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Feasibility of Drone Imagery for Monitoring Performance of a Modified Drill in a Conservation Farming System

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Abstract

In this paper, performance of a no-till corn planter in a soil covered with previous wheat residue was evaluated. Three levels of crop residue cover (CRC): 30, 45 and 60%, two planting schemes; on-bed and in-furrow and two forward speed: (4 and 8 km h^{-1}) were considered as treatments. The field was evaluated by ground and air observations. The purpose of this study was to investigate the capability of aerial images captured by an unmanned aerial vehicle (UAV) in identifying the distances between corn seedlings and as a result, assessing the quality of planter performance. Collected data from ground and aerial imagery were used to calculate seed establishment indices including multiple index, miss index, quality of feed index, precision index and also emergence rate index (ERI), for each plot. Images captured from10 m altitude (4.5 mm $pixel^{-1}$) could give satisfactory results in relation to our objectives. Our results show that acceptable correlations existed between terrestrial and aerial seedlings spacing data sets ($0.94<R<0.98$) suggesting the aerial imagery is a good choice for evaluating the seed establishment and estimating ERI. Aerial imagery data source underestimated quality of feed and precision indices, overestimated miss index and could not provide processed data range needed for computing multiple index due to low image resolution, weeds presence within crop rows and overlapping of leaves.

Keywords: Aerial imagery, Crop residue cover (CRC), Seed establishment indices, Unmanned aerial vehicle (UAV)

Introduction

Farming practices have undergone huge changes to cope with increasing demands for more food and safeguarding environment (Zheng *et al.*, 2012). A considerable number of studies have been conducted to explore advantages and best management practices including soil preparation, previous residue management and planting into partially covered soils. Conservation farming techniques are often associated with previous surface crop residue management. Keeping certain amount of previous residue helps retaining some soil moisture and reducing soil erosion through increased water infiltration into soil, in addition this practice provides more carbon source needed for maintaining a proper C/N ratio (Naresh *et al.*, 2016). On the other hand farming practices such as conservation tillage helps to reduce energy needed for crop production thus cheaper farming can be realized. Some farmers avoid to adopt conservation farming due to possibility of poor stand establishment which might ultimately reduce crop yield. Available conventional planters fail to place seeds into soils which are less tilled. The adverse effects of planting into residue covered soils have been emphasized by Swan *et al.* (1994) and Fallahi and Raoufat (2008). Inadequate seeding depth, low uniformity in seed spacing, variation in seed placement depth and decrease in crop yield are a few adverse effects reported by above researchers.

Planter attachments such as coulters are valuable tools for cutting the residue and help achieving proper seeding depth, on the other hand, row-cleaners clear the seeding row from residue and clods helping a good drill and seed placement. These attachments are necessary tools for a successful planting into a partially residue covered soils where conventional planters fail to penetrate into the top soil.

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Raoufat and Matbooei (2007) concluded that using row cleaner in farms with 50% crop residue cover at a forward speed of 7 km h^{-1} resulted in the best plant establishment, uniformity in seed spacing and desirable values of emergence rate, miss, quality of feed and precision indices. Dadi and Raoufat (2012) found that using a winged chisel furrow opener preceded by a row cleaner equipped with treader wheels arrangement removes appreciable amounts of residue on the planting row in a conservation farming system. They observed better cleaning of crop residue at higher forward speeds, but this caused an increase in miss index that was not desirable.

As the conservation farming is extending throughout the world certain tillage and planting systems have been developed including no-till planters. These planters, place seeds into covered or partially covered residue soils. The performance of the planter shall be monitored by measuring seedling spacings. Currently, data acquisition from farms relies on manual field-data collection, survey responses, and agricultural censuses, but it is extremely difficult to acquire the data systematically and continuously over large areas using these methods. Alternatively, remote sensing techniques have the potential to survey different practices in farms inexpensively and efficiently in a systematic, timely and cost-effective manner (Zheng *et al.*, 2014; Rostami and Afzali Gorouh, 2017). Satellites and aircrafts have been widely employed to monitor crop growth, estimate crop yield and also for site specific management applications. In spite of few advantages, acquiring images from satellites and air crafts is expensive and not easy for farmers and researchers to access. Low quality of acquired images from satellite and air crafts, effect of weather conditions on imagery and adverse effects of satellite sensor characteristic is other limiting factors. As an alternative, unmanned aerial vehicles (UAVs) have been used for aerial imagery and has found applications in crop monitoring and management (Jannoura *et al.*, 2015; Xiang and Tain, 2011). The UAVs are able to fly at lower altitudes as compared to airplanes and satellites. They can capture ultrahigh resolution images and therefore have been recently used to capture images of objects such as small plants and patches (Xiang and Tian, 2011). The flight preparation time for UAVs is low and imagery can be scheduled even on cloudy days therefore the UAVs image acquisition system is more flexible. The costs of imagery and data acquisition for the UAVs are lower compared to satellites and other available aircrafts, commercial cameras having various degrees of image resolution and configuration have been marketed which can be mounted on UAVs as desired giving the operators and researchers more flexibility (Sankaran *et al.*, 2015). Many researchers have concluded that commercial cameras are powerful parts of data acquisition systems for UAVs especially when green vegetation is to be monitored both from air and land. In summary low cost and high resolution of the UAVs equipped with proper image capture and acquisition hardware makes this a good choice for assessing green vegetative cover such as broadly and wheat on farms (Torres-Sanchez *et al.*, 2014).

Precision agriculture is one of the areas which has adopted UAV for the last 12 years. For instance, biomass and nitrogen status of corn, alfalfa and soybean crops have been estimated by unmanned helicopters equipped with camera and image acquisition systems by Hunt, Cavigelli, Daughtry, McMurtrey, and Walthall in 2005. In similar studies unmanned radio controlled helicopters used to acquire thermal and narrow band multispectral images to estimate biophysical parameters correlated with leaf area index, water stress and chlorophyll content (Berni, Zarco-Tejada, Suarez, and Fereres, 2009). In another study remote sensing technology was used to estimate grain yield and total aerial biomass of a rice crop (Swain, Thomson, and Jayasuriya, 2010). Having aerial images, they established regression equation between measured parameters and normalized difference vegetation index (NDVI) given by images and obtained regression coefficients of 0.72 and

0.76 for grain yield and aerial biomass, respectively. In an investigation conducted by Aguera, Carvajal, and Saiz (2011) an acceptable correlation was established between applied nitrogen to sunflower and NDTI extracted from images captured by a quadcopter at a height of 70 m above the crop (Vega *et al.*, 2015).

In another research performed by Zhang *et al.*, 2018, the distances between corn seedlings (2-3 fully expanded leaves) were calculated by using the images captured by a Phantom 3 Professional flying at five altitudes: 1, 2, 3, 4 and 5m. They developed a method by training an algorithm in an indoor facility with plastic corn plants. Then, the method was scaled up and tested in a field with maize plant spacing that exhibiting natural variation. Their major problem was the presence of weeds specially weeds growing within crop rows. They could achieve reliable results at an altitude of 5m. In summary they concluded that it is possible to precisely quantify the distance between corn plants.

Varela *et al.* (2018) aimed to develop a reliable, timely, and unbiased method for counting corn plants based on ultra-high-resolution imagery acquired from unmanned aerial systems (UAS) to automatically scout fields and apply it to real field conditions. Their data processing included five steps: (1) images were converted into excess greenness (ExG)-vegetation index, (2) row detection and contours were delineated, (3) geometric descriptors were built from contours, (4) classifier training, and (5) classifier testing. Their results showed that for successful model implementation, plants should have between two to three leaves when images are collected (to avoid overlapping) and best workflow performance was reached at 2.4 mm resolution corresponding to 10 m of altitude.

Because planting space is still a critical parameter for crop growth models, it is critical to focus on how to measure plant to plant distances in a row. The UAV systems represent a powerful tool that can be used to collect high-resolution real-time images of cropping systems, and thereby support the calculation of plant interval distances. In this study, our objective was to investigate the ability of a low cost drone; DJI Phantom 3 Professional[1] equipped with a commercial RGB camera for monitoring performance of a corn planter in a conservation farming system. Two important issues in conservation farming are the specification of the tilling machine (if used) and of the planter. Adequate literature is available on specifications of the planters suitable for placing seeds in partially residue covered soils (Raoufat and Mahmoodie, 2005; Bahrani *et al.*, 2007; Dadi and Raoufat, 2012; Nejadi and Raoufat, 2013) considering recommendations by above researchers, it is decided to use a newly manufactured no-till planter made by Tarashkadeh Company[2].

Materials and Methods

I: Experimental site

Our research was conducted in one of the Experimental Stations of College of Agriculture, Shiraz University, Shiraz, Iran (29°44´2″N, 52°35´33″E upper left point and 29°43´59.6″N, 52°35´40″E lower right point). The selected farm was covered with fresh previous irrigated wheat residue averaging 8000 kg ha^{-1}.

II: Plots preparation

In subsequent operations, the previous crop residue was reduced and adjusted to the three desired levels considered for this study. First the loose straw discharged from combine was baled out from the field and only 3500 kg ha^{-1} was left (equivalent to 60% CRC) and considered as R1. The remaining fallen residues were removed out and residue was adjusted to 1700 kg ha^{-1} (equivalent to 45% CRC) forming the second level R2. For preparing the third level, (R3) the remaining crop residue was grazed and established at 620 kg ha^{-1} (equivalent to 30% CRC). This level corresponds to minimum residue level recommended for conservation farming (CTIC, 2010). To prepare a field having various scenery of seed placement, seeds were

1- Dà-Jiāng Innovations Science and Technology Co, Shenzhen, China
2- www.Tarashkadeh.com

planted at two forward speeds of 4 and 8 kmh^{-1} on plots having residue cover levels of 30, 45 and 60 %. The conventional local practice of planting on-bed and in-furrow was also considered. Therefore, a total of 12 treatments in 3 replications was considered for our study. The statistical design was split-split plot arranged as a complete block design, main plots were crop residue, sub plots were planting scheme and sub-sub plots were planter forward speed. Each plot was measured 4×30 m^2. The corn was a hybrid single cross 704 with emergence rate of 92% and purity of 98%. Corn was planted in plots by a no-till planter made by Tarashkade Company. Each unit of the four-row planter included a plain coulter and a wave coulter. The former assisted in placing fertilizer and the latter assisted in pulverizing a narrow band ready for falling seeds. The row spacing was adjusted to 60 cm and theoretical seed spacing of 15.5 cm. Sowing date was July, 31th 2016 and on the next day first irrigation was done. After irrigation, the plots were closely monitored for any seedling emergence.

III: Data collection

Measurements in each plot were the number of seeds emerged daily and the distance between consecutive seedlings. Newly emerged seedlings were counted every day in a 6 meters length in the middle of each row in each plot. Counting continues until no changes was seen in the number of newly emerged seedlings. The measurements were taken both on the ground and by the drone. For terrestrial measurements on the August 20th 2016, a measuring tape was placed on each row and distances between consecutive seedlings were measured and recorded. Drone images were captured from each plot at 14 different altitudes (4, 6, 8,…and 30m) on the 20th and the 27th August 2016. Pixel resolution of images captured at different altitudes and different time intervals after planting (20 and 27 days after planting), were examined to find the best altitude and timing for drone imagery. Only the images captured at 10 meter height (4.5 mm $pixel^{-1}$) could give satisfactory results in relation to our objectives. It should be noted that although resolution for imagery at lower altitudes was better but captured scenery was small. On the other hand, given the condition of the plot, imagery at altitudes more than 10 m height could not give satisfactory pixel information for detecting single corn seedlings. As images captured at earlier stages of corn growth had less leaves overlapping problem so the first drone imagery taken on the 20th August was selected for further analysis.

IV: Data processing

Due to presence of heavy residues, weeds, shadow and leaves overlapping it was impossible to analyze images using written code programs like Matlab[1], therefore the analysis was continued semi manually with the help of ImageJ[2] and Excel[3] programs. Fig.1 shows a part of aerial image of a plot with the least residue level (30% CRC), planted on-bed at 8 km h^{-1}, having the least problem of weed and leaves overlapping taken on the 20th August 2016.

For measuring distances between corn seedlings a rectangular marker of 1×0.22 m^2 in yellow color (for calibration purpose) was placed in each plot so that the hovering drone camera could capture images of each specific plot and the marker laid on it. For each plot, the captured image from a 10m height was retrieved in ImageJ program and as demonstrated in Fig.2 the marker length was calculated by using the tools “straight” and “measure” commands. Then the distance between adjacent seedlings was measured in the same way. Camera distortion was not a problem as measurements were performed for each plot separately and the equivalent seedling spacing was calculated by using the length of the yellow marker in the plot image. In the next step measured distances from ImageJ were moved to spreadsheet (Excel 2013) and converted to real distances in centimeters by equation (1).

1- Matrix Laboratory
2- National Institutes of Health, USA, http://imagej.nih.gov/ij
3- Microsoft Corporation

$$Seedling\ spacing\ (cm) = \frac{seedling\ spacing\ (pixel)}{length\ of\ marker\ (pixel)} * 100(cm) \quad (1)$$

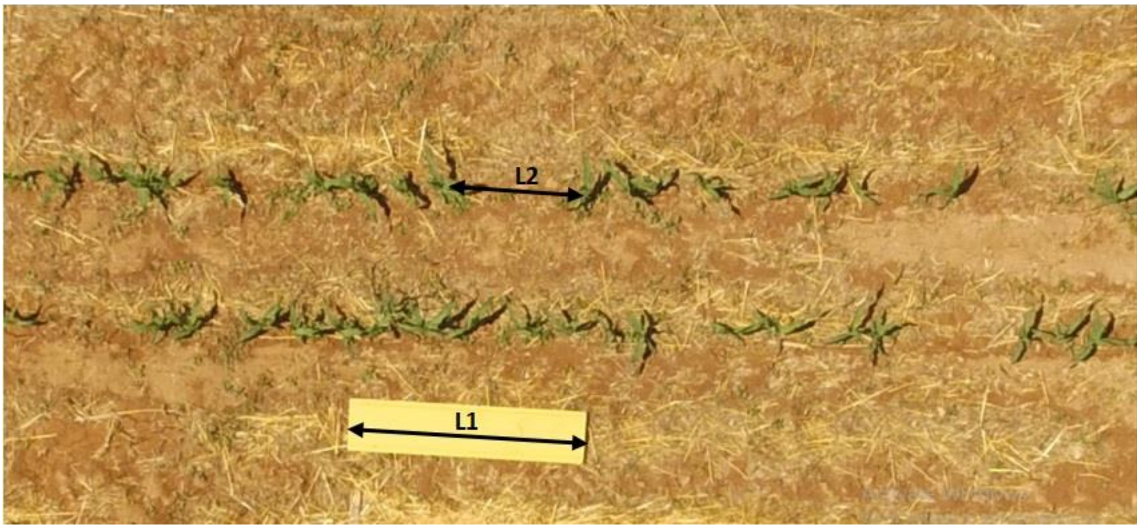

Fig.1. Image captured from 10m height by drone (L1: length of marker, L2: seedling spacing)

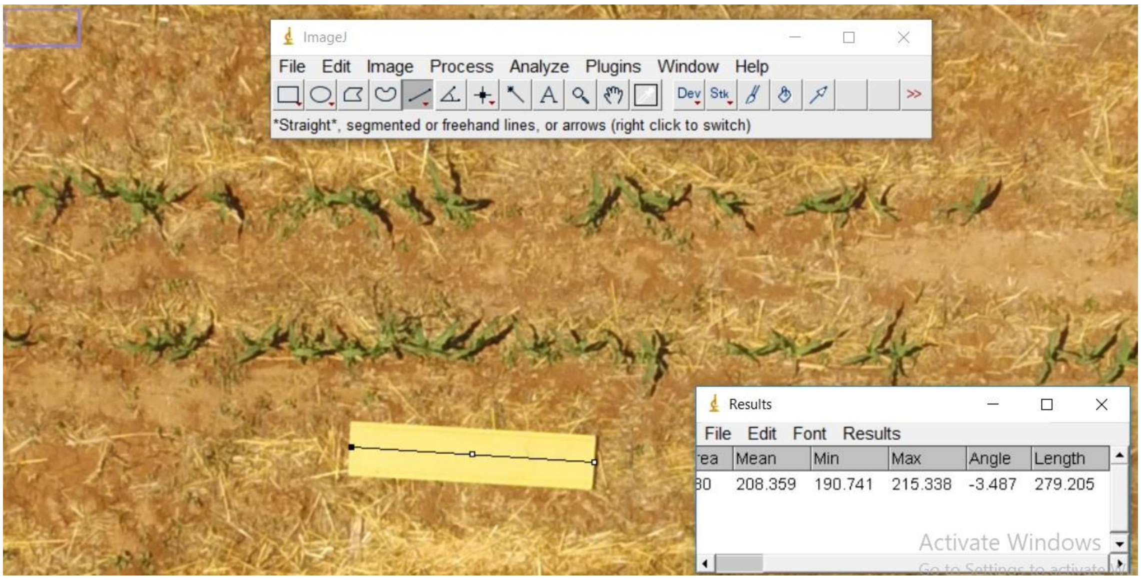

Fig.2. Measuring seedling spacing in ImageJ

For terrestrial measurements a measuring tape was placed in each row and consecutive distances between seedlings were measured and recorded. At this stage two sets of data were at hand, one gathered manually and one concluded from drone imagery. In the next step, the existence of a linear correlation between these two sets of data was investigated. In addition, multiple index, miss index, quality of feed index and precision index were calculated. In the following section these indices are briefly introduced.

Multiple index: The theoretical spacing is the distance between seedlings assuming that there were no skips, multiples, or variability and is based on the manufacturer's specifications. It will theoretically be equal to the mode of distribution of spacing. The multiple index D is the percentage of spacing that are less than or equal to half of the theoretical spacing. That is:

$D = \frac{n_1}{N} \times 100$

Where, n_1 is the number of spacing that are more than zero but no more than half times the theoretical spacing; and N is the total number of distances measured. Smaller values of D indicate better performance (Kachman and Smith, 1995).

Quality of feed index: The quality of feed index A is the percentage of spacing that are more than half but no more than 1.5 times the theoretical spacing. That is:

$A = \frac{n_2}{N} \times 100$

Where, n_2 is the number of spacing that are more than half but no more than 1.5 times the theoretical spacing; and N is the total number of distances measured. Larger values of A indicate better performance than smaller values. In other words, the quality of feed index is a measure of how often the spacing are close to the theoretical spacing (Kachman and Smith, 1995).

Miss index: The miss index M is the percentage of spacing greater than 1.5 times the theoretical spacing. That is:

$M = \frac{n_3}{N} \times 100$

Where, n_3 is the number of spacing that are more than 1.5 times the theoretical spacing; and N is the total number of distances measured. Smaller values of M indicate better performance than larger values (Kachman and Smith, 1995).

Precision: Precision, C is a measure of the variability in spacing between plants after accounting for variability due to both multiples and skips. A practical upper limit is 29%. Smaller values of C indicate better performance than larger values. The precision is the coefficient of variation of spacing that are classified as singles. That is:

$C = \frac{S_2}{X_{ref}} \times 100$

Where, S_2 is the sample standard deviation of spacing that are more than half but no more than 1.5 times the theoretical spacing. And x_{ref} is the theoretical spacing of plants (Kachman and Smith, 1995).

Emergence Rate Index (ERI): For each treatment an ERI was determined by counting the number of plants emerged from a mid-6 m length of rows for several days after planting (DAP) using the following equation introduced by Erbach (1982):

$ERI = \sum_{n=1}^{x} \frac{EMG_n - EMG_{n-1}}{DAP_n}$

Where, n is the nth emergence observation, EMG_n is the percentage of seeds planted emerged on the day of the nth emergence observation, EMG_{n-1} is the percentage of seeds planted emerged on the day of the (n-1)th emergence observation equal to 0 when n=1 and DAP_n is the number of days after planting when the nth emergence observation was taken. In this study counts were made on 7, 10, 12, 14 days after planting and stopped when no further increase in emerged counts was observed.

Results and Discussion

I. General relationship between two sets of data

Data on seedlings spacing after emergence gathered manually and corresponding data on seedlings spacing is obtained from drone imagery were retrieved in Excel program, the relationship between these two sets of data was examined and their correlation coefficient: R related to their linear relationships was calculated (Table 1). This table shows that there is a good relationship between ground data and aerial ones and therefore, it is possible to use drones to evaluate the seedling emergence and indices of seed stand establishment.

As mentioned in the previous paragraph the first drone imagery was accomplished on the same day when ground measurements were taken. Seven days later aerial imagery was repeated to look for the existence of any change in imagery results. Correlation coefficients between the ground and aerial data for the two sets are reported in Table 1. It shows that ground and aerial observations are well correlated and therefore aerial imagery has the potential to replace the tedious ground measurements. Furthermore this table shows that there is no significant difference between the two data sets and therefore we can conclude that do not need to rush for aerial imagery. However it should be pointed out that the timing interval between planting date and aerial data collection should not be so long as weeds and accelerated leaf growth hinder aerial imagery and reduce the accuracy of results.

Table 1- Correlation coefficient R between terrestrial and aerial seedling spacing data

Plot	R (Terrestrial 20-8-2016 vs. Drone 20-8-2016)	R (Terrestrial 20-8-2016 vs. Drone 27-8-2016)
R1P1V1	0.97	0.97
R1P1V2	0.97	0.96
R1P2V1	0.95	0.95
R1P2V2	0.96	0.98
R2P1V1	0.96	0.95
R2P1V2	0.96	0.94
R2P2V1	0.95	0.95
R2P2V2	0.97	0.95
R3P1V1	0.98	0.95
R3P1V2	0.96	0.97
R3P2V1	0.94	0.94
R3P2V2	0.97	0.95

R1= 60% CRC; R2=45% CRC; R3=30% CRC; P1= on-bed; P2= in-furrow; V1=4km h^{-1}; V2=8km h^{-1}

It should be noted that the present study was aimed to the asses capability of aerial imagery on a local farm covered with high residue and considerable weeds. The full automatic analysis of images is not possible for such farm. Other researchers, including Zhang *et al.*, 2018 and Varela *et al.*, 2018 have worked in fields having considerably less residue and weeds, hence they have been able to proceed in a more automatic approach.

The statistical analysis of data gathered manually and from aerial imagery, for these indices related to seed placement showed that the amount of CRC, planting scheme and forward speed of planter had no significant effect on indices related to seed placement, therefore it can be concluded that the no-till planter used, performed satisfactorily.

Table 2 shows that none of the indices have been significantly affected by the sources of variation for both terrestrial and aerial data sources. In other words stand establishment indices can be estimated using aerial imagery data sources with no significant loss of accuracy.

II. Planter performance indices

In the next step means of four indices of multiple index, quality of feed index, miss index and precision index from terrestrial and aerial sources have been compared. The deviation between the indices calculated by drone data and the ones calculated by terrestrial data is shown in Table 3.

Table 2- Analysis of variance of seed establishment indices for ground and aerial data

Source of variation	df	Multiple index		Quality of feed index		Miss index		Precision index	
		Terrestrial	drone	Terrestrial	drone	Terrestrial	drone	Terrestrial	drone
		F	F	F	F	F	F	F	F
Replication	2	0.30^{ns}	0.25^{ns}	2.02^{ns}	0.08^{ns}	3.40^{ns}	0.08^{ns}	0.19^{ns}	1.89^{ns}
Residue (R)	2	1.16^{ns}	1.35^{ns}	0.85^{ns}	0.22^{ns}	0.80^{ns}	0.16^{ns}	0.16^{ns}	0.44^{ns}
Position (P)	1	2.05^{ns}	1.38^{ns}	4.43^{ns}	0.07^{ns}	3.78^{ns}	0.20^{ns}	0.71^{ns}	0^{ns}
Velocity (V)	1	3.94^{ns}	5.38^{ns}	5.61^{ns}	1.23^{ns}	3.35^{ns}	0.53^{ns}	0.68^{ns}	0.15^{ns}
RP	2	0.18^{ns}	1.43^{ns}	0.30^{ns}	0.66^{ns}	0.38^{ns}	0.40^{ns}	1.01^{ns}	1.03^{ns}
RV	2	0.57^{ns}	1.35^{ns}	1.70^{ns}	1.32^{ns}	1.76^{ns}	0.91^{ns}	0.02^{ns}	2.06^{ns}
PV	1	0.71^{ns}	1.38^{ns}	0.01^{ns}	2.26^{ns}	0.91^{ns}	1.69^{ns}	1.44^{ns}	1.22^{ns}
RPV	2	1.09^{ns}	1.43^{ns}	0.04^{ns}	2.67^{ns}	1.48^{ns}	2.07^{ns}	0.14^{ns}	0.08^{ns}
Error	12								

^{ns} means no significant difference at $P \leq 0.01$

Table 3- Comparison of means of seed establishment indices for ground and aerial data

Plot	Index, %	Terrestrial 20-8-2016	Drone 20-8-2016	Deviation I	Drone 27-8-2016	Deviation II
R1P1V1	Multiple index	6.68	0.00*	+6.68	0.00*	+6.68
	Quality of feed index	79.74	74.56	+5.18	60.48	+19.26
	Miss index	13.57	25.43	-11.86	39.52	-25.95
	Precision index	25.89	22.42	+3.47	18.03	+7.86
R1P1V2	Multiple index	9.51	3.84	+5.67	0.00*	+9.51
	Quality of feed index	68.15	52	+16.15	49.05	+19.1
	Miss index	22.34	44.16	-21.82	50.95	-28.61
	Precision index	26.52	24.96	+1.56	19.31	+7.21
R1P2V1	Multiple index	7.67	0.00*	+7.67	0.00*	+7.67
	Quality of feed index	74.95	63.22	+11.73	53.19	+21.76
	Miss index	17.37	36.78	-19.41	46.81	-29.44
	Precision index	24.39	21.69	+2.7	15.50	+8.89
R1P2V2	Multiple index	12.88	0.00*	+12.88	0.00*	+12.88
	Quality of feed index	65.94	72.98	-7.04	58.25	+7.69
	Miss index	21.36	28.14	-6.78	40.65	-19.29
	Precision index	26.38	19.93	+6.45	20.05	+6.33
R2P1V1	Multiple index	7.57	0.00*	+7.57	0.00*	+7.57
	Quality of feed index	76.71	66.97	+9.74	48.98	+27.73
	Miss index	15.71	33.03	-17.32	51.01	-35.3
	Precision index	23.67	21.25	+2.42	14.10	+9.57
R2P1V2	Multiple index	9.95	0.00*	+9.95	0.00*	+9.95
	Quality of feed index	78.01	73.61	+4.4	47.86	+30.15
	Miss index	12.04	26.39	-14.35	52.14	-40.1
	Precision index	23.15	18.99	+4.16	21.54	+1.61
R2P2V1	Multiple index	12.82	0.00*	+12.82	0.00*	+12.82
	Quality of feed index	68.67	64.64	+4.03	52.42	+16.25
	Miss index	18.51	35.36	-16.85	47.58	-29.07
	Precision index	25.53	22.96	+2.57	17.44	+8.09
R2P2V2	Multiple index	12.18	0.00*	+12.18	0.00*	+12.18
	Quality of feed index	68.65	65.89	+2.76	59.60	+9.05
	Miss index	19.51	34.11	-14.6	37.06	-17.55
	Precision index	27.64	19.01	+8.63	19.16	+8.48
R3P1V1	Multiple index	6.60	0.00*	6.60	0.00*	+6.60
	Quality of feed index	83.89	73.83	10.06	56.94	+26.95
	miss index	9.49	26.17	-16.68	43.06	-33.57
	precision index	25.69	17.32	+8.37	17.74	+7.95
R3P1V2	multiple index	7.15	1.80	+5.35	0.00*	+7.15
	quality of feed index	73.73	63.54	+10.19	50.39	+23.34
	Miss index	19.12	34.65	-15.53	49.61	-30.49
	Precision index	24.27	23.86	+0.41	16.43	+7.84
R3P2V1	Multiple index	3.33	0.00*	+3.33	0.00*	+3.33
	Quality of feed index	78.44	71.39	+7.05	54.52	+23.92
	Miss index	18.22	30.16	-11.94	45.48	-27.26
	Precision index	24.08	21.71	+2.37	16.32	+7.76
R3P2V2	Multiple index	12.97	1.85	+11.12	0.00*	+12.97
	Quality of feed index	69.14	63.89	+5.25	61.18	+7.96
	Miss index	17.89	34.26	-16.37	38.81	-20.92
	Precision index	27.05	24.13	+2.92	16.09	+10.96

*: Aerial imagery partially failed to provide data needed for computing this index

R1= 60% CRC; R2=45% CRC; R3=30% CRC; P1= on-bed; P2= in-furrow; V1=4km h^{-1}; V2=8km h^{-1}

Examination of Table 3 shows that aerial imagery partially failed to provide data needed for computing multiple index. As can be seen from this table for most of the indices studied (except multiple index) data collected from drone imagery could give values more or less equal to those from ground data, however these values are either underestimated or overestimated as compared to the control (indices computed from ground data). To examine the extent of difference between each index as computed by ground or aerial data sources, drone index data were deducted from its corresponding values (columns 5 and 7 Table 3). Careful inspection of data reported in columns 5 and 7 indicates that for miss index drone imagery gives higher values and for other two indices (quality of feed index and precision) the drone imagery gives lower values. Fortunately for all treatments similar conclusions could be drawn.

III. Emergence Rate Index

Analysis of variance of data on ERI indicates that only residue levels and planting position affect this index (Table 4). Further analysis was performed (Table 5) to seek for any difference between treatments and their interactions. The comparison showed that amounts of CRC and two planting schemes; on-bed and in-furrow had significant effect on rate of corn emergence and this maybe be due to the ability of CRC in maintaining soil moisture and also presence of more water in furrows. Speed had no significant effect on this index confirming the ability of the modified corn planter to perform well at various forward speeds.

Table 4- Analysis of Variance of ERI

Source of variation	df	Sum of Squares (SS)	Mean Square (MS)	F
Replication	2	45.78	22.89	1.12^{ns}
Residue	2	336	168	8.24^{**}
Position	1	297.9	297.9	14.61^{**}
Velocity	1	46.04	46.04	2.26^{ns}
RP	2	7.34	3.67	0.18^{ns}
RV	2	1.99	0.99	0.05^{ns}
PV	1	6.25	6.25	0.31^{ns}
RPV	2	0.97	0.48	0.02^{ns}
Error	12	244.70	20.39	
Total	35	1278.36		

** Significant difference at P≤0.01

Table 5- Duncan's multiple range test for ERI%

Plot	ERI% mean	Overall effect of residue × planting position	Overall effect of residue level
R1P1V1	19.37^{abc}	19.84^{ab}	22.34^{a}
R1P1V2	20.32^{abc}		
R1P2V1	23.10^{ab}	24.84^{a}	
R1P2V2	26.59^{a}		
R2P1V1	14.60^{bc}	15.79^{bc}	18.41^{a}
R2P1V2	16.98^{abc}		
R2P2V1	19.37^{abc}	21.03^{ab}	
R2P2V2	22.70^{ab}		
R3P1V1	10.87^{c}	11.35^{c}	14.86^{a}
R3P1V2	11.83^{c}		
R3P2V1	17.14^{abc}	18.37^{abc}	
R3P2V2	19.60^{abc}		

a b c: Means with the same letter are not significantly different at P≤0.01

R1=untouched; R2= raked and baled out; R3= well grazed; P1= on-bed; P2= in-furrow; V1= 4 km h^{-1}; V2= 8 kmh^{-1}

Means of ERI% have been statistically compared in Table 5. This table shows that treatment R1P2V2 corresponds to the maximum ERI% in our study. While the minimum ERI was noticed for treatment R3P1V1. Table 5 shows that as speed is changed from V1 to V2 there is a considerable increase in percent ERI throughout all processed data. Although significant difference exists between all six data points in this table it can be seen that as we move our planting position from on-bed scheme to in-furrow scheme increasing change occurs in our ERI values. Although not necessarily in a significant manner. Overall effects of residue levels on ERI in our study has also been dealt with in Table 5. Although not significant, a decreasing effect was noticed for decreasing the residue level. As speed increases from V1 to V2 there is a considerable increase in ERI throughout all 12 plots (Fallahi and Raoufat, 2008; Dadi and Raoufat, 2012; Nejadi and Raoufat, 2013).

Conclusions

An acceptable linear correlation with $0.94<R<0.98$ existed between seedling spacing, obtained from terrestrial and aerial measurements. Therefore it can be concluded that drone imagery can be used as a reliable tool for monitoring planter performance in the residue covered fields. This study results are in line with those of Zhang *et al.* (2018) and Varela *et al.* (2018). We obtained satisfactory results from experimental sites covered with considerable previous residues. It should be mentioned that the experimental site of Zhang *et al.* (2018) and Varela *et al.* (2018) was clear of ample residue experienced in this study. The study showed that none of the establishment indices have been significantly affected by the sources of variation for both terrestrial and aerial data sources, therefore stand establishment indices can be estimated using aerial imagery data sources with no significant loss of accuracy. It could be seen that for most of the indices (except multiple index), data collected from drone imagery gives values which slightly underestimated or overestimated indices as compared to the control (indices computed from ground data); for miss index drone imagery gives higher values and for other two indices (quality of feed index and precision) the drone imagery gives lower values. Fortunately for all treatments similar conclusions could be drawn. The CRC and planting scheme had significant effects on ERI, which is logical because seed emergence needs optimum temperature and humidity and presence of crop residue retains soil water and keeps soil temperature suitable for seed emergence. In-furrow planting and planting on higher levels of residue resulted in conditions which were more favorable for higher ERI. The maximum and minimum ERI were noticed for treatment having residue level of 60% planted in-furrow at forward speed of 8 kmh^{-1}(R1P2V2) and treatment having residue level of 30% planted on-bed at 4 kmh^{-1}(R3P1V1), respectively. It is recommended that for better results aerial imagery be confined to days seedlings have 2-3 fully expanded leaves and the field sprayed for eradicating weeds. However employing state-of-the-art cameras and existence of less residue are a plus.

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امکان‌سنجی پایش عملکرد یک کارنده‌ی اصلاح شده در سیستم کشاورزی حفاظتی با استفاده از تصاویر هواپیماهای بدون سرنشین

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چکیده

در این مقاله، عملکرد یک کارنده کشت مستقیم ذرت در زمین پوشیده از بقایای گندم (سه سطح پوشش بقایای ۳۰، ۴۵ و۶۰ درصد، دو طرح کاشت روی پشته و داخل جوی، سرعت کاشت ۴ و ۸ کیلومتر بر ساعت) از طریق مشاهدات زمینی و هوایی ارزیابی شد. هدف از این مطالعه بررسی توانایی تصاویر گرفته شده توسط پرنده‌ی بدون سرنشین برای تشخیص فواصل بین بوته‌های ذرت و در نتیجه ارزیابی کیفیت عملکرد کارنده بود. داده‌های جمع‌آوری شده از زمین و تصاویر هوایی برای محاسبه شاخص‌های استقرار بذر شامل شاخص‌های چندتایی، نکاشت، کیفیت تغذیه، دقت و همچنین شاخص سرعت جوانه‌زنی برای هر پلات، استفاده شد. تصاویر اخذ شده از ارتفاع ۱۰ متری (۴/۵ میلی‌متر بر پیکسل) نتایج خوبی با توجه به اهداف ما داشت. نتایج نشان داد که همبستگی قابل قبولی (ضریب همبستگی بین ۰/۹۴ تا ۰/۹۸) میان داده‌های زمینی و هوایی فاصله بین بوته‌های ذرت وجود دارد و می‌توان نتیجه گرفت که تصویربرداری هوایی انتخاب مناسبی برای ارزیابی استقرار بذر و تخمین سرعت جوانه‌زنی می‌باشد. داده‌های تصاویر هوایی مقادیر شاخص های کیفیت تغذیه و دقت را کمتر و مقادیر شاخص نکاشت را بیشتر از نتایج داده‌های زمینی تخمین زد و نتوانست داده‌های لازم برای محاسبه شاخص چندتایی را به‌دلیل دقت پایین تصاویر، حضور علف‌های هرز مابین ردیف محصول و هم‌پوشانی برگ‌ها فراهم کند.

واژه‌های کلیدی: پرنده بدون سرنشین، پوشش سطحی بقایا، تصویربرداری هوایی، شاخص‌های استقرار بذر

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