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USING UAV IMAGERY TO MEASURE PLANT AND WATER STRESS IN WINTER WHEAT FIELDS OF DRYLANDS, SOUTH PUNJAB, PAKISTAN

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Unmanned Aerial Vehicles (UAVs) can help farmers to monitor their crops and provide irrigation and inputs as and when the crops need, reducing risks to yields. This study uses UAV imagery to measure water and plant stress in the winter wheat fields, lying in high, medium and low Desertification Vulnerability Indexed (DVI) zones of South Punjab, a region that has an agrarian economy subject to severe desertification. UAV flights were conducted in nine wheat fields in three districts of Bahawalpur, Rahim Yar Khan and Rajanpur. Flights were operated at 15 m altitude above ground level at midday, February 2019, presenting good resolution images of 30.48ppi, in RGB, with a pixel depth of 16 Bit, from a DJI Phantom 3 Standard quadcopter. *Dronedeploy* was used for image pre-processing and generating orthomosaics of the nine fields. Orthomosaics were uploaded on the Agremo app, where water stress and plant stress analysis of the sampled fields was performed. Agremo generated maps were reclassified in Arc Map 10.5. Fatehpur Union Council, lying in the High DVI zone, was found to suffer most severe plant stress, potential plant stress, and water stress with 34.83%, 51.16% and 42.35% of the crop affected respectively. The sample fields in high DVI zones in two of the three study districts suffered the highest amounts of plant stress and water stress. The conclusions offer guidance to policy makers on where water redistribution may need to be considered so that exacerbating desertification risk can be avoided, particularly in the most vulnerable zones.
Keywords: Unmanned aerial vehicle, crop water stress index, plant stress, desertification vulnerability index.

INTRODUCTION

The United Nations Convention to Combat Desertification (1994) refers to desertification as an extreme form of land degradation, affecting the arid, semi-arid and dry sub-humid regions, or drylands, of the world. About 41% of the world's total land area is covered by drylands, which are home to more than two billion people (Reed and Stringer, 2016). These areas have some of the highest poverty rates (Anjum *et al.*, 2010). Desertification processes in drylands can reduce crop productivity, with significant economic consequences.

Around 90% of the land in Pakistan is either currently desertified or susceptible to desertification in the future (Anjum *et al.*, 2010; Khan and Ali, 2015). Agriculture forms the second most significant sector of Pakistan's economy (Raza *et al.*, 2012) contributing 19.8% of GDP and employing 42.3% of the country's total labour force (Iftikhar and Mahmood, 2017). The country suffered a significant decline in its agriculture sector's growth rate, from 2.9% in 2013 to 2.1% in 2014, owing to the extreme weather conditions (GoP, 2014). With a population of nearly 208 million (GoP, 2017), of which almost 63% reside in rural areas, millions of people are either directly or indirectly associated with agriculture (Raza *et al.*, 2012). The country's drylands provide a source of livelihood to two-thirds of its population (Playán and Mateos, 2006). For agrarian economies like Pakistan, an increase in spatial coverage and intensity of aridity is emerging as a major environmental problem (IUCN, 2017). The research presented in this paper seeks to advance knowledge to help manage the aridity challenge.

It is common for plants, not only in dryland regions, to suffer from deficits of both soil and atmospheric water during their life cycle. This water deficit has severe impacts on the plant's primary productivity (Wilson *et al.*, 2001). Plants respond differently to water stress, depending on their genotypes, and while plants have built-in capabilities of stress avoidance, and tolerance, these attributes vary among species. Responses may vary from adaptive changes to damaging impacts on the plants (Chaves *et al.*, 2002). Plant stress among the winter wheat farms of the study area is measured in this paper and linked to the desertification vulnerability of different parts of the region.

Photosynthetic performance, physiology and many other plant characteristics are influenced by water stress (Osakabe *et al.*, 2014; Gonulal, 2020). One of the most widely used indexes for detecting fluctuations in water deficit of plants, calculated using canopy temperatures, is the crop water stress index (CWSI). The CWSI has been used to assess the crop water deficit of various crops like grapes, wheat, rice, and cotton etc., as it is directly related to a reduction in yield

(Ganji and Kaviani, 2013; Möller *et al.*, 2006, p. 99; Park *et al.*, 2017; Zhang and Kovacs, 2012). The CWSI is also used for managing irrigation practices (Wanjura *et al*., Reginato and Garrett as cited in Irmak *et al.*, 2000). For Crop Water Productivity (CWP) to be enhanced, proper irrigation management is necessary (Yihun *et al.*, 2013) and by being able to identify the specific areas in fields under water stress, time and resources can be optimally used. Determining the crop water availability in drought vulnerable areas such as drylands has become a necessity (Dalezios *et al.*, 2019).

While satellite imagery has long been used to calculate CWSI at a large scale, there has been a recent shift towards the use of UAV imagery to monitor shifts in CWSI at a smaller scale, with a higher spatial resolution (Berni *et al.*, 2009; Zarco-Tejada *et al.*, 2012), giving more precise information about when and where crops require water. This paper picks up on this new technology and tests it in the context of wheat cultivation in Pakistan, focusing on study fields in areas with different vulnerabilities to desertification.

The values of CWSI calculated for a selected crop in different soils and climates can prove instrumental in deciding the irrigation timing and shaping the yield per hectare. This technique is in turn helpful in estimating the plant stress (Irmak *et al.*, 2000). Air and soil water content, transpiration along with crop water stress, have a great impact on the canopy temperature (Jackson *et al.*, 1981). Water deficiency leads to stomata closure, which becomes a direct cause of higher canopy temperatures in that particular area (Guilioni *et al.*, 2008). A strong positive relationship exists between canopy temperature and crop water stress, while a negative relationship exists between the former with transpiration and soil moisture (Chaves *et al.*, 2002). Thus, farmers are able to assess the irrigation requirements of the field, by measuring the crop water stress (Chaves *et al.*, 2002; Hoffmann *et al.*, 2016; Irmak *et al*., 2000). Studies show that the temperature of the leaves increases due to stomatal closure, followed by a reduction in evaporative cooling and transpiration, which might result from short-term water deficit. This kind of temperature increase has a strong correlation with crop water stress level (Gago *et al.*, 2013), and has been studied through thermal infrared thermometers (Alchanatis *et al.*, 2010; Santesteban *et al.*, 2017). The UAV platform can be used with various sensors (RGB, multispectral, infrared, thermal, etc.) (Matese *et al.*, 2015; Nebiker *et al.*, 2016), each of which offer strengths for different purposes. RGB images captured through UAV in the present study are also used for water and plant stress analysis for the fields under study

UAV images have been used in recent studies to predict grain yield according to the entire growth cycle of wheat, to quantify impacts of different elements like nitrogen (N), phosphorus, zinc etc., on wheat crops, and explore relationships between Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI), and between nitrogen uptake and Green Normalized Difference Vegetation Index (GNDVI) in wheat fields (Hassan *et al.*, 2019; Latif *et al.*, 2018; Schirrmann *et al.* 2016; Lelong *et al.*, 2008).

UAV have been used around the world to investigate plant stress (Su *et al.*, 2018), develop water stress maps (Hoffmann *et al.*, 2016), assess water status within a vineyard (Santesteban *et al.*, 2017), and measure water stress in nectarine and peach orchards (Park *et al.*, 2017). Schirrmann *et al.* (2016) mention that use of UAV in precision agriculture can only become more practically applicable in fields across the globe, if image processing and analysis is made as convenient for the farmer as possible. For such purposes, various online applications are available. Agremo is one such app, available on the *Dronedeploy* UAV and mapping platform. The same app and mapping platform were used in this study for easy image processing. The ideal time to perform plant stress analysis is in the mid-season (Agremo). Agremo uses advanced Artificial Intelligence, machine learning and computer vision to go beyond NDVI, so that commercial drones and RGB sensors can be sufficient for remote sensing.

The Plant Health tool in *Dronedeploy* permits analysis of plant health variability within a field, and can quantify damage and even predict the yield within a field. Relative vegetation health is demonstrated by comparing the value captured of each band, RGB, in the current study. Constant monitoring can help to identify plant health trajectories over time, and can help farmers to better understand the onset of drought conditions (Gopinath, 2015).

Wheat crops continue to provide essential daily nutrition for 35% of the world's population. However, there remains a dearth of improved means to enhance wheat yields (Holman *et al.*, 2016). By quantifying the amount of plant and water stress that the wheat plants in the study area were witnessing at the time of survey (Feb, 2019), this study paves the path for future research to focus on understanding the reasons behind plant and water stresses, while also demonstrating novelty by linking the findings to DVI zones. Building on and extending the growing body of existing work, the current study therefore aims to investigate whether UAV imagery can prove helpful in analysing the plant and water stress level in the comparative wheat fields, in different desertification vulnerability zones of South Punjab. Desertification intensity varies in the study region, and thus the stresses that the crops endure were also anticipated to differ.

MATERIALS AND METHODS

The study area comprised three districts in South Punjab, Pakistan, namely Bahawalpur, Rahim Yar Khan and Rajanpur, all lying in the dryland region of south Punjab, with a highly agrarian economy (Fig. 1). The Global Aridity Index values for these districts, for the year 2016 are 0.04, 0.04 and 0.07 respectively, while the Erinc Aridity Index values for the study area districts were 3.3, 3.28 and 6.15 respectively

(Javid, 2017). A recent study on the climatic classification of Pakistan, placed the three districts under study in the current research, in the category of Arid and Drought stricken regions, concluding that the arid area in Pakistan has increased from 20.9% to 22.7% over the period 2000 to 2018 (Javid *et al.*, 2019).

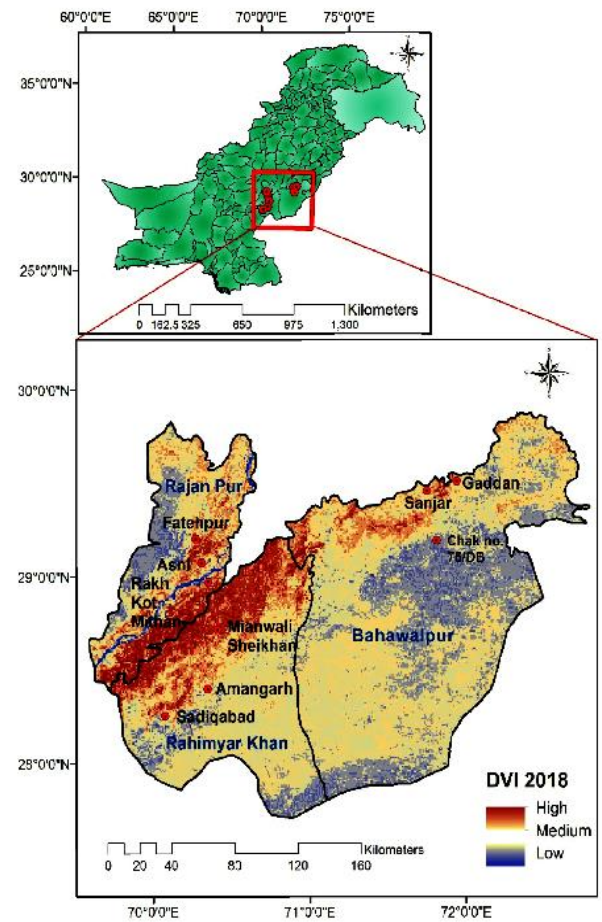

Figure 1. Study area

This region was focused on because it is emblematic of the challenges faced across Pakistan's drylands. The meteorological characteristics of the study area have been presented in Table 1.

Wheat (*Triticum aestivum*) is the staple food crop and most widely grown food grain in the region, with 841,000 ha under wheat cultivation in 2014-15 (GoP, 2017). Three wheat fields in three different union councils were surveyed in each district (Table 2), based on desertification vulnerability mapping performed for the region, which divided each district into High, Medium and Low desertification vulnerability zones (Mazhar *et al.*, 2018). The three union councils of each district were chosen on the basis of ease of accessibility given the difficult terrain. Due to limitation of time and funds, only one wheat field from each category of DVI zones, in each district, was surveyed, thus the findings of these nine fields are not fully representative of the entire study area. Many aspects can be improved in future studies. For example, lack of resources caused the present study not to take into account the variations in the plant stress and water stress for the entire growth season of the wheat crop under study, since the sample fields were at a great distance from one another, situated in different desertification vulnerability zones of three districts, covering a total area of 49, 029km^2 (GoP, 1999a; GoP, 1999b; GoP, 2000). Therefore, in future studies it is recommended that three flights in different stages of crop development must be conducted in each sample field and an average of their NDVI values could be used to prepare efficient crop health maps.

In all the sample fields, the wheat was at the booting stage of growth, and a uniform area of 1 acre (0.404 ha) was chosen for the survey. The survey was performed during the period 25-27 Feb 2019. In the month of February, wheat in Pakistan ideally has entered the heading or flowering stage, where water requirements increase and water deficiency may have severe impacts on the yield (Naheed and Mahmood, 2009). Despite the intention, during the study, the wheat crop was found to be at the late booting stage, owing to late sowing and water availability issues. However, another research explores impacts of irrigation water on wheat plants, concluding that booting is the most sensitive stage to salinity caused due to mismanaged irrigation practices (Mojid *et al.*, 2013). This suggests the timing of our study, therefore, still has relevance.

UAV flights consisted of a single flight at 15 m altitude, per field, above ground level at midday, presenting good resolution images of 30.48ppi, in RGB, with a pixel depth of 16 Bit. RGB areal images were captured from the DJI Phantom 3 Standard quadcopter, which has a built in 2.7K camera and a 3-Axis Gimbal, capable of capturing 12MP still photos, and which uses GPS for positioning outdoors. Throughout the fieldwork, images were captured with the gimbal facing vertically downwards, to enhance the aerial

Table 1. Meteorological characteristics of the study area.

District	Rainfall	Mean Maximum Annual Temperature	Mean Minimum Annual Temperature	Potential Evapotranspiration
Bahawalpur	112.20 mm	33.58°C	19.56°C	235.85 mm
Rahim Yar Khan	119.13 mm	35.42°C	19.62°C	252.54 mm
D. G. Khan	205.73 mm	32.94°C	18.76°C	226.46 mm
	Data source: PMD			Data source: (Javid, 2017)

Table 2. Location of nine sample winter wheat fields.

District	Union Council	Basti/village	Latitude	Longitude	Survey date	DVI Zone
Bahawalpur	Sanjar	Hafiz Abad	29.435	71.805	25-2-2019	High
	Gaddan	Gaddan	29.4821	72.0028	25-2-2019	Medium
	Chak no. 75/DB	Chak 75/DB	29.1680	71.8610	25-2-2019	Low
Rahim Yar Khan	Mianwali Sheikhan	Basti Gamo Khan Jatoi	28.7106	70.4280	27-2-2019	High
	Amangarh	Moza Sar Bhori	28.3953	70.3599	27-2-2019	Medium
	Sadiqabad	Chak 173/P	28.2532	70.0843	27-2-2019	Low
Rajanpur	Fatehpur	Basti Talok	29.1990	70.2937	26-2-2019	High
	Asni	Basti Cheema	29.0691	70.3290	26-2-2019	Medium
	Rakh Kot Mithan	Basti Kalar	28.9677	70.3721	26-2-2019	Low

quality of the images, as mentioned by Su *et al.* (2018). In the *djigo* app, the waypoint route for all the nine wheat fields were generated to obtain more than 60% overlap of frontal and lateral photos. The survey was performed at nadir view angle in clear sky conditions.

***Dronedeploy for image Pre-Processing*:** The obtained multispectral images were uploaded on *Dronedeploy*, a drone surveying and 3D mapping application which generated the orthomosaic photos of the sample fields after performing orthorectification in the geometric correction phase during image pre-processing.

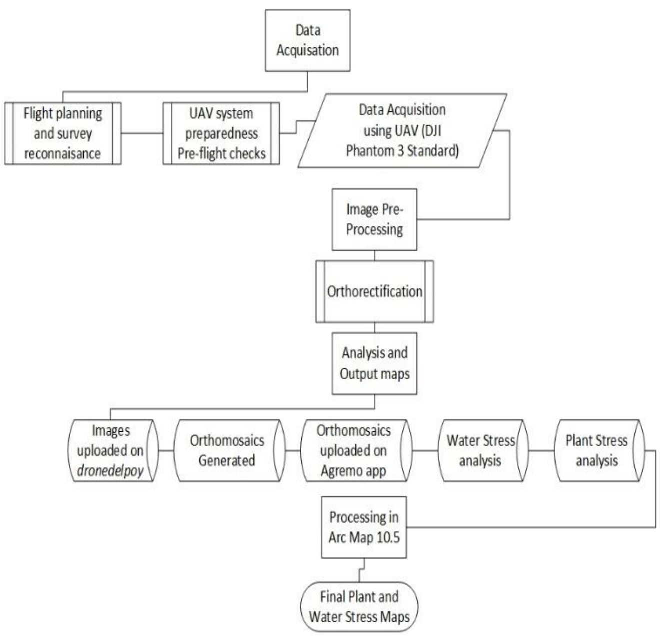

Figure 2. Methodological Framework

Similar software is used for pre-processing of images in other studies as well, for example, Su et al. (2018). The Agremo app of *Drondeploy* was used to perform the water stress and plant stress analysis of the nine sample fields. The Agremo generated maps were finalized in Arc Map 10.5 and reclassified to segregate the area of the classes of the different plant health analysis performed in this study. The detailed methodological process is presented in figure 2. The definitions used in the study are set out below regarding the different stresses that were analysed.

***Plant Stress Analysis*:** Plant stress has been defined as ‘any unfavourable condition or substance that affects or blocks a plant’s metabolism, growth or development’ (Lichtenthaler as cited Kranner *et al.*, 2010 p. 656). Initial stress, which might be triggered due to many reasons, most commonly water deprivation, converts into strain, which can cause plant damage, and in severe cases of irreversible damage, might lead to plant death (Kranner *et al.*, 2010).

***Water Stress Analysis*:** Hopkins and Huner, 2009, as cited in Gerhards *et al.* (2016 p. 27) define water stress as “dehydration in the plant due to lack of available water required to keep cell concentrations at an acceptable and healthy level”. Water stress is regarded as the most critical factor that leaves drastic impacts on plant growth, productivity and photosynthesis activity (Klem *et al.*, 2018; Osakabe *et al.*, 2014). Its significance is further enhanced under climate change. The Agremo website declares that the analysis of water stress can prove instrumental in spotting the areas suffering from drought, or standing water, water deficiencies in crops, or areas suffering from irrigation problems within a field. This analysis is helpful for the farmers to adjust their irrigation according to the precise needs of crops in different parts of fields. There is no ideal time for this analysis; for the regular crop monitoring cycle this analysis can be performed throughout the cropping season (Agremo).

***CSWI*:** CWSI is the thermal normalized index developed to address the environmental variabilities that affect the relationship between plant temperature and stress (Leinonen *et al.*, 2006). CWSI results in values ranging from 0 to 1, with those close to 1 showing higher levels of stress (Idso *et al.*, 1981). The formula to calculate CWSI is presented in equation 1:

$$CWSI = (T_{canopy}-T_{wet})/(T_{dry}-T_{wet}) \qquad (1)$$

Where T_{canopy} represents the canopy’s surface temperature, and T_{dry} are “reference surfaces that are completely wet or dry to simulate maximum and minimal leaf transpiration under the exposed environmental conditions" (Gago *et al.*, 2013, p. 16; Zarco-Tejada *et al.*, 2013). CWSI continues to be an efficient indicator of crop water stress, since it takes into account the difference between foliage and air temperature (Park *et al.*, 2017). Water stress was calculated in the current study, using Agremo app, in *Dronedeploy*.

RESULTS AND DISCUSSIONS

***Plant Stress Analysis Results*:** The results demonstrated that among the three fields surveyed in Bahawalpur District, the Plant stress was highest in the wheat field of Sanjar union council, which was in the High Desertification Vulnerability Zone, with 12.31% of its wheat crop affected, and 36.07% of the crop under potential plant stress. Gaddan union council of District Bahawalpur (Fig. 3a), lying in the medium DVI zone, undergoes plant stress affecting 5.71% of its crop and potential plant stress affecting another 22.85% of its one-acre sample wheat field.

The results suggest that in District Rahim Yar Khan, the sample wheat field in Sadiqabad union council, lying in the Low Desertification Vulnerability zone has 5.55% of the wheat plants under plant stress (Fig. 3b). Amangarh union council, lying in the Medium Desertification Vulnerability zone, undergoes greatest potential plant stress of 20.93% as compared to other two union councils of Mianwali Sheikhan and Sadiqabad (Table 3).

In District Rajanpur, Fatehpur union council, lying in the High Desertification Vulnerability zone, undergoes the greatest plant stress of 34.83% and potential plant stress of 51.16%, i.e., more than half of the field is under severe potential plant stress (Table 3), thus rendering the crop vulnerable to failure. Among the remaining two union councils, Rakh Kot Mithan stands more vulnerable than Asni, since its one-acre sample field suffers 4.76% plant stress and 31.42% potential plant stress (Fig. 3c).

***Water Stress Analysis Results*:** The water stress analysis of the sample fields of Bahawalpur revealed that the one-acre sample field in Sanjar union council (Fig. 4a), which falls in the High Desertification Vulnerability zone according to (Mazhar *et al.*, 2018) suffers the greatest amount of water stress, i.e. 25.51% and a potential water stress of 15.83% (Table 4). Therefore, almost 41% of the wheat in the sample field is under water stress or potential water stress, and thus is not getting enough water to be a healthy crop. Among the other two union councils of District Bahawalpur, which fall under the Medium and Low Desertification Vulnerability zones, Chak 75/B has greater potential water stress of 39.06% as compared to 22.85% of the sample wheat field in Gaddan union council (Fig.4a).

Table 3. Plant Stress Analysis for the Fields in High, Medium and Low DVI Zones of Bahawalpur, Rahim Yar Khan and Rajanpur.

District	Union Council	DVI Zone	Fine (ha)	% Fine	Potential Plant Stress (ha)	% Potential Plant Stress	Plant Stress ha)	% Plant Stress
Bahawalpur	Sanjar	High	0.17	51.61	0.12	36.07	0.04	12.31
	Gaddan	Medium	0.02	71.42	0.00	22.85	0.00	5.71
	Chak 75/B	Low	0.13	61.32	0.05	27.83	0.02	10.84
Rahim Yar Khan	Mianwali Sheikhan	High	0.09	90.90	0.00	5.05	0.00	4.04
	Amangarh	Medium	0.03	76.74	0.00	20.93	0.00	2.32
	Sadiqabad	Low	0.01	94.44	0.00	0.00	0.00	5.55
Rajanpur	Fatehpur	High	0.01	13.95	0.04	51.16	0.03	34.83
	Asni	Medium	0.16	77.10	0.03	14.48	0.01	8.41
	Rakh Kot Mithan	Low	0.06	63.80	0.03	31.42	0.00	4.76

Table 4. Water Stress Analysis for the Fields in High, Medium and Low DVI Zones of Bahawalpur, Rahim Yar Khan and Rajanpur.

District	Union Council	DVI Zone	Fine (ha)	% Fine	Potential water stress (ha)	% Potential water stress	Water stress (ha)	% Water stress
Bahawalpur	Sanjar	High	0.20	58.65	0.05	15.83	0.08	25.51
	Gaddan	Medium	0.02	77.14	0.00	22.85	0.00	0.00
	Chak 75/B	Low	0.13	60.93	0.08	39.06	0.00	0.00
Rahim Yar Khan	Mianwali Sheikhan	High	0.09	90.90	0.00	5.05	0.00	4.04
	Amangarh	Medium	0.03	75.00	0.00	20.45	0.00	4.54
	Sadiqabad	Low	0.01	100.00	0.00	0.00	0.00	0.00
Rajanpur	Fatehpur	High	0.02	31.76	0.02	25.88	0.03	42.35
	Asni	Medium	0.06	57.54	0.00	5.66	0.03	36.79
	Rakh Kot Mithan	Low	0.16	77.10	0.03	14.48	0.01	8.41

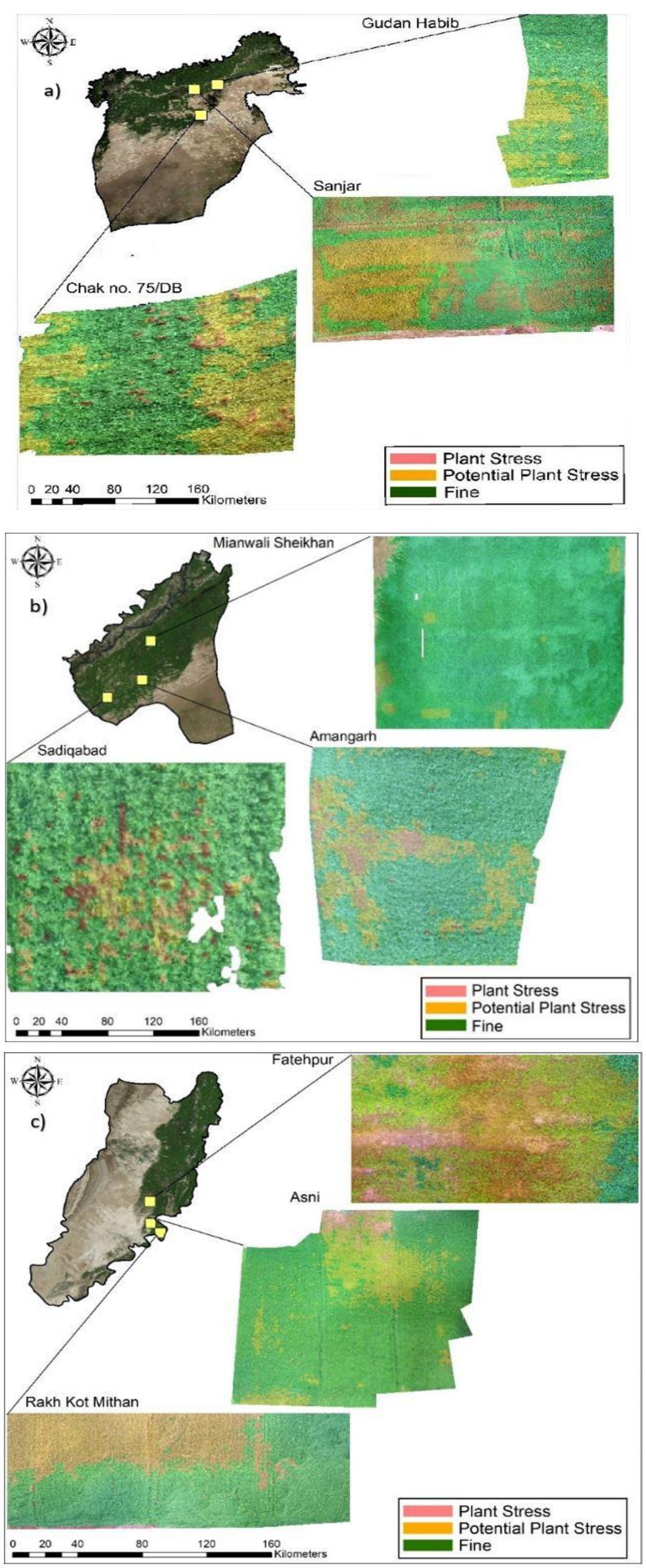

Figure 3. Plant Stress in Wheat Fields in Experimental Fields of a) Bahawalpur b) Rahim Yar Khan c) Rajanpur

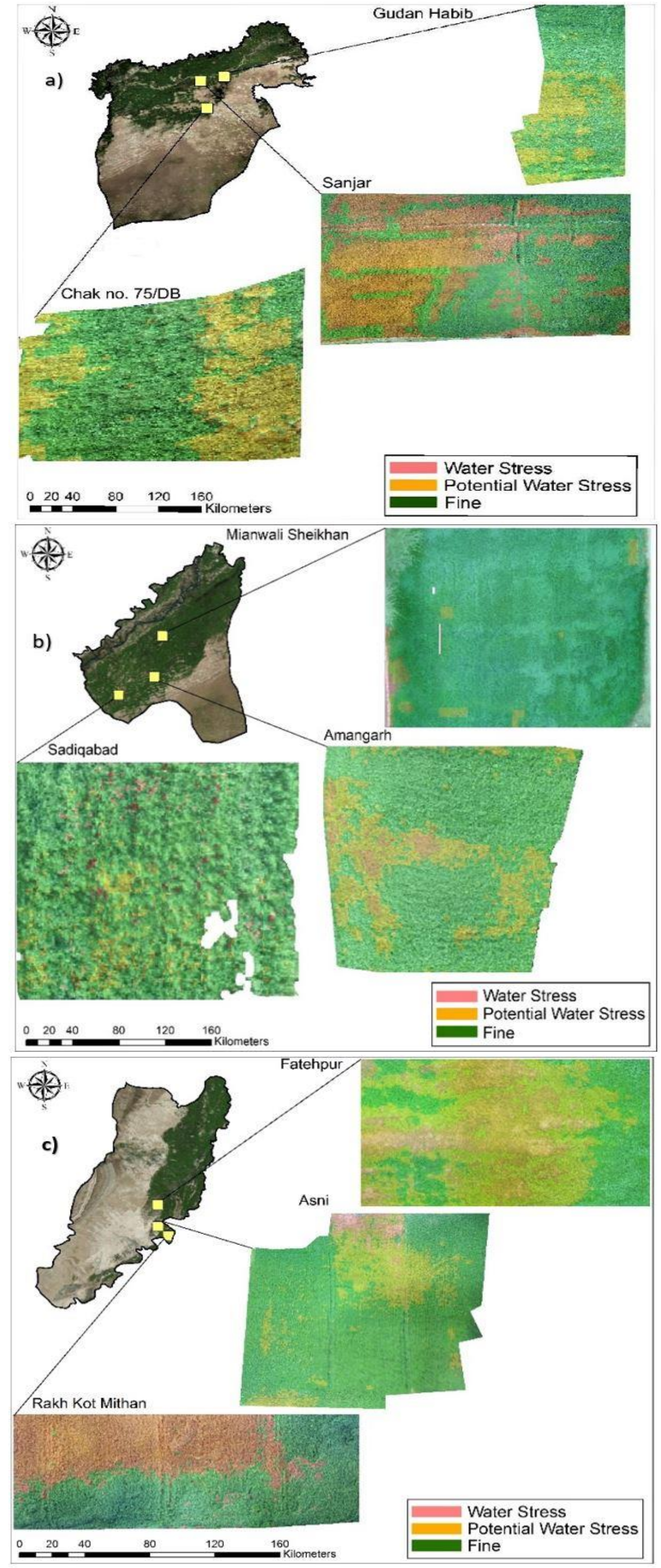

Figure 4. Water Stress in Wheat Fields in Experimental Fields of a) Bahawalpur b) Rahim Yar Khan c) Rajanpur

Among the three districts, the sample fields in the union councils of Rahim Yar Khan were under least water stress, with Amangarh suffering from 4.54% water stress (highest water stress among the three union councils of Rahim Yar Khan) and 20.45% potential water stress (Table 4). Mianwali Sheikhan had 4.04% while Sadiqabad had 0% of their sample wheat fields, under water stress (Fig. 4b). The wheat field in Fatehpur union council in District Rajanpur, lying under the high DVI zone, faces the most threatening water stress of 42.35%, with potential water stress of 25.88% (Table 4). Rakh Kot Mithan's wheat field was the second most severely hit by water stress, with 8.41% of the field under water stress and 14.48% under potential water stress. In Asni union council of District Rajanpur, the situation was not as severe as compared to the former two union councils of Rajanpur, where 36.79% of the sample field was under water stress and 5.66% was under potential water stress (Fig. 4c).

The results of the current study demonstrate that the plant and water stress analysis performed on the images captured through the use of DJI Phantom 3, were able to reveal a snapshot of the stress levels of winter wheat in different DVI zones of South Punjab, in an efficient manner. UAV imagery was used for calculating the plant stress and water stress for wheat crop, and took into consideration the spatial location of such stress variations in high and medium low, desertified zones. This analysis extended the water stress analysis already presented in the literature (Irmak *et al.*, 2000; Park *et al.*, 2017; Santesteban *et al.*, 2017), as it makes an explicit link to desertification intensity, and thus provides an insight into the vulnerability of the farming community of the region.

Comparing the nine wheat fields, plant stress and water stress were highest in Fatehpur union council's wheat fields, lying in the High DVI zone of District Rajanpur (Fig. 3c and 4c), which implies that there exists a positive relation between the DVI zones and the amount of stress that the wheat crop of the region undergoes. Potential plant stress is also highest in the Fatehpur union council, whereas potential water stress is highest in Chak 75/B lying in Low DVI zone of District Bahawalpur. The High DVI zones in two among the three districts under study, i.e., Rajanpur and Bahawalpur, had highest plant stress and water stress. However, the areas lying in Medium DVI zone might be facing high levels of plant and water stress in future, since their vulnerability might shift on the intensity scale. Many natural and anthropogenic factors are responsible for plant stress and water stress on the wheat crop of this region, including its geographical location on the periphery of the Cholistan desert, weak canal systems in the area, extreme temperatures and low annual rainfall. Together, these aspects make it even more vital that farmers use accessible technologies to stay informed and be in a position to efficiently manage their irrigation.

The plant stress and water stress values suggest decreased yields at harvest time. Timely irrigation to the most water stressed parts of the fields, provided by the farmer, can minimize their financial losses. The patterns of stresses identified through this study can prove to be helpful for the local farming community since this region faces some of the most catastrophic climate risks (Ghazanfar *et al.*, 2015).

UAV captured images are a reliable input for the water and plant stress analysis of the wheat fields in desertified landscapes. Similar results regarding water stress in barley crops (Hoffmann *et al.*, 2016) were able to show that WDI maps generated by UAVs were capable of determining accurate absolute water stress values and variations within fields. Park *et al.* (2017) mapped the water stress for nectarine and peach orchards and compared between full and deficient irrigation impacts, however, water and plant stress analysis has not been studied before in relation to the severity of desertification in any region, and the present study aimed at filling this void of literature. More research needs to be conducted for calculating indices like the TCARI/Optimized Soil Adjusted Vegetation Index (OSAVI), Photochemical Reflectance Index normalized (PRlonrm), and NDVI, to check if they correlate with the indicators of water stress like stomatal conductance and water potential, in desertified landscapes (Baluja *et al.*, 2012; Berni *et al.*, 2009; Zarco-Tejada *et al.*, 2013).

Precise monitoring and more efficient irrigation are two ways that desertification can be managed and mitigated. Timely irrigation is essential since both under and over irrigation can result in ~~including~~ reduced crop yields and quality (Adeyemi *et al.*, 2017). Precision agriculture allows farmers to make adjustments to irrigation and other inputs as required (Mahlein, 2016). This enables them to achieve improved production from the agricultural fields using optimized agronomic inputs and fostering a more sustainable environment. Precision farming supports enhancements in management efficiency. Farmers can be equipped with the ability to execute alternative plans to enhance their crop yield, only if they can identify the vulnerable regions that lie within their fields, using real time monitoring of the water status of their field (Park *et al.*, 2017). Use of UAV in precision agriculture offers a promising advancement in this regard (Latif *et al.*, 2018). However, it needs to be accompanied by the water management systems that can support farmers to respond quickly to the information provided by UAV.

***Conclusion*:** This study concludes that low cost UAV based imagery can be successfully used for plant stress and water stress analysis in wheat fields lying in different DVI zones. The use of online resources like *Dronedeploy* and Agremo app, offer easy handling of data, and make analysis easier for farming communities to perform relevant analysis for the optimal agricultural production.

The farmers of the study area are mostly unable to afford a UAV on their own, which would be desirable for the constant monitoring of their crop during the entire growth season. Thus, it is recommended that the Agricultural Mechanization

Research Institute, Multan, Pakistan, could carry out conducive research about the benefits of crop monitoring using UAV in this arid zone of south Punjab to better identify the most appropriate timings and regularity of crop stress assessments. The Field Director General Agriculture, for Punjab, Pakistan, is a department with one of the functions to promote farm mechanization in Punjab, so could play a useful supporting role. Farm mechanization is carried out through research which facilitates the adaptation of modern equipment in agriculture in order to ensure greater outputs per hectare. It is recommended that the Field Director General Agriculture for Punjab could plan team based surveys using UAV in the High DVI zones of the study area, at regular intervals, on priority basis, followed by similar surveys for the Medium DVI zone, during the entire growth period. Such initiatives by the Government can play a pivotal role in reducing the risks of crop failure, particularly in those zones that have been shown to be highly vulnerable to desertification. Similar Government supports will also be needed such that in light of the information provided by UAV surveys, farmers can act to modify their irrigation timings and practices accordingly. Government, in this regard, is suggested to provide sufficient water supply in the canals of the region, to ensure higher yields of wheat, from this region. Special measures on an urgent basis should be taken to support farmers residing in the high DVI zone, since UAV provide a reliable platform to analyze the crop health of wheat fields. For more extensive analysis, similar plant and water analyses are suggested to be performed on the same fields for the entire growing season. In desertified zones across the globe, similar timely analysis of stresses that the crops suffer from, during the entire growing season, are recommended to be performed using UAV. This is essential for timely identification of exact areas that need farmer and policy attention, in order to ensure production potentials are reached.

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