient pesticide spray without crop damage. Standardized parameters (1.5 m height, 5 m s^{-1} speed) ensured effective delivery and uniform distribution (CV = 23%), yielding high insecticidal efficacy (92-74%). UAV spraying surpassed conventional methods, enhancing pesticide activity duration (Qin *et al.*, 2016). Another experiment was conducted to standardize the fertilizer and pesticide spraying in a paddy field in Parit Keladi Village, Indonesia. Impact assessments on paddy growth, including leaf length and tiller number, were carried out. The drone achieved ground coverage of 6-7.5 m at a 4 m altitude, equipped with four nozzles and a 1.6 L min^{-1} spraying flow rate. This study introduced drone technology to conventional paddy fields, significant in Indonesia and other Asian countries (Panjaitan, Dewi, Hendri, Wicaksono, & Priyatman, 2022). Hence, these experiments ensure optimal drone functions such as effective pesticide delivery, fertilizer application, and better crop production.

Maize

Maize is also one of the important staple crops in the world. The Agricultural Research Station of the Tamil Nadu Agricultural University, situated at Bhavanisagar, Tamil Nadu, India, conducted a study on delivering nutrients to maize via foliar spray using battery-operated and fuel-operated drones and a traditional knapsack hand sprayer. They utilized battery-operated and fuel-operated drones with specific parameters. A battery-operated drone features a 10-liter tank and a 16000 mAh battery, with a spraying width of 3.5 meters and a flying height of 0.75 to 1 meter above the crop canopy. The fuel-operated drone has a 16-liter tank and a 4-liter fuel tank, with a spraying width of 4 meters and a flying height of 0.75 to 1 meter above the crop canopy. UAV spraying surpassed conventional methods and enhanced biometric attributes. The benefits of drone spraying include a reduction in the amount and expenses of nutrients, lower cost compared to traditional spraying techniques, and significantly decreased spray fluid necessity (Kaniska *et al.*, 2022).

Cotton

Cotton is an important commercial crop, and to ensure improved penetration and uniform distribution of applied chemicals, UAV spraying requires optimizing flight height, spray volume, and droplet size. In Xinjiang, experiments were conducted, and the parameters selected include spray volume (8.7, 12, and 15 L ha^{-1} in 2018; 18, 22.5, and 30 L ha^{-1} in 2019), droplet size (100, 150, and 200

μm in both years), and flight height (1, 2, and 3 m in 2018 only). The study found that adjusting flight height, spray volume, and droplet size notably affects spray penetration. Lowering drone flight height, increasing spray volume, and enlarging droplet size enhance droplet distribution at the lower cotton canopy. However, flight parameters minimally affect droplet distribution uniformity (P. Chen *et al.*, 2021). Understanding droplet distribution and drift and cotton aphid and spider mite control effectiveness and cotton leaf adhesion and absorption in UAV spraying. Droplets were collected using Kromekote card and filter paper, and parameters such as droplet density, coverage rate, deposition, and drift percentage were statistically examined. The combined results showed that at a UAV flight altitude of 2 meters, droplet uniformity, coverage rate, deposition, and drift ability increased (Lou *et al.*, 2018).

Sugarcane

The ideal spraying parameters for sugarcane crops were determined to be a spray volume of 15 L ha^{-1}, a flight height of 3 m, and a flight velocity of 4 m s^{-1} (Zhang *et al.*, 2020). The most effective spraying parameters identified were a flight height of 6.0 m and a flight velocity of 2.5 m s^{-1}, resulting in a minimal pesticide usage of 15.38 L ha^{-1}. These findings offer valuable insights for selecting suitable parameters for single-rotor drone applications in sugarcane protection (Zhang *et al.*, 2021). The artificial neural network has proven to be a reliable predictive model for non-destructive nitrogen estimation in sugarcane using drone-captured aerial images (Hosseini, Masoudi, Sajadiye, & Abdanan Mehdizadeh, 2021).

Pulses

For Black gram, the Agricultural Research Station, Tamil Nadu Agricultural University located at Bhavanisagar, Tamil Nadu, India, experimented with applying nutrients to black gram via foliar spray using battery-operated and fuel-operated drones with the traditional knapsack hand sprayer. (P. Chen *et al.*, 2021; Freeman & Freeland, 2015) utilized battery-operated and fuel-operated drones with specific parameters. A battery-operated drone features a 10-liter tank and a 16000 mAh battery, with a spraying width of 4 meters and a flying height of 1 meter above the crop canopy. The fuel-operated drone has a 16-liter tank and a 4-liter fuel tank, with a spraying width of 4 meters and a flying height of 1 meter above the crop canopy. Drone spraying showed greater efficiency than manual knapsack sprayers (Nandhini, Thiyagarajan, & Somasundaram, 2022). While for Green gram, Anbil Dharmalingam Agricultural College and Research Institute, in Tiruchirappalli, India conducted a study to assess the viability of utilizing drones for foliar nutrient spraying on the growth characteristics, yield, and economic aspects of green gram cultivation and used drones with specific parameters including a tank capacity of 10 L, a Spraying width of 3.5 m, and a Flight height of 1.5 m (Dayana, Ramesh, Avudaithai, Sebastian, & Selvaraj, 2022).

Papaya

The effectiveness of droplet distribution utilizing an unmanned aerial vehicle across various application rates (12.0, 15.0, and 18.0 L ha^{-1}) and spray nozzles (XR110015 and MGA015) targeting different layers (upper, middle, and lower) of papaya fruit clusters was assessed. They utilized a DJI T10 drone with specific parameters, including a payload of 10 L, a spraying width (m) of 3-5.5, a flight height of 2.5 meters above the crop canopy, and a flight speed of 5.0 m s^{-1} (Ribeiro, Vitória, Soprani Júnior, Chen, & Lan, 2023). Thus, the results of these experiments help in standardizing the protocols and operating procedures for drone application among different crops and it could increase and improve crop productivity.

Table 2- Application of UAVs with the set of parameters (spraying width, flight height, flight speed, and nozzle type) in various crops

Crop	UAV type	Application	Payload (tank capacity (L))	Nozzle type	Spraying width (m)	Flight speed (m s^{-1})	Flying height (m) above the crop canopy	Reference
Rice	Hexacopter Drone	Pesticide	16	-	-	5	1.5-2	(Subramanian *et al.*, 2021)
Rice	Hy-B-15l (Single Rotor)	Pesticide	15	Tee Jet 110067	4-5	5	1.5	(Qin *et al.*, 2016)
Rice	Hexacopter Drone	Fertilizer and Pesticide	16	-	-	4	2	(Panjaitan *et al.*, 2022)
Maize	Battery-Operated	Nutrients	10	Flood Jet	3.5	4-5	0.75 to 1	(Kaniska *et al.*, 2022)
Maize	Fuel-Operated	Nutrients	16	Flood Jet & Atomizer	4	4-5	0.75 to 1	(Kaniska *et al.*, 2022)
Cotton	Xag P Series Plant Protection Uav	-	15	Centrifugal Nozzles	3.5	-	1-3	(P. Chen *et al.*, 2021)
Cotton		Fertilizer and Pesticide	10	Centrifugal Nozzles	1.5 – 3	1-8	2	(Lou *et al.*, 2018)
Sugarcane	Quad-Rotor Electric Drone	Pesticide	15	Centrifugal Nozzles	-	4	3	(Zhang *et al.*, 2020)
Sugarcane	Single-Rotor Drone	Pesticide		Centrifugal Nozzle	-	2-3	6 (above the ground level)	(Zhang *et al.*, 2020)
Sugarcane	Tiger Drone	Fertilizer	10	Flat Fan		3-6		(Koondee, Saengprachathanarug, Posom, Watyotha, & Wongphati 2019)
Black Gram	Battery-Operated	Nutrients	10	Flood Jet	4	4-5	1	(Nandhini *et al.*, 2022)
Black Gram	Fuel-Operated	Nutrients	16	Flood Jet & Atomizer	4	4-5	1	(Nandhini *et al.*, 2022)
Greengram	Ad610d	Nutrients	10	Flat Fan Standard Nozzle	3.5	-	1.5	(Dayana *et al.*, 2022)
Papaya	Dji T10		10	XR110015 and MGA015)	3-5.5	5	2.5	(Ribeiro *et al.*, 2023)

Potentials of drone technology

Advanced data analytics and technology are coupled to optimize resources and agronomic

practices, encompassing the potential of drones as a critical facet in sustainable agricultural systems (Vairavan, Kamble, Durgude, Ingle, & Pugazenthi, 2024). The increasing accessibility of drone technology is enabling its integration into precision agriculture practices (Dutta, Singh, Mondal, Paul, & Patra, 2023) (Fig. 2). In precision agriculture (PA), drones are utilized to efficiently monitor various stages of crop growth, facilitating the collection and processing of extensive data about crop health across different developmental stages (Shafi *et al.*, 2019). Precision agriculture utilizes a range of technologies, including the Global Positioning System, Geographic Information System, Remote Sensing, sensors, and data analysis, to gather information on crop conditions and soil diversity. Subsequently, this data can be employed to make well-informed decisions regarding the application of inputs such as water, fertilizer, and pesticides (Vairavan *et al.*, 2024). Unmanned Aerial Vehicles (UAVs) are frequently employed in agriculture to conduct Remote Sensing (RS) tasks, such as surveying crop fields and overseeing livestock (Freeman & Freeland, 2015). Specifically, UAVs equipped with multispectral cameras have proven valuable in assessing crop yields, tracking crop height, mapping weed distribution, and monitoring biomass. Additionally, the use of UAVs with high-resolution cameras and various sensors allows for the observation of topographic alterations within watersheds (Ali, Al-Ani, Eamus, & Tan, 2017).

These surveys provide precise coordinates of contaminations, which can be integrated into water quality monitoring plans for additional sampling. In addition to remote sensing (RS) and Unmanned Aerial Vehicles (UAVs), specialized sub-systems can be employed for on-site measurements of water quality parameters such as pH, dissolved oxygen, electrical conductivity, and temperature in surface waters (Capolupo, Kooistra, Berendonk, Boccia, & Suomalainen, 2015). Complementing on-site measurements, the utilization of tailor-made water collection devices can enhance water sample collection, thereby improving water quality monitoring in larger water bodies.

Precision agriculture applications using UAVs cover a wide range of tasks, including crop health monitoring, pesticide and fertilizer spraying, vegetation growth monitoring for yield estimation, vegetation health monitoring and pest management, irrigation management, water stress assessment, nutrient monitoring and deficiency analysis, evapotranspiration (ET) estimation, and weed control.

Crop monitoring and management

In precision agriculture, drones play an instrumental role in tasks such as field mapping and crop condition monitoring, as depicted in Fig. 3 (Hafeez *et al.*, 2022). Equipped with a diverse array of advanced sensors, including multispectral and thermal cameras, drones facilitate the collection of remote sensing data, enabling comprehensive observation of crops. Analysis of this data allows for the evaluation of crop health, detection of diseases or pests, and tracking of overall plant growth. Leveraging drones for crop monitoring and cutting-edge management empowers farmers to make data-driven decisions regarding irrigation, fertilization, and pest management (Delavarpour *et al.*, 2021). Drones equipped with various sensors, including those for visible, near-infrared (NIR), and thermal infrared wavelengths, enable continuous monitoring of crops throughout the growing season. By computing multispectral indices derived from reflection patterns, these drones can assess crop conditions including water stress, nutrient deficiencies, pest infestations, and diseases. Even before visible symptoms manifest, early detection facilitates timely intervention and serves as an early warning system for effective remedial actions (Simelli & Tsagaris, 2015). Unmanned Aerial Vehicles (UAVs) can survey extensive hectares of fields in a single flight. Thermal and multispectral cameras are mounted on the underside of the quadcopter to capture observations and record the reflectance of the vegetation canopy (Colomina & Molina,

2014).

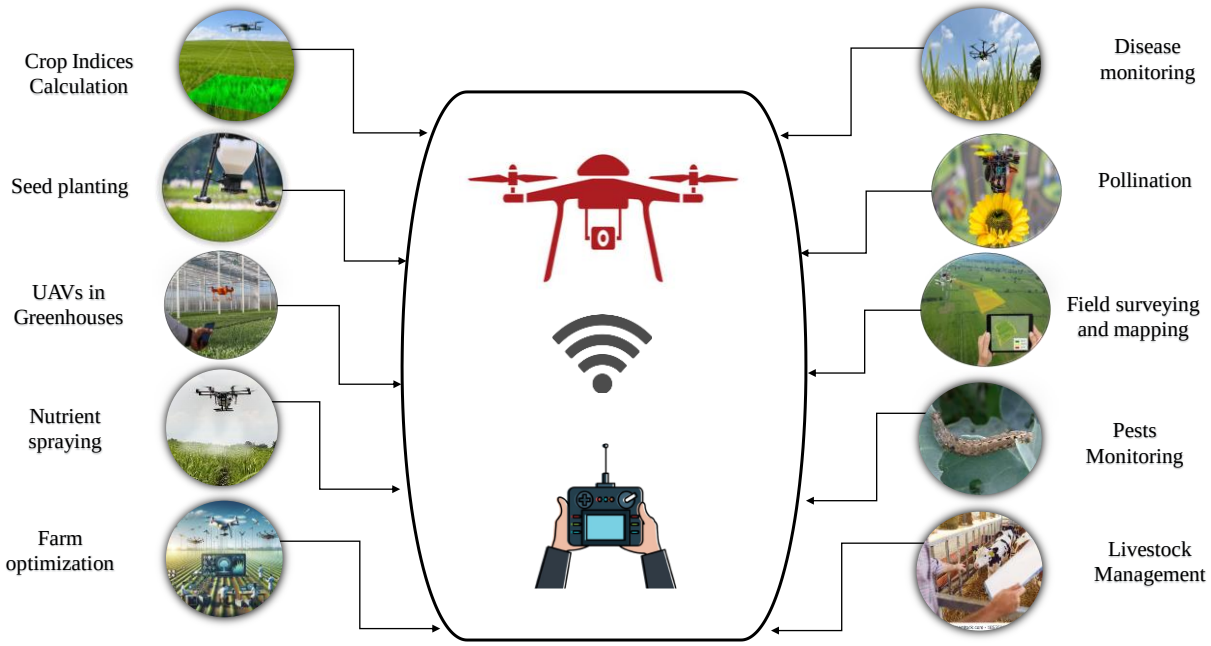


Fig. 2. Application of drone technology in precision agriculture

The camera captures one image per second, storing it in onboard memory before transmitting it to the ground station via telemetry (Delavarpour *et al.*, 2021). A UAV-based monitoring system addresses precision management in crop production (Ni *et al.*, 2017). The UAV crop-growth monitoring system comprises three primary components: the UAV platform, the crop-growth sensor affixed to the UAV, and the ground-based data processor (Delavarpour *et al.*, 2021). The crop-growth sensor, mounted on the UAV platform, records reflection spectra from the crop canopy in real-time. Subsequently, the ground-based data processor wirelessly receives and processes this data. By estimating indices such as NDVI, RVI, LNA, LAI, and LDW, and providing critical insights into crop growth, the processor contributes to crop growth and health-monitoring models (Ma, Zhu, Zhou, Zou, & Zhao, 2019). These technological advancements will provide farmers with more precise and comprehensive information about their crops, leading to increased yields, reduced input costs, and enhanced overall farm profitability (Ennouri & Kallel, 2019).

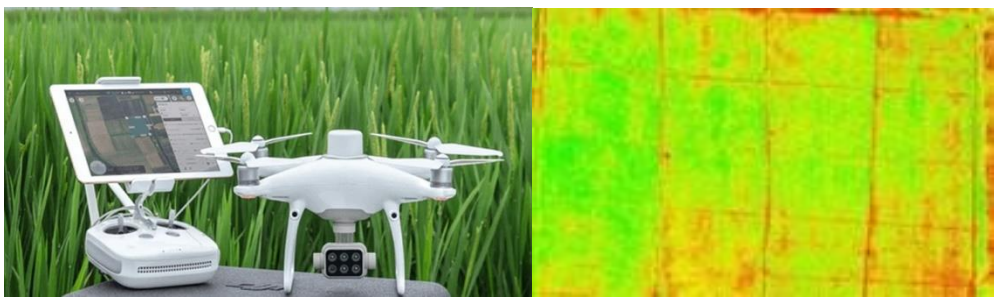


Fig. 3. DJI P4 Multispectral drone and vegetative indices (NDVI)
(Source: https://www.dji.com/global/p4-multispectral)

Nutrient and Deficiency Monitoring

In agricultural contexts, ensuring plants receive optimal nutrient levels is crucial for achieving robust growth and maximizing yields. Essential nutrients such as nitrogen, phosphorus, and potassium play distinct roles; nitrogen promotes leaf growth, phosphorus supports root and stem strength, and potassium enhances disease resistance. The NDVI Index aids in pinpointing areas of crop stress, enabling targeted intervention.

UAVs equipped with near-infrared (NIR) and multispectral imagery facilitate early detection of management zones, allowing proactive measures before visible symptoms manifest. Currently, nutritional assessments often rely on subjective visual inspections or labor-intensive laboratory leaf analyses, both of which have limitations in accuracy and efficiency (Dezordi, Aquino, Aquino, Clemente, & Assunção, 2016).

Alternative methods such as the chlorophyll meter (SPAD) provide indirect estimates, albeit with drawbacks including time consumption and potential inaccuracies (Balasubramaniam & Ananthi, 2016; Jia, Chen, Zhang, Buerkert, & Römheld, 2004; Nauš, Prokopová, Řebíček, & Špundová, 2010). Consequently, there is a growing emphasis on exploring novel approaches for identifying and quantifying plant nutritional deficiencies (Ali *et al.*, 2017).

Many studies in the literature derive vegetation indices (VI) from imagery and establish correlations with nutrient content through regression models, often employing linear models. Although less prevalent, other categories of variables have also been incorporated into regression models, such as the spectra of average reflectance (Capolupo *et al.*, 2015), selected spectral bands (Severtson *et al.*, 2016), color features (Yakushev & Kanash, 2016), and principal components (Berni, Zarco-Tejada, Suárez, & Fereres, 2009).

Field surveying and mapping

Field surveys using drones have become a vital tool for efficient and precise data collection in agriculture (Rejeb *et al.*, 2022). Drones can capture high-resolution imagery and detailed data on crop health, soil conditions, and topography, providing insights that were previously challenging to obtain on a large scale (Inoue, Ito, & Yonezawa, 2020). With advanced sensors, including multispectral, thermal, and LiDAR, drones can assess factors like plant stress, moisture levels, and canopy cover in real time (Olson & Anderson, 2021). Unmanned aerial vehicles (UAVs) equipped with LiDAR and GNSS sensors to enhance agricultural field mapping. It describes the development of a UAV-based mapping system designed to assess crop height and volume, providing a high-resolution view of field conditions, which is particularly beneficial for precision agriculture (Christiansen, Laursen, Jørgensen, Skovsen, & Gislum, 2017)

These UAV-based surveys allow for the rapid identification of issues such as pest infestations, nutrient deficiencies, and water stress. By generating 2D and 3D maps, drones help in creating site-specific management plans, enabling farmers to make data-driven decisions on fertilization, irrigation, and crop protection (Kim, Kim, & Sim, 2019).This approach not only reduces the time and labor associated with traditional field surveys but also enhances precision, leading to increased productivity and sustainability in agriculture (Aslan, Durdu, Sabanci, Ropelewska, & Gültekin, 2022).

Site-specific nutrient management

In an agricultural context, the application of fertilizers and chemicals is crucial for crop health and yield optimization. Drones have revolutionized precision agriculture, particularly through specialized applications such as precision spraying (Mogili & Deepak, 2018). UAVs, with advanced capabilities like GPS, autonomous flight control, real-time image transmission, and various sensors,

efficiently gather high-resolution spatial data for rapid analysis. They are capable of performing regular surveillance and monitoring abnormal conditions (Chen *et al.*, 2021). Drones offer the capability to deliver chemicals such as fertilizers and pesticides, adjusting quantities based on spatial crop variability and pest severity. Integrating UAVs with sprayer systems supports accurate, site-specific application in extensive crop fields, necessitating the use of heavy-lift UAVs for larger spraying areas (Sarghini & De Vivo, 2017). The lightweight and inexpensive Quadcopter (QC) system, also referred to as an Unmanned Aerial Vehicle (UAV), was proposed by researchers (Kedari, Lohagaonkar, Nimbokar, Palve, & Yevale, 2016).

Researchers have proposed lightweight and cost-effective quadcopter (QC) systems for indoor and outdoor crop spraying, autonomously controlled via Android devices. Leveraging machine learning algorithms ensures precise identification and treatment of insect pests, enabling targeted interventions without compromising healthy crops (Mogili & Deepak, 2018). These drones not only reduce the need for pesticides but also minimize environmental impact, offering improved efficiency and cost-effectiveness compared to conventional spraying methods (García-Munguía *et al*., 2024).

Utilizing drones for precise interventions allows farmers to apply fertilizers, pesticides, and herbicides with exceptional accuracy. This targeted approach minimizes the use of chemicals, leading to cost savings and a reduced environmental footprint compared to conventional widespread spraying methods (Puri *et al.*, 2017). Moreover, drones can be automated to fly independently over designated regions, pinpointing areas of interest by assessing crop health factors like moisture, nutrition, and pest presence. The data gathered offers crucial insights for proactive crop management, empowering farmers with enhanced control and understanding, and fostering sustainable and efficient agricultural practices (Delavarpour *et al.*, 2021).

Advancements in technology have introduced drones to agriculture, offering an innovative and efficient method to reduce chemical usage and promote smart farming, minimizing potential environmental impacts (Bongiovanni & Lowenberg-DeBoer, 2004). Reduction of chemical dependency in agriculture is just one of the advantages of drone technology; it also facilitates enhanced crop monitoring, early pest and disease identification, and efficient land mapping for improved resource management (Hafeez *et al.*, 2022). Incorporating drone technology into agriculture reduces reliance on chemicals and advocates for sustainable and resource-efficient farming methods, ultimately yielding positive environmental outcomes (Talaviya, Shah, Patel, Yagnik, & Shah, 2020).

Water conservation and soil health

Multiple factors contribute to water stress in crops, and characterizing this stress can be difficult (Berni *et al.*, 2009). Derived variables from thermal images often depend on subtle temperature fluctuations to identify stresses and other phenomena. Consequently, thresholds and regression equations established under specific conditions typically do not apply under even slightly different circumstances. Scientists employed a variety of sensors and modeling techniques to assess instances of water stress. The deployment of drones fitted with specialized sensors can be used to calculate these indices, which could help in the monitoring of water stress. Using multispectral, hyperspectral, or thermal infrared imagery, vegetation indices (NDVI, GNDVI, etc.), the difference between canopy and air temperatures (Tc- Ta) or direct canopy temperature (Dutta & Goswami, 2020), and crop water stress index (CWSI) can be calculated.

Drones are also instrumental in monitoring soil health, capturing detailed images and data to evaluate factors such as erosion, compaction, and nutrient levels. Utilizing drone-supplied data for decision-making allows farmers to improve soil fertility and

overall health, promoting sustainable long-term growth (M. Tahat, Alananbeh, Othman, & Leskovar, 2020). Additionally, drones facilitate the acquisition of valuable data and insights, enabling farmers to make informed decisions regarding soil management strategies, ultimately enhancing soil health and productivity (Merwe, Burchfield, Witt, Price, & Sharda, 2020).

Evapotranspiration (ET) estimation

Evapotranspiration (ET) is a vital process that involves water transfer from the land to the atmosphere through soil evaporation and plant transpiration. With careful concerns about water scarcity, population growth, and climate change, the estimation of evapotranspiration has become a significant focus in agricultural research. Evapotranspiration estimates vary based on the specific functions of different types of unmanned aerial vehicles (UAVs). Fixed-wing UAVs are ideal for large-scale fields because of their two-hour average flying time. In contrast, quadcopters are used for quick missions in smaller fields because of their shorter flying duration, around 30 minutes (Dutta & Goswami, 2020). When utilized as remote sensing platforms, UAVs introduce new research challenges, including drone image processing and flight path planning. An example includes using a fixed-wing UAV to gather thermal data for estimating ET through two-source energy balance models (Hoffmann *et al.*, 2016). Unmanned aerial vehicles (UAVs) can reduce these temporal and spatial constraints. The UAVs can be equipped with lightweight sensors and cameras to capture high-resolution pictures. The spatial resolution of UAV photographs can reach the centimeter level, compared to satellite imagery. Additionally, UAVs can fly whenever needed, allowing for high-temporal images. So, various UAV-based techniques are used for evapotranspiration (Niu, Zhao, Wang, & Chen, 2019). Utah State University developed an airborne digital system to gather multispectral and thermal images for evapotranspiration estimation (Xia *et al.*, 2016). These cameras have the following spectral bands: Near-infrared (NIR) (0.780 µm- 0.820 µm), Blue (0.465 µm- 0.475 µm), Green (0.545 µm- 0.555 µm), and Red (0.645 µm- 0.655 µm). UAV platforms with lightweight sensors can give higher quality, and higher spatial and temporal resolution images as compared to other satellite-based remote sensing techniques (Niu *et al.*, 2019).

Decision-making system for farm optimization

Agricultural remote sensing proves highly beneficial by enabling the comprehensive observation of crops on a broad scale, employing a synoptic, remote, and non-invasive approach. Typically, this technology employs sensors mounted on Unmanned Aerial Vehicles (UAVs) to capture the reflected or emitted electromagnetic radiation from plants (Weiss, Jacob, & Duveiller, 2020). The collected data is then processed to generate valuable insights and products. These insights encompass various characteristics of the agricultural system, showcasing their spatial and temporal variations. Functional traits refer to the biochemical, morphological, phenological, physiological, and structural features that govern the performance or fitness of organisms, particularly plants (Weiss *et al.*, 2020). Plant traits, categorized as typological, biological, physical, structural, geometrical, or chemical, exhibit variations across plant species and locations. Remote sensing (RS) establishes a crucial link with traits such as leaf area index, chlorophyll content, and soil moisture (Martos, Ahmad, Cartujo, & Ordoñez, 2021). Accurate interpretation relies on factors like crop phenology, type, soil characteristics, weather, and more.

Remote sensing yields key information products like plant density, leaf biochemical content, and soil moisture, aiding in assessments of crop health, disease, irrigation timing, nutrient status, and yield predictions. This data is crucial for interpreting crop health, disease incidence, irrigation needs, nutrient deficiencies, and yield predictions (Weiss *et al.*, 2020). With the global population on the

rise, frequent shifts in climate patterns, and limited resources, meeting the food demands of the current population has become a formidable challenge (Kamilaris & Prenafeta-Boldú, 2018). Precision agriculture, also referred to as smart farming, has emerged as an innovative solution to address the existing sustainability issues in agriculture. The integration of drone technology in precision agriculture facilitates sophisticated analytics and data-centric decision-making, leading to optimized farm operations (Gopal, Singh, & Aggarwal, 2021). This acquired knowledge enables farmers to make well-informed decisions regarding irrigation schedules, nutrient management, and pest control, ultimately enhancing productivity and minimizing waste. Additionally, the application of advanced analytics aids in identifying trends and patterns within the collected data, empowering proactive and timely interventions to mitigate risks and maximize crop yields (Sishodia, Ray, & Singh, 2020).

Crop protection

Data-driven disease detection

Crop diseases, whether fungal, bacterial, or viral, pose significant threats to agricultural productivity. Timely detection enables proactive measures such as removing infected plants to prevent spread. Image-based tools are instrumental, especially when manual assessment is impractical, unreliable, or inaccessible, with UAVs enhancing surveillance capabilities (Ziya, Mehmet, & Yusuf, 2018). RGB and multispectral images have traditionally been utilized, with ongoing exploration into hyperspectral and thermal imagery (Calderón Madrid, Navas Cortés, Lucena León, & Zarco-Tejada, 2013; Dash, Watt, Pearse, Heaphy, & Dungey, 2017). Drones equipped with multispectral sensors monitor wheat crops, identifying fungal diseases like rust and powdery mildew early. This allows for targeted fungicide applications, reducing chemical use and protecting crop health (Joshi, Sandhu, Dhillon, Chen, & Bohara, 2024). Thermal imaging, in particular, aids in detecting water stress induced by specific diseases. UAVs equipped with infrared cameras offer detailed insights into plant internal structures (Hardin & Jensen, 2011), capturing various data types such as visual, thermal, and infrared with precision. Integration of this data into analytics platforms facilitates actionable insights and predictive capabilities, supporting sustainable decision-making (Baradaran Motie, Saeidirad, & Jafarian, 2023; Lee, Sudduth, & Zhou, 2024; Lu, Dai, Miao, & Kusnierek, 2024; Manfreda *et al.*, 2018; Zhao *et al.*, 2024).

Pest surveillance and management

The combination of a sprayer system mounted on a UAV for pesticide spraying presents a promising opportunity for effective pest management and vector control. This integrated solution offers precise site-specific application, particularly beneficial for extensive crop fields. To cover large areas efficiently, heavy-lift UAVs become essential for the spraying operation (Sarghini & De Vivo, 2017). The spraying drone has various components (Fig. 4) and Drones with an integrated spraying system flow chart are displayed in Figure 5. The effectiveness of the spraying system, when attached to the UAV, is enhanced by the use of a PWM (Pulse Width Modulation) controller in pesticide applications (Huang, Hoffmann, Lan, Wu, & Fritz, 2009). A prototype is being designed to create a UAV capable of adjusting the mean diameter droplet size up to 300mm. The growing popularity of UAVs in spraying operations is attributed to their speed and precision (Huang, Reddy, Fletcher, & Pennington, 2018). On the contrary, crop quality may be compromised due to issues such as inadequate coverage during spraying, overlapping in crop areas, and ineffective treatment of the outer edges of the field. To address these challenges, a control loop algorithm was implemented in agriculture operations, employing a swarm of UAVs to handle the precise spraying of pesticides (Yao, Jiang, Zhiyao, Shuaishuai, & Quan, 2016). These unmanned aerial vehicles take responsibility for overcoming the mentioned factors and ensuring more effective and uniform pesticide application across the entire

crop field.

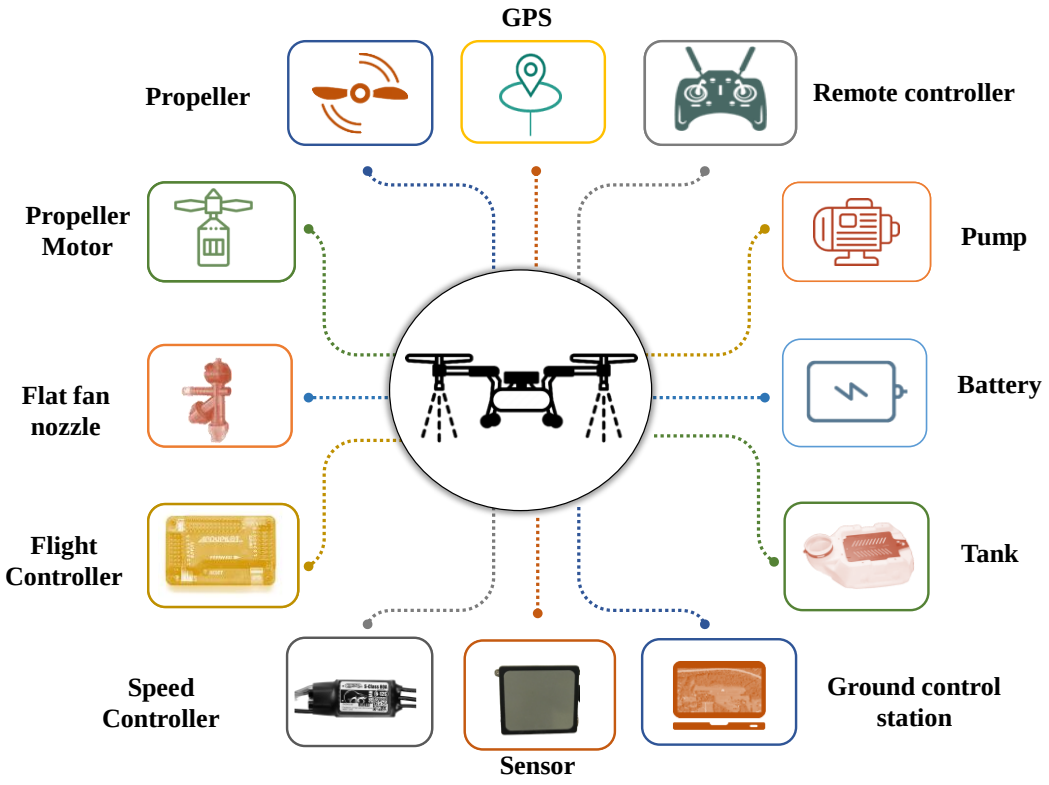


Fig. 4. Components of a spraying drone

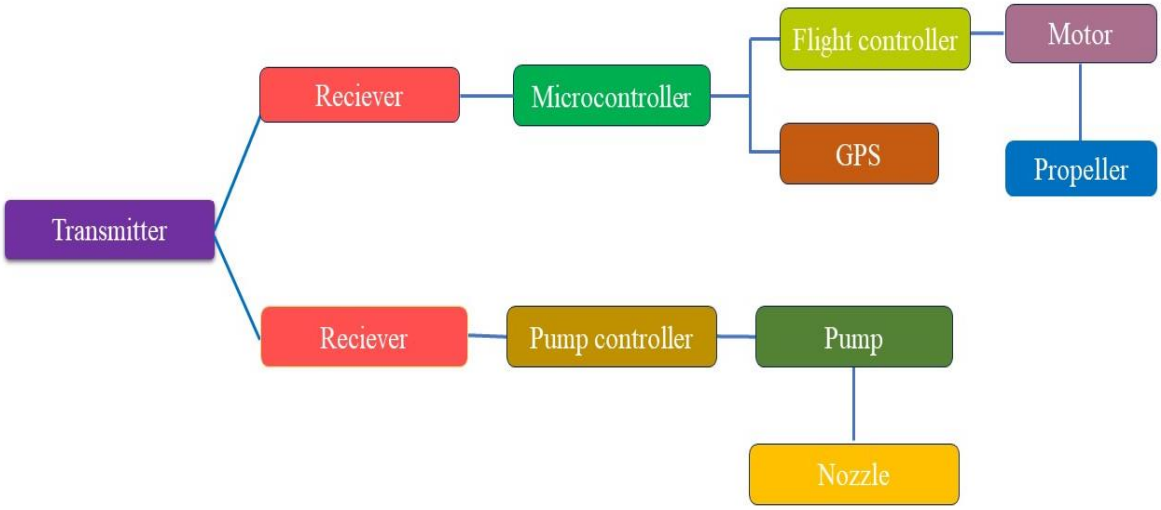


Fig. 5. Flow chart of UAVs for pesticide application

Pollination

Drones offer an appealing solution for crop pollination due to their airborne nature, much like bees, making them well-suited for the task. Drone technology is more accessible than other types of robotics (Wikifactory, 2020). These devices are either directly operated by a pilot, follow a predefined path defined by the arrangement of orchard rows, or

use a 3-D representation of the environment produced from a previous pass by scouting drones (Alkhamis, 2021). Among the various techniques being investigated, spraying water-suspended pollen grains using a drone has proven to be an effective method for pollinating date palm trees (Mohamed, Shukla, Keerthika, & Mehta, 2023). Other methods include aerial pollen dispersal and the use of drone-generated air vortices to facilitate pollination directly. These approaches show promise for enhancing pollination in hybrid grain production, as well as in self-compatible crops grown in controlled environments, such as strawberries, tomatoes, peppers, and eggplants (Broussard, Coates, & Martinsen, 2023). Drone pollination serves as a legitimate method of supplementary pollination, capable of enhancing crop yields and supporting a healthy economy (Guzman, Chamberlain, & Elle, 2021).

Seed planting

Drones are revolutionizing seed planting in agriculture by enhancing precision and efficiency (Khanpara, Patel, Parmar, & Mehta, 2024). Drones can be equipped with sensors and cameras capable of assessing soil conditions and delivering real-time information to farmers. This information can be utilized to optimize seed sowing, ensuring that seeds are planted accurately in terms of location, depth, and density (Paul *et al.*, 2022). Drones enable rapid seed sowing, reducing the working time. They can cover extensive areas rapidly and efficiently, making them especially suitable for farmers managing large fields (Monteiro, de Alencar, Souza, & Leão, 2021). A recent study by Dampage, Navodana, Lakal, and Warusavitharana (2020) highlights the effectiveness of drones in precision seeding, particularly in rice fields. Drones have shown to improve seed placement accuracy, minimize waste, and ensure uniform distribution, which are critical factors in optimizing crop yield and reducing labor.

Weed Control

Undesirable plants, or weeds, pose challenges in crops by competing for resources, potentially reducing yields. Herbicides are commonly used in conventional farming, but their excessive application may lead to herbicide-resistant weeds, impacting crop growth. Employing hyperspectral images to distinguish between weed spectral signatures with varying glyphosate resistances is explored (Li, Fan, Huang, & Tian, 2016). For example, RGB sensors are used to categorize different types of weeds (Huang *et al.*, 2018).

Drones equipped with hyperspectral sensors were utilized by researchers to track weeds based on the density of leaves and the amount of chlorophyll in the plant canopy (Malenovský, Lucieer, King, Turnbull, & Robinson, 2017). Moreover, weeds poses a significant risk to environmental health. To address these issues, site-specific weed management relies on accurate weed cover maps for precise herbicide spraying. Drones capture field images to create such maps. Utilizing drones for herbicide spraying proves effective for both pre-emergence and post-emergence weed control. It allows spraying in diverse field conditions, including mud, weeds, and various weather conditions. The drone application ensures efficient weedicide use and is user-friendly, portable, and easy to maintain (Dutta & Goswami, 2020).

UAVs in Greenhouses

In greenhouses, drones serve as compact, efficient tools for monitoring the controlled environment and applying inputs in hard-to-reach areas without disturbing the plants (Erdogan, 2023). UAVs can capture data from nearly any location within the three-dimensional environment of a greenhouse, simplifying and enhancing tasks like localized climate control and crop monitoring. They enable regular, consistent observation of crops, whether weekly or even hourly, allowing for the detection of changes in plant health over time. Aerial perspectives reveal issues such as water stress, soil inconsistencies, and pest infestations more effectively (Aslan *et al.*,

2022). Additionally, advancements in camera technology mean that plant diseases, often invisible to the human eye, can be identified with ease through the use of specialized sensors, including hyperspectral, multispectral, and infrared imaging, allowing for thorough, precise monitoring (Roldán, Joossen, Sanz, Cerro, & Barrientos, 2015).

Livestock monitoring

In the field of livestock monitoring, drones offer numerous applications for animal husbandry and prove valuable for overseeing extensive herds. Animals on the farm are fitted with sensors or radio-frequency identification (RFID) tags, enabling tracking of feeding patterns and movements. Drones are employed to monitor livestock more frequently, accomplishing this in a shorter time frame without extensive personnel involvement (Ajakaiye, 2023). The concept of remote-sensing fencing or virtual boundaries involves creating a virtual obstacle or security barrier within a specified spatial area, particularly useful in the context of free-range livestock grazing. Equipped with high-resolution infrared cameras, these drones can promptly identify diseased animals based on their heat signatures. Once a diseased animal is detected, it can be isolated from the rest of the herd, allowing for early intervention and treatment. This application positions drones as a tool for precise dairy farming (Rathod & Shinde, 2023).

Pitfalls in drone technology for sustainable agriculture

Every technology encounters initial limitations, and drones are no exception. Drones in sustainable agriculture face challenges such as limited battery life, connectivity issues in remote areas, and regulatory hurdles. These issues can impact efficiency and effectiveness, but ongoing research aims to overcome these obstacles and maximize drone potential.

Limited battery life

The main limitation of UAVs is that their maximum flying time is limited by the energy provided by batteries. When drones cover large areas or lengthy flights for data collection purposes, this limitation can cause difficulties (Mohsan *et al.*, 2022). One main constraint concerns technological capabilities, particularly battery life and flight duration (Table 3). Currently, the market has a maximum operating duration of approximately thirty minutes, due in large part to constraints in battery capacity and weight (Dutta & Goswami, 2020). This constraint significantly reduces the area coverage of drones that can be used for spraying, monitoring, and surveying.

Table 3- Battery life and flight duration factors affecting flight duration for different types of agricultural drones

Drone Type	Average battery life (min)	Range of flight duration (min)	Factors affecting flight duration	Reference
Multi-rotor drones	20-30	15-45	Size, weight, motor power, payload weight, weather	(Elouarouar & Medromi, 2022)
Fixed-wing drones	30-60	20-90	Size, battery capacity, motor efficiency, spraying rate, wind	(Elmeseiry, Alshaer, & Ismail, 2021)
Vertical Take-Off and Landing (VTOL) drones	25-40	18-50	Motor type, payload weight, spraying intensity, flying speed	(Dündar, Bilici, & Ünler, 2020)
Hybrid drones	30-45	20-60	Battery capacity, hybrid propulsion efficiency, payload weight, flight distance	(Rajabi, Beigi, & Aghakhani, 2023)

Cost scalability

The expense of buying and maintaining agricultural drones is a hurdle for farmers (Emimi, Khaleel, & Alkrash, 2023). The

operational cost is also very high, including batteries, sensors, and other equipment that are necessities for operations and may need to be upgraded or replaced regularly. Moreover, there are expenses related to operator training and following rules (Singh, 2023).

Technology constraints

There is insufficient knowledge of drone technology among farmers. Many farmers lack exposure to advanced technologies and may find it difficult to understand and trust drone capabilities in precision agriculture (Khaspuria *et al.*, 2024). Additionally, training and knowledge transfer systems are often underdeveloped, making it harder for farmers to gain hands-on experience with drone operations and data interpretation. Addressing this issue requires targeted educational programs, simplified drone interfaces, and partnerships with local agricultural extension services (Dhillon & Moncur, 2023). Such efforts could bridge the knowledge gap, encouraging broader adoption and maximizing the potential benefits of drones in agriculture.

Data analysis and interpretation

Another significant constraint is data analysis. Drones equipped with hyperspectral sensors often generate many terabytes of data, requiring proper storage, specialized software for processing, and analysis by experts with years of experience. As a result, there is a significant delay between data collection and obtaining results. While multispectral data processing is significantly faster than hyperspectral data processing, accuracy is very low (Yang, Everitt, Bradford, & Murden, 2009). The remote and rural settings of many farms introduce challenges related to connectivity and the real-time processing of intricate sensor data collected by drones (Islam *et al.*, 2021). Agriculture drones collect massive amounts of data, which makes data analysis and interpretation very challenging and time-consuming to handle and analyze (Emimi *et al.*, 2023).

Adverse weather conditions

The unfavorable weather conditions could restrict the sensing and response of drone activity (Leite-Filho, de Sousa Pontes, & Costa, 2019). Additionally, weather conditions like heavy winds or precipitation pose operational difficulties for drones, particularly those with lighter structures. In general, drone flight missions are designed/planned in such a way as to minimize the above-mentioned constraints. In response to the constraints occurring under unfavorable conditions, may require atmospheric, radiometric, and geometric corrections to require accurate data collection and processing, which are usually application-specific.

Atmospheric Correction

The sun emits electromagnetic energy (EM) toward Earth, but before it reaches the surface, some of it is absorbed and dispersed by dust and gases in the atmosphere. Aerial imagery for surface reflectance observations is influenced by various processes related to the propagation of electromagnetic radiation within the atmosphere-surface system. Under clear sky conditions, the relevant processes include gaseous absorption, molecular scattering, aerosol scattering and absorption, as well as water surface reflection. In instances of cloudy conditions, the presence of cloud droplets scattering makes surface sensing challenging, with the cloud signal predominantly prevailing. An exception arises when clouds are optically thin or cover only a small portion of the pixel, meaning their impact on pixel reflectance is less than 0.2 (Frouin *et al.*, 2019).

The quality of information derived from aerial image measurements, including vegetation indices, is affected by atmospheric effects. Errors induced by atmospheric effects have the potential to elevate uncertainty by up to 10%, varying depending on the spectral channel (Chen *et al.*, 2021). Moreover, much of the signal received by an imagery sensor from a dark object, like an area experiencing water stress, is attributable to the atmosphere at visible wavelengths, assuming that near-infrared and middle-infrared image data are

unaffected by atmospheric scattering effects. Consequently, pixels from dark targets serve as indicators of the amount of upwelling path radiance in that band. To access accurate surface reflectance, the influence of the atmosphere and surface must be eliminated. This necessitates an atmospheric correction model, particularly in scenarios where Vegetation Indices *(D'Sa et al.,* 2016) are utilized in vegetation monitoring and in dark scenes where features like water stress and drought can be masked by atmospheric scatters.

Atmospheric correction removes atmospheric effects, variable solar illumination, sensor viewing geometry, and terrain influence on image reflectance values, thereby determining their true values. Supplying, calibrating, and adjusting for atmospheric conditions at the time of imaging are crucial atmospheric correction prerequisites.

Radiometric Correction

Radiometric calibration involves establishing the functional relationship between incoming radiation and sensor output, such as Digital Number (Saeed, Younes, Cai, & Cai, 2018). Accurate radiometric calibration is essential for change detection and interpretation, especially when images are captured at different dates, times, locations, or by different sensors. It ensures that changes in the data reflect actual field changes rather than variations in the image acquisition process or conditions (e.g., changes in light intensity). Many image collections involving hyperspectral cameras (e.g., crop phenotyping, disease detection, and yield monitoring) necessitate precise radiometric calibrations.

Several potential solutions can mitigate radiometric variation. Light intensity fluctuates over time due to changes in solar elevation, atmospheric transmittance, and cloud cover. Therefore, conducting image collection flights during periods of minimal solar elevation could reduce radiometric variation in collected data. Additionally, digital camera exposure settings should be carefully chosen based on overall light intensity, either manually or automatically (Hunt, Cavigelli, Daughtry, Mcmurtrey, & Walthall, 2005).

Geometric correction

Unmanned Aerial Vehicles (UAVs) capture imagery for aerial mapping of agricultural landscapes, but this data often contains geometric distortions arising from various factors such as sensor position variations, platform motion, and Earth's rotation. These distortions, categorized as internal and external factors, lead to inconsistencies in pixel size and inaccurate geographic coordinates of image pixels. Geometric correction is essential to rectify these distortions and ensure the accurate representation of features in the corrected image (Kallimani, Heidarian, van Evert, Rijk, & Kooistra, 2020). By calibrating intrinsic camera parameters like focal distance and lens distortion, geometric correction restores the geometric integrity of the image, facilitating precise spatial analysis.

Regulatory and legal hurdles

A significant challenge in integrating drones for precision agriculture is ensuring compliance with the diverse regulatory requirements that govern the use of unmanned aerial vehicles (UAVs) in various geographic areas (Table 4). Depending on the geographical area, drones might necessitate registration, licensing, certification, insurance, or permission to operate within specific airspace or over designated land (Stöcker, Bennett, Nex, Gerke, & Zevenbergen, 2017). Moreover, drone pilots need to follow regulations regarding safety, privacy, security, and environmental concerns linked with their drone operations. These rules may differ depending on factors such as the type, size, weight, speed, altitude, and intended use of the drone, emphasizing the necessity for operators to be knowledgeable about and adhere to the relevant legal stipulations and limitations applicable to their particular drone usage and geographic location (Memisoglu, 2019).

Despite drones being utilized in agriculture for the past two decades, regulations about their use in agricultural settings are still nascent worldwide. Although India's utilization of drones in agriculture lags behind that of the US and China, New Delhi has taken proactive measures to establish regulatory frameworks for global drone governance. This initiative is partly driven by the recognition of the potential security implications of drone technology for India, as well as the strategic advantage of leading in this domain to safeguard national interests. At the international level, the International Civil Aviation Organization (ICAO) plays a pivotal role in developing rules and regulations for drone operations, with its initial efforts dating back to 2007. However, it was not until 2011 that the ICAO issued its first set of rules in Circular 328. In December 2018, the Indian government introduced a drone policy facilitating drone applications, particularly for agricultural purposes.

The Directorate General of Civil Aviation (DGCA), and the Government of India (GOI), regulations implicitly permit the use of Remotely Piloted Aircraft Systems (RPAS), i.e., Drone/UAV for agricultural purposes except to spray pesticides until specifically cleared. The DGCA RPAS Guidance Manual provides procedures for the issue of Unique Identification Numbers (Dezordi *et al.*, 2016). Unmanned Aircraft Operator Permits (UAOP) strictly regulate drone operations in various designated areas, including densely populated zones, near airports, during poor weather, and around sensitive facilities. Operators above 18 years old must maintain a visual line of sight, possess a valid license plate and insurance, and refrain from exceeding altitude limits or flying multiple drones simultaneously. Addressing issues related to regulation, ethics, and implementation is imperative, necessitating alignment with existing legal and moral principles and adaptation to rapid technological advancements for the establishment of an effective governance framework for UAVs in India (Swetha, Bharath Kumar, Sanwal Singh, & Urmila, 2024).

In developing countries like Iran, one of the primary barriers to the adoption of drone technology in agriculture is the inability to purchase drones directly from manufacturers, as many drone-producing companies are restricted by international sanctions (Runde, Carter, Bandura, & Ramanujam, 2019). This lack of access limits local farmers' ability to implement drone-based precision agriculture, which could otherwise improve efficiency and crop health assessment.

Table 4- Regulatory and legal hurdles

Challenge	Description	Impact	Reference
Complex permitting processes	Obtaining permits for airspace usage, data collection, and pesticide spraying can be time-consuming and expensive.	Discourages adoption, particularly for small-scale farmers.	(Pathak, Sharma, & Nagar, 2020)
Unclear data ownership and privacy	Lack of clarity on data ownership and privacy raises concerns about farmer data being used without their consent.	Farmers hesitate to share sensitive data, hindering its potential for analysis and improvement.	(Altawy & Youssef, 2016)
Limited liability and insurance frameworks	Existing frameworks might not adequately address agricultural applications like spraying or livestock monitoring.	Creates uncertainty for farmers and service providers in case of accidents.	(Singh, 2023)
Variable regulations across borders	Differing regulations in different countries create challenges for cross-border operations and data sharing.	Hinders global collaboration and technology advancement.	(Pathak *et al.*, 2020)
Evolving technology and policy gaps	The rapid evolution of drone technology often outpaces regulatory frameworks.	This leads to hesitant adoption by farmers and discourages innovation by developers.	(Rajagopalan & Krishna, 2018)

To overcome drone access restrictions in developing countries, encouraging local companies to develop and manufacture drones suitable for agricultural needs could create an alternative supply, and partnering with neighboring countries for technology transfer and drone expertise can also help. Additionally, promoting regional drone production can create self-reliance, reduce dependency, and support precision agriculture, driving sustainable agricultural development.

Agricultural drones make precision farming and resource optimization possible, yet there are drawbacks related to data processing, cost scalability, and regulatory compliance. By overcoming these obstacles, drones in various fields will reach their full potential (Emimi *et al.*, 2023).

Conclusion

Drone technology holds immense potential for transforming agricultural practices, fostering sustainability, and boosting its efficiency. UAV adoption in agriculture enables the farming community to contribute to the global pursuit of conserving the environment and economic resilience. Its versatile applications span across various domains, including crop health monitoring, precision spraying, data-driven decision-making, and soil health assessment, aligning with the objectives of Sustainable Development Goal 2 (Zero Hunger). The adoption of drones in precision agriculture can also contribute significantly to climate action by curbing greenhouse gas emissions linked to conventional farming methods. Through optimized resource management and reduced reliance on chemical inputs, drones play a vital role in mitigating the agricultural sector's impact on climate change, thereby supporting Sustainable Development Goal 13 (Climate Action). Nonetheless, several challenges impede the widespread adoption of drone technology. Issues such as short battery life and operational limitations during adverse weather conditions present practical barriers that need to be addressed for broader implementation. Regulatory frameworks vary significantly across regions, necessitating adherence to complex guidelines and obtaining permits. This variability, coupled with the high initial cost of drones and the requisite expertise in operation and data analysis, can pose barriers for small-scale farmers.

To overcome these challenges, particularly in developing countries, implementing an agricultural drone subsidy system can be crucial. Such a system would provide financial support to smallholder farmers, reducing the upfront costs associated with acquiring drone technology. By offering subsidies or low-interest loans, governments and international organizations can make drone technology more accessible, enabling even small-scale farmers to benefit from its advantages. Moreover, subsidies could also be directed towards training programs, ensuring that farmers gain the necessary skills to effectively utilize drones and interpret the data they collect.

The undeniable potential benefits of drone technology warrant continued research and development efforts. Key focuses include improving battery life, enhancing sensor capabilities, and streamlining regulations to enhance accessibility and adoption. Additionally, capacity-building initiatives and training programs can equip farmers with the necessary skills and knowledge to effectively leverage this technology. By addressing these challenges and harnessing the transformative power of drones, agriculture can transition towards a future characterized by sustainability and efficiency, thereby ensuring sustainable agriculture and food security. Collaborative approaches involving multiple stakeholders can play a crucial role in ensuring a more effective transfer of UAVs to farmers' fields.

Future direction

In the realm of agricultural technology, the potential of drone technology stands out

prominently, offering efficiency and adaptability across various agricultural operations. For small-scale farmers, the expense of buying and maintaining agricultural drones may be a hurdle. Wider use and accessibility of drone technology depend on its scalability and affordability, including equipment, training, and support services (Emimi *et al.*, 2023). However, challenges such as the high initial investment costs and the necessity for policy reforms remain significant hurdles in popularizing drones and making them accessible to farmers. Moreover, a pressing need exists for robust research endeavors aimed at optimizing operational protocols and validating the efficacy of drone applications. One critical area of investigation involves understanding the intricate dynamics of drone-induced airflow and its impact on liquid distribution during spraying operations.

Recent studies have highlighted the correlation between the rotational speed of drone rotors and the deposition of liquid droplets on various plant surfaces. It has been observed that higher rotor speeds result in a lower deposition of liquid on lower plant levels, indicating the potential for altered distribution patterns due to the airflow generated by drone rotors. Consequently, the efficacy and uniformity of pesticide deposition remain uncertain, underscoring the necessity for detailed research to inform and refine field spraying processes. Beyond this, numerous unresolved issues persist, necessitating further investigation and refinement to realize the full potential of drone technology in agricultural settings. These research endeavors are crucial for addressing existing limitations, enhancing operational efficiency, and ensuring the effective utilization of drone technology for agricultural purposes.

Conflict of Interest: The authors declare no competing interests.

Authors Contribution

Kannan Pandian: Conceptualisation, Supervision, Review & editing

Rishikesavan: Writing– original draft, Writing– review & editing

S. Pazhanivelan: Editing– original draft

R. Kumaraperumal: Review & Editing

N. Sritharan: Writing– original draft

D. Muthumanickam: Conceptualisation & editing

M. Mohamed Roshan Abu Firnass: Writing– review & editing

B. Venkatesh: Data analysis and validation

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مقاله مروری
جلد ۱۵، شماره ۳، پاییز ۱٤۰٤، ص ٤۹۰-٤٥۹

مروری بر پتانسیل و مشکلات استفاده از فناوری هواپیماهای بدون سرنشین در کشاورزی پایدار

اس. ریشیکساوان[۱]، پی. کنان[۲*]، اس. پاژانیولان[۲]، آر. کومارپرومال[۱]، ان. شریثارن[۳]، دی. موهومانیکام[۱]، ام. محمد روشن ابو فرناس[٤]، بی. ونکاتش[٥]

تاریخ دریافت: ۱۴۰۳/۰۵/۲۱
تاریخ پذیرش: ۱۴۰۳/۰۹/۲۱

چکیده

هواپیماهای بدون سرنشین (پهپاد) به‌عنوان یک فناوری با پتانسیل بالا در کشاورزی دقیق ظهور کرده‌اند و از اهداف توسعه پایدار (SDGs) با تقویت شیوه‌های کشاورزی پایدار، بهبود امنیت غذایی و کاهش اثرات زیست‌محیطی حمایت می‌کنند. این مقاله مروری بر تحلیل دقیق کاربردهای چندگانه فناوری هواپیماهای بدون سرنشین در کشاورزی، مانند نظارت بر سلامت محصول، پاشش آفت‌کش و کود، کنترل علف‌های هرز و تصمیم‌گیری مبتنی بر داده‌ها برای بهینه‌سازی مزرعه در نظر گرفته شده است. این مقاله بر نقش پهپادها در سمپاشی دقیق، ترویج مداخلات هدفمند و به حداقل رساندن اثرات زیست‌محیطی در مقایسه با روش‌های مرسوم تاکید دارد. هواپیماهای بدون سرنشین نقش حیاتی در مدیریت علف‌های هرز و ارزیابی سلامت محصول دارند. تمرکز این مقاله بر اهمیت داده‌های جمع‌آوری‌شده توسط هواپیماهای بدون سرنشین برای به‌دست آوردن اطلاعات لازم برای تصمیم‌گیری در مورد آبیاری، کوددهی و مدیریت کلی مزرعه است. با این حال، استفاده از وسایل نقلیه هوایی بدون سرنشین (پهپاد) در کشاورزی با چالش‌های ناشی از عمر باتری‌ها، زمان محدود پرواز و مشکلات اتصال، به‌ویژه در مناطق دورافتاده، مواجه است. چالش‌های قانونی، چارچوب‌های نظارتی و محدودیت‌هایی در مناطق مختلف نیز وجود دارد که بر عملکرد هواپیماهای بدون سرنشین تأثیر می‌گذارند. با تحقیق و توسعه مستمر، چالش‌های ارائه‌شده را می‌توان حل کرد و از حداکثر پتانسیل پهپادها برای دستیابی به کشاورزی پایدار استفاده کرد.

واژه‌های کلیدی: بهینه‌سازی منابع، تصمیم‌گیری مبتنی بر داده، کشاورزی دقیق، نظارت بر محصول، وسایل نقلیه هوایی بدون سرنشین (پهپاد)

۱- گروه سنجش از دور و GIS، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۲- مرکز نانوفناوری کشاورزی، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۳- گروه برنج، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۴- گروه علوم خاک و شیمی کشاورزی، دانشگاه کشاورزی تامیل نادو، کویمباتور، تامیل نادو، هند
۵- گروه مهندسی عمران، دانشکده مهندسی و فناوری دولتی آلاگاپا چتیار، کارائیکودی، تامیل نادو، هند
(*- نویسنده مسئول: Email: kannan.p@tnau.ac.in)

https://doi.org/10.22067/jam.2024.89334.1276

مندرجات

مقالات پژوهشی

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ایمان احمدی

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ارزیابی تاثیر نرخ تغییر شکل خاک برای تخمین مصرف انرژی برهمکنش خاک و تایر با استفاده از رابطه فشار-نشست خاک ۳۷۷
هادی اسدالهی، بهزاد محمدی الستی، عارف مردانی، مهدی عباسقلی پور

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تحلیل انرژی، محیط‌زیستی و اقتصادی سامانه نوین سبز یکپارچه با ساختمان: دیدگاه ساکنان و جنبه‌های اجتماعی ۴۱۸
محمد مهدی ناصریان، رسول خدابخشیان کارگر

مقالات مروری

چشم‌انداز مکانیزاسیون کشت مستقیم بذر برنج: مروری جامع ۴۳۴
اس. مانوج کومار، آر. کارتیکین، کا. تیروکوماران، ای. سنتیل، پی. دهانان‌چژیان

تدوین چارچوب روش‌شناختی برای مطالعات تعاونی‌های کشاورزی- مروری نظام‌مند توسط پریسما ۴۵۸
مهدی بامداد، مرتضی زنگنه، سیدحسین پیمان

مروری بر پتانسیل و مشکلات استفاده از فناوری هواپیماهای بدون سرنشین در کشاورزی پایدار ۴۹۰
اس. ریشیکساوان، پی. کنان، اس. پاژانیولان، آر. کومارپرومال، ان. شریثارن، دی. موهومانیکام، ام. محمد روشن ابو فرناس، بی. ونکاتش

نشریه ماشین های کشاورزی

با شماره پروانه ۸۹/۱۲۶۳۹ **و درجه علمی – پژوهشی شماره** ۳/۱۱/۳۷۸۱ **از وزارت علوم، تحقیقات و فناوری**

۸۹/۶/۱۳ **۸۹/۳/۱۷**

"بر اساس مصوبه وزارت عتف از سال ۱۳۹۸، کلیه نشریات دارای درجه "علمی-پژوهشی" به نشریه "علمی" تغییر نام یافتند."

جلد ۱۵ شماره ۳ پاییز ۱۴۰۴

صاحب امتیاز: دانشگاه فردوسی مشهد

مدیر مسئول: سید محمدرضا مدرس رضوی — استاد- گروه مکانیک دانشکده مهندسی (دانشگاه فردوسی مشهد)

سردبیر: محمدحسین عباسپور فرد — استاد- گروه مهندسی مکانیک بیوسیستم (دانشگاه فردوسی مشهد)

اعضای هیئت تحریریه:

آق خانی، محمدحسین	گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران
ابونجمی، محمد	گروه فنی کشاورزی، پردیس ابوریحان دانشگاه تهران، ایران
پوررضا، علیرضا	گروه مهندسی بیولوژیک و کشاورزی، دانشگاه کالیفرنیا، دیویس، آمریکا
خوش تقاضا، محمدهادی	گروه مهندسی مکانیک بیوسیستم، دانشگاه تربیت مدرس، تهران، ایران
راجی، عبدالغنی	گروه مهندسی کشاورزی و محیط زیست، دانشکده فنی، دانشگاه ایبادان، نیجریه
روحانی، عباس	گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران
سعیدی راد، محمدحسین	مرکز تحقیقات کشاورزی و منابع طبیعی خراسان رضوی، بخش تحقیقات فنی و منهدسی، مشهد، ایران
سوپاکیت، سایاسونترن	دانشکده کشاورزی، دانشگاه کاستسارت، تایلند
عباسپور فرد، محمدحسین	گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه فردوسی مشهد، مشهد، ایران
علیمردانی، رضا	گروه ماشین‌های کشاورزی، دانشگاه تهران، پردیس کرج، ایران
عمادی، باقر	گروه مهندسی شیمی و بیولوژیک، دانشگاه ساسکاچوان، ساسکاتون، کانادا
غضنفری مقدم، احمد	گروه مهندسی مکانیک بیوسیستم، دانشگاه شهید باهنر کرمان، کرمان، ایران
کدخدایان، مهران	گروه مهندسی مکانیک، دانشکده مهندسی، دانشگاه فردوسی مشهد، مشهد، ایران
لغوی، محمد	گروه مهندسی بیوسیستم، دانشگاه شیراز، ایران
محتسبی، سید سعید	گروه ماشین‌های کشاورزی، دانشگاه تهران، تهران، ایران
مدرس رضوی، محمدرضا	گروه مهندسی مکانیک، دانشکده مهندسی، دانشگاه فردوسی مشهد، مشهد، ایران
نصیراحمدی، ابوذر	گروه مهندسی کشاورزی، دانشگاه کاسل، آلمان

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جلد ۱۵ شماره ۳
سال ۱۴۰۴
(شماره پیاپی: ۳۷)

شاپا: ۶۸۲۹-۲۲۲۸

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