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Comparative geospatial approach for agricultural crops identification in inter-fluvial plain - A case study of Sahiwal district, Pakistan

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Agricultural crop cover identification is a major issue and time-consuming effort to verify the crop type through surveys of the individual field or using prehistoric methods. To establish the scenario of crop identification, the stage of crop provides diverse spatial information about the variety of crops due to its spectral changes. The main aim of this study was to the identify the crop types and their behavior using remote sensing and geographical information system-based approach. Moreover, two main methods were applied to the Sentinel-2 satellite data in which one is random forest based supervised classification and another was Normalize Difference Vegetation Index (NDVI) density estimation method through the google earth engine to procure the data in time-efficient way. This study also established the comparison between classified and vegetation index based seasonal compositional datasets for wheat, cotton, maize, and fodder crops. Study discussed the best fit technique for crops identification in the light of observed methods. Furthermore, the vegetation index ranges by the zonal statistics of the field samples were established according to crop precision. Results showed that -22.94, -43.72, 20.61, and 32.49 % dissimilarities existed in wheat, fodder, cotton, and maize results respectively, after comparison of both techniques. Although, the accuracy assessment was performed on the classified dataset for validation of results by confusion matrix accuracy assessment process using field sample data. Moreover, the vegetation index was used to evaluate crop land surface temperature to estimate the crop growth stage valuation that revealed noticeably enthralling outcomes. The results determined that the classified accuracies of wheat, cotton, maize and fodder were 84, 80, 81 and 71 % respectively. This study also revealed that the random forest classifier has used more features and information potentially during the classifier trainings but vegetation index just implies the limited number of features such as crop growing status.
Keywords Sentinel-2, crop precision, vegetation index, random forest, land surface temperature, google earth engine.

INTRODUCTION

In the South Asian region Pakistan, Afghanistan, India and Bangladesh are very rich in agriculture and key contributor amongst the other countries of this region (Shahzaman *et al.*, 2021). Pakistan is a very rich country in agriculture productively whereas, 18.5 % of GDP is based on the agriculture sector (FAO, 2020). The role of agriculture to manage the sustainable natural resources calls for the development of effective cropland planning and planning strategies (Matton *et al.*, 2015). Information of the early stage of crop planted area with preliminary estimation and crop identification can be valuable for farmland management and it also substantial for realistic decisions for agricultural management (Valero *et al.*, 2021). To obtain precise crop information the remote sensing technology much beneficent for timely and accurate for crop type mapping (Fekri *et al.*, 2021).

A variety of environmental, conservation, and political concerns which are important for monitoring of agricultural practices (Asam *et al.*, 2015) as well deification of estimated crop grown area. For that purpose, the manual method for agricultural crop identification, using Girdawai based field to field survey to maintain the record of the agricultural crop, has been much difficult and time-consuming. After 2005, Pakistan's satellite-based crop monitoring system flourished due to the timeliness and reliability of crop statistics. Estimating the area of crops through the area frame sampling

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system relies primarily on the quality of data (Ahmad *et al.,* 2014). Advances in digital image processing and geographic information system (GIS) have expanded the scope for satellite imagery to derive more precise crop information (Pradhan, 2001; Kamthonkiat *et al.,* 2005). Remote sensing approaches were designed to characterize the type of grassland and vegetation change for conservation planning, mapping pasture and grassland productivity along with derivation of biophysical properties (Franke *et al.,* 2012).

On global scale, the agricultural monitoring community of practice of the Group on Earth Observations (GEO) along with Integrated Global Observing Strategy (IGOL) also calls for an operational system to monitor the vegetation pattern on global scale. Furthermore, various studies are based on supervised or unsupervised algorithms with spectacles keen to cropland mapping from time series or single-date remote sensing images (Petitjean *et al.,* 2012; Xiong *et al.,* 2017). The classification of crops provides essential information that is useful for the management of agricultural resources in various decision-making processes (Saini and Ghosh, 2018). Abou EL-Magd and Tanton (2003) analyzed that the accuracy of conventional land uses classification of irrigated agriculture using satellite data. They analyzed that the rice and cotton crops silhouette with other land use classes. Although, the field verifications confirmed that the overall accuracy of their classification was 93.5%. Lozano-Tello *et al.* (2021) used Sentinel-2 satellite data for crop cover classification and used 83 images per year with 12 spectral bands crop identification. In this research the sentinel 2 satellite data had been used for agriculture crop assessment. The Sentinel-2 satellite Multi-Spectral Instrument (MSI) has thirteen spectral bands with three different spatial resolutions as well as Sentinel-2 data has been used for various remote sensing applications (Wang *et al.,* 2016; Belgiu and Csillik, 2018). In this research the Sentinel-2 satellite data were used for crop land mapping. Although, the remote sensing is the technique of acquiring accurate information from the surface patterns of the earth without physical contact with it. In today's date, this technology uses satellites to detect and classify objects on the earth's surface and in the atmosphere and oceans by using the signals of electromagnetic radiation emitted from aircraft or satellites (Chuvieco, 2009). Zafar and Waqar (2014) used the satellite data with crop calendars in Okara District, Pakistan for crop mapping of wheat, rice, potato, autumn, spring maize and sugarcane.

Wardlow and Egbert (2008) used the NDVI data in their research for crop related mapping in U.S. Central Great Plains and the multi-temporal NDVI data had been gathered throughout the season of specific crop. Bharathkumar and Mohammed-Aslam (2015) said that the NDVI has the magnitude information of vegetation which can be used as crop health. Although, the remote sensing technology is also utilized extensively to monitor the vegetation stress though different satellite observations based on normalized difference vegetation index (NDVI) and Land surface temperature (LST) (Friedl *et al.,* 2002). At present, many researchers use the GIS and Remote Sensing techniques together to study the impact of LST and NDVI on land use land cover (Dong *et al.,* 2018). The LST is often used in many scientific domains such as climate change, evapotranspiration, hydrological cycle, vegetation (Kalma *et al.,* 2008). Sun and Kafatos (2007) found that LST retains positive correlation with NDVI, during the winter and it is negative during warm seasons. Govil *et al.* (2020) noticed that the LST and NDVI has moderate to strong negative correlation because lower range of NDVI indicates rise in temperature (Sruthi and Aslam, 2015). Variations in NDVI are main cause of change in the land surface temperature whereas, NDVI and LST relation depends seasonally. In the built-up and barren areas surface temperature will be partially high with respect to the vegetated area (Malik *et al.,* 2019).

Primary objective of this study was to identify the crops variety in the inter-fluvial plain of Sahiwal District of Province Punjab, Pakistan with most appropriate techniques in both; random forest based classification method for crops identification and NDVI based classification by using raster ranges with the help of field signatures scenario. Although, the validation can be performed on the bases of filed sample as 80 % signature has been used for classification and the remaining for validation purposes. In this research, the relation of crop land surface temperature with NDVI was also observed on selected time span. This technique may be time saving and cost efficient method for the concerned department and associated community in the field of agriculture. Although, the research results may refer a best technique in both methods which may be reliable.

***Study Area*:** Sahiwal is situated in inter-fluvial plane of river Sutlej and river Ravi. Sahiwal is the district of Province Punjab, Pakistan with a population of 389,605 (PBS, 2017). Spatially, Sahiwal district lies at 30°39′40″N 73°6′30″E which has been settled from the pre-historic era. Sahiwal District has two tehsils: Chichawatni Tehsil and Sahiwal Tehsil (Fig. 1). Harappa is an archaeological site fall in the District Sahiwal which was built in 2600 BCE approximately. Climate of Sahiwal is extreme and soil is very fertile. Whereas, in geological perspective the soil layer of the area of interest consisted on hard clay or brown colored loam and it also has thick fine silt and fine sand. So, the top layer of soil is very fertile for multi-cropping system. Moreover, variety of crops are cultivated there in observed study area. Therefore, a case study was conducted in Sahiwal District for the year of 2019 to observe the crop grown area. Sahiwal has canal irrigation system and it is known for cultivation of food items. Figure 1 is also showing the existing classes of settlements, transportation and irrigation networks of the study area. A number of agriculture crop cultivated in that region and their climate condition has variations across Sahiwal. In Punjab province, Sahiwal district is very fertile zone for agricultural activities.

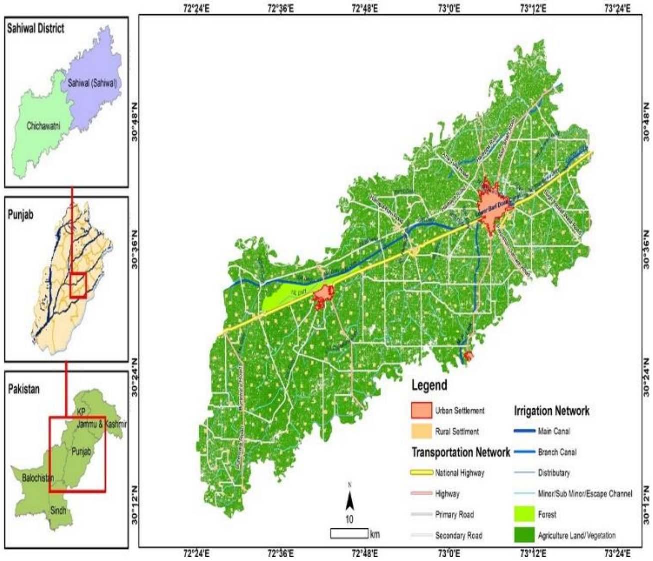

Figure 1. Study area map of District Sahiwal, Punjab, Pakistan.

MATERIALS AND METHODS

The crop area estimation method is conventionally based on the Village Master Sampling (VMS) system from revenue department. It was developed in the late 1970s by Federal Bureau of Statistics, Pakistan (Ahmad *et al.*, 2014). The main concern of remotely sensed data in geospatial fields is that how much corrected information is interpreted by using satellite datasets. It belongs to the result accuracy which is totally based upon the preliminary data. Furthermore, Geographic Information System (GIS) is a computer system designed to capture, store, integrate, analyze and display data from geographic perspective. The depiction of the measured or analyzed data in some types of display - maps, graphs, lists, or summary statistics (Choudhury, 2013). This research work was based upon the crop identification using multiple geospatial techniques which are discussed to make the results much accurate in this regard as well as the methods which were used in this research following below:

***Data acquisition and processing*:** Two type of datasets were used to accomplish the results in which one was field sample data and another was satellite data. Sentinel-2 satellite data was used for the purpose of classification and NDVI analysis. Sentinel-2 is European Satellite which provides multispectral data at medium spatial resolution with fair revisit time of five (05) days as well in various research studies Sentinel 2 imagery has been used for crop mapping (Inglada *et al.,* 2015; Inglada *et al.*, 2017; Drusch *et al.*, 2012). Sentinel-2 data have also been freely available at United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). Whereas the Sentinel-2's Multispectral Imager (MSI) has 13 spectral bands (Table 1).

Table 1. Sentinel-2 Satellite bands composition and specification

Bands	Characteristics	Spatial Resolution (m)	Central Wavelength (µm)
B 1	Coastal and Aerosol	60	0.443
B 2	Blue	10	0.490
B 3	Green	10	0.560
B 4	Red	10	0.665
B 5	Vegetation Red Edge	20	0.705
B 6	Vegetation Red Edge	20	0.740
B 7	Vegetation Red Edge	20	0.783
B 8	NIR	10	0.842
B 8A	Vegetation Red Edge	20	0.865
B 9	Water vapour	60	0.945
B 10	SWIR - Cirrus	60	1.375
B 11	SWIR	20	1.610
B 12	SWIR	20	2.190

Sentinel data were acquired temporally because in Pakistan the crop cultivation and harvesting time is not same as well as cultivation processes are varying time to time. Rabi crop (winter season crop) in Pakistan starts from October to December and is harvested in two months April and May. Kharif is summer season crop; although crop productivity is also dependent upon the timely availability of water (Agriculture, 2018). Crops have different appearances dependent on their growth and cultivation period. So, one image is not enough for major crops identification in Pakistan, as some of the crops might have almost indistinguishable appearances at the beginning of their growth. Time series of images according to the peak growth stage were used to differentiate the crops from each other. The satellite data acquisition with respect to the specific crop season were acquired for crops observation. The satellite images of sentinel-2 were used for seasonal crop composite for better results interpretation of the study area. These images were also used for supervised classification and NDVI analysis purpose. The temporal datasets have been considered based on quality image availability in between the pre-sowing period to crop harvest depend upon the crop type. Sahiwal district contributes its share of agriculture production; mainly wheat, maize and cotton crops are grown here (SUPARCO, 2011). These crops are also significant in the field of research in agriculture sector. Khaliq *et al.* (2008) conducted a study on maize production of Sahiwal in 2008 whereas Khan *et al.* (2016) mapped the wheat grown area using Landsat satellite data over Pakistan in the year 2013-14. Wheat is planted in the winter season or Rabi, which begins in October to December and ends in April to May in Pakistan. This article covered four major crops of Sahiwal district including wheat, cotton, maize and fodder in their respect season. Some previous studies showed that after wheat and rice, maize is considered as the third most important crop of the area. It is the highest yielding crop of world and has tremendous significance in many countries including Pakistan. Reliable crop land mapping and estimation help the policy makers in import and export of trades (Dorosh and Salam, 2008; Ahmad *et al.,* 2018). In this research Landsat-8 data also used for its exceptional record of the land surface. The LST has also been used in the analysis of temperature with vegetation abundance relationship (Wan *et al.,* 2004). It was used to make composite of months in the area of interest. February and March for wheat and fodder crop surface temperature extraction similarly, for maize and cotton crops the composites of August-September were used. To compare with the spatial resolution of NDVI Sentinel-2; the Landsat data were resampled to 10 meter. LST images were also resampled to have the same pixel sizes with NDVI outputs, that been generated using Nearest Neighbor method of resampling (Liu and Weng, 2009).

***Google Earth Engine*:** Google Earth Engine (GEE) is a time efficient interface to handle multiple datasets and produce the output according to our need. It's easy to do complex calculation and generate results of heavy raster in more efficient way with this interface (Wei *et al.,* 2022). According to Shelestov *et al.* (2017) google earth engine (GEE) platform can be very useful and efficient for cropland mapping of huge area. Although, multi-temporal satellite imagery is available and it can classify the crop land with the help of GEE. It is well established that all stakeholders in agriculture, such as farmers, resource managers, marketing, finance and government need timely and accurate information on crop areas and production for strategic decision-making. Shelestov *et al.* (2017) also described the characteristics of GEE after using it in crop mapping of their study area. His research found that GEE is cloud platform which provides good performance towards the remote sensing products and for classification accuracy purpose random forests classifier, decision tree and support vector machine (SVM) are also available. The results in this research are both classified and NDVI analysis were derived using google earth engine.

***Image Classification and Accuracy Assessment*:** Image classification is a technique used to extract meaningful information from the satellite imagery (Raza *et al.,* 2019). This research was conducted in inter-fluvial plain to identify the agricultural crops and their patterns. Field survey is the basic need for supervised classification aimed at better results, where as it has been applied by using google earth engine. The training sample were collected by the field visit in 2019 as per the following schedule; March for wheat and fodder; August for maize and cotton with the help of GPS and geo-tagged photos. Figure 2 is showing the signatures of different crops exist in the study area.

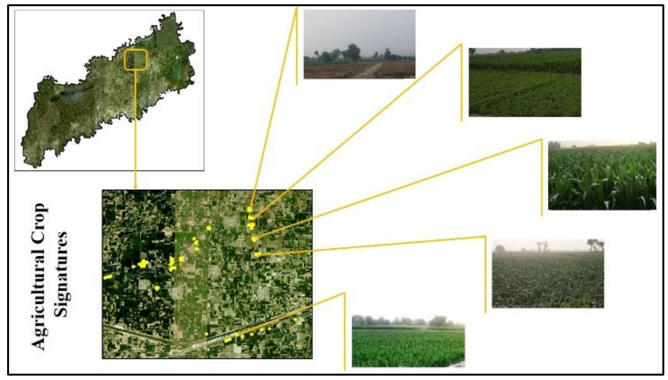

Figure 2. GPS and Geo-tagged photos-based field samples collection for agricultural crops.

In the study area, many crops are cultivated throughout the year in which wheat, rice, cotton, fodder, maize and vegetables are very common but this research is based upon selective seasonal crops. The field signatures were applied on the Sentinel-2 imagery composite according to crop suitability to excerpt the crops in the study area. In past Yang *et al.* (2011) used two satellite images of different growth stage that were classified based on five supervised classification techniques, including minimum distance, Mahalanobis distance, maximum likelihood, spectral angle mapper (SAM), and support vector machine (SVM). In order to classify types of crop, these techniques were applied to 10-m subset images. Furthermore, Saini and Ghosh (2018) used the random forest algorithm and support vector machine (SMV) method on sentinel-2 satellite imagery to identify the crops land area and describe that the random forest algorithm accuracy is higher than SMV. In this research supervised classification was done by the help of random forest classifier (RFC) on the base of training samples. Random forest is an algorithm which can produce the accuracy of classification and shows the excellent results for numeral applications of remote sensing (Yin *et al.,* 2018). Extraction of selected crop was done by using mask for specific crop in the study area. The results of the multiple iterations were amalgamated to identify the crops or crops grown in each field during the season. Although, the accuracy of classification in this research has been verified by the confusions matrix accuracy assessment method. Confusion matrix has been providing the accuracy of mapped features to improve the results of classification (Foody, 2002).

***NDVI based Crop Elucidation*:** The main principle of detecting vegetation using NDVI is the high absorptivity of vegetation pigments (chlorophyll). The satellite data showed great potential for agricultural purposes including crop and grass chlorophyll (Clevers and Gitelson, 2013). NDVI was calculated by using the formula in Eq *(i)*:

$$NDVI = (NIR - RED) / (NIR + RED) \quad \ldots\ldots\ldots\ldots \quad (i)$$

According to the formula, NIR is reflection of near-infrared spectrum and RED is reflection of spectrum in red range as well as these index values range from -1 to +1. The plus values show the vegetation normally, but the minus value shows the other uncultivated land such as: clouds, water and snow; although, the value near to (0) zero shows the existence of rocks and bare soil (EOS 2020). Various studies in practice shows that the normalized difference vegetation index (NDVI) was derived by dividing the difference between infrared and red reflectance measurements by their sum. Based on this formulation, it offers an effective measure of photosynthetic active biomass (Sarkar and Kafatos, 2004). In this research, NDVI composition and results are produced with the help of google earth engine. Supervised classification results compared with the NDVI results which can be compiled by using field signature. From the NDVI raster overplayed field sample points value for each crop were extracted against each signature with respect to specific crop from the NDVI raster. In this study the ranges of observed crops were selected and classified the selective ranges for respective crop that were also gotten from sample coverage area. The ranges got after extraction of the sample points values with zonal statistical method from NDVI were 0.49 to 0.72, 0.29 to 0.40, 0.47 to 0.68, and 0.17 to 0.48 for wheat, cotton, maize and fodder, respectively (Table 2).

Table 2. Derived NDVI Ranges on the bases of agricultural crop field signatures.

Sr.	Agricultural Crop	No. of Signatures	Signatures based NDVI Array (Range)	
			from	to
1	Wheat	151	0.49	0.72
2	Cotton	128	0.29	0.40
3	Maize	133	0.47	0.68
4	Fodder	119	0.17	0.48

***Extraction of Land Surface Temperature*:** Being one of the highly essential parameters of surface-atmosphere interactions, land surface temperature (LST) plays a key role in modeling hydrological, ecological, agricultural and meteorological processes on the surface of earth (Zhou *et al.*, 2011; Li *et al.*, 2013). Not only measurements of radiant surface temperature can collect, but with the help of remote-sensing instruments the amount of reflecting energy in the red and near-infrared portions of the electromagnetic spectrum can also observed to quantify the severity of abrupt changes in vegetation (Yue *et al.*, 2007). In this study, the crop surface temperature is extracted using Landsat Satellite data. Composite of land surface temperature for the months of February and March were used to extract the temperature ranges on wheat and fodder with respect to the field signatures point as well as it was extracted with classified layer of each crop as crop mask. Whereas, for maize and cotton crops, the composites of August-September were used.

RESULTS

In this research, four (04) agricultural crops were identified using remote sensing based methodology. These crops were wheat, maize, cotton and fodder. Figure 3 shows the agricultural crops pattern in district Sahiwal which were derived from the supervised classification for the observed crops so that, the Figure 5 also showing the annual production area for observed crop of the studied region. The research determined that 317519 acres' (ac) areas has been occupied by the wheat and 170842, 114948, 125980 ac cultivated with fodder, cotton and maize respectively (Table 3). The acre is formulating (1 acre = 4046.86 m^2) in this study to measure the tracts of land and it is also use as unit of land globally as well in Pakistan.

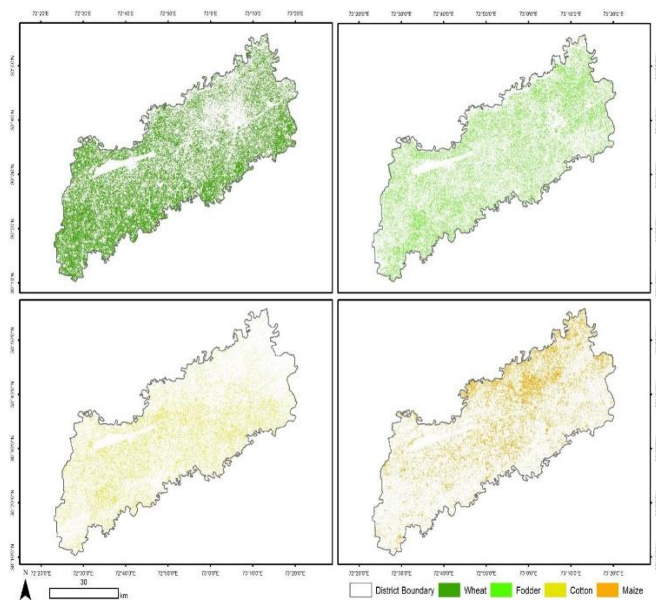

Figure 3. Classified crops map by using random forest classifier.

Table 3. Fallouts description of agricultural crops of district Sahiwal.

Sr.	Crop	NDVI (ac)	Classified (ac)	Difference (ac)	Variation (%)
1	Wheat	390367	317519	-72848	-22.94
2	Fodder	245537	170842	-74695	-43.72
3	Cotton	91712	114948	23236	20.61
4	Maize	85042	125980	40938	32.49

Main purpose of this research is to identify the more suitable technique for crop cover estimation. Figure 4 showing the area estimations with possible difference of two approaches methods for wheat, fodder, cotton and maize crops in District Sahiwal. Whereas, the blue and orange lines are showing the area of crops both NDVI and classified results respectively.

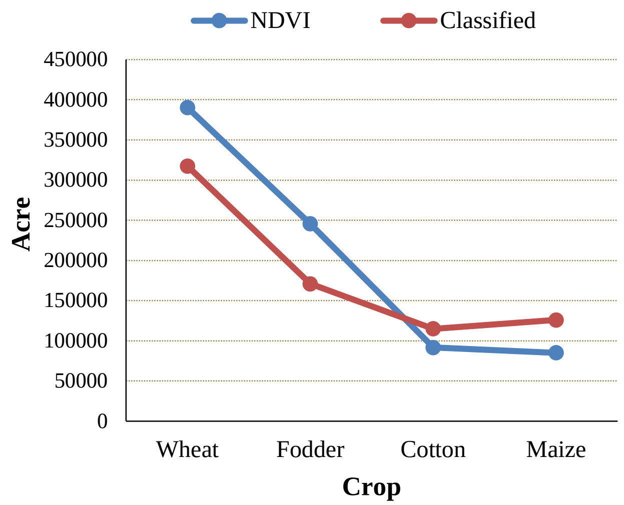

Figure 4. Results comparison graph of the identified crops by classification and NDVI ranges determination process.

In Figure 5 is showing the map of signature based NDVI ranges for observed crops. Whereas, wheat crop is derived with the help of NDVI for the month of February - March as well the range based upon the signatures that collected with the help of filed survey and identified a range from 0.49 to 0.72. The area estimated for wheat crop is 390367 which has -22.94 **%** difference with respect to supervised classification. Furthermore, the imagery of sentinel for the months of February-March were used to identify the fodder with the selective range of NDVI which can be determined by the collected signatures value of selected crop. In this research fodder signature range determined from 0.17 to 0.48 with 245537 acres identified area. The signatures intensity of fodder was very close to the forest reflectance so the forest area can also be the part of fodder in NDVI analysis and -43.72% variant with classified crop results. Table 3 is showing the variation and difference of NDVI and classification based results. In which the difference and variations values were calculated considering the classified crop results were more accurate with respect to the NDVI based crop assessment method. The variation percentages are showing the increase (+) or decrease (-) of crop area with respect to the classified area of crop (Table 3).

In this study the NDVI applied on the sentinel imagery composite for the month of August-September to extract the maize and cotton crop ranges with respect to its season. Later, the range identified for maize was 0.4736 to 0.6835. Which also shows the 91712 acres' area that had been derived as maize crop from NDVI results. It showed 32.49% variation with respect to the supervised classification results. Meanwhile, the NDVI from the imagery composite for the month of August- September was analyzed for better visualization of cotton crop result. NDVI range lies from 0.29 to 0.40 for cotton which can be derived from signatures of selected crop with 85042 acres' area coverage. The difference between classified and NDVI based results is 20.61 %. Climate of cotton precinct in Pakistan lies in an arid to semi-arid constituency in Punjab, Pakistan.

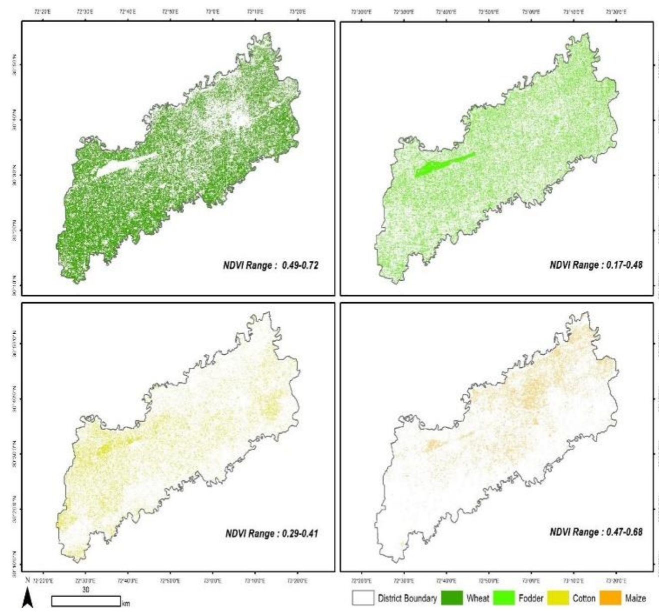

Figure 5. Resultant map of crops by using NDVI sample based ranges selection method.

In Sahiwal district, wheat crop cultivation was 352000 acres in the year 2016-17 which was 387000 acres in 2015-2016. As well cotton crop 138000 acres 2016-17 and 212000 acres reported in 2015-16. 117100 acres' maize had been reported in 2016-17 which 99100 acres were in 2015-16 while, Rabi fodder in 2016-17 was 94900 acres and 98700 acres reported in 2015-16 (AIMS, 2017). Figure 6 is showing the percentages and the acres' difference of wheat, fodder, cotton and maize which were used in the study area. Which has been showing the increase or decrease trend of each observed crop. In this study crop land surface temperature variations were also analyzed for wheat, fodder, cotton, and maize in two observations in first, the temperature was observed with respect to the crop and its mask. In second phase, temperature ranges were observed based upon the field samples. The crop mask (supervised classified) was used for each crop to assess the variations in crop land temperature (Fig. 7). Results showed that wheat crop land temperature was 14.51 to 27.53 °C. Whereas, 20.08 to 36.85 °C, 14.51 to 27.01 °C and 19.83 to 36.97 °C were reported for maize, fodder and cotton crop respectively. Thus, the high NDVI value shows the lowest temperature and low NDVI shows highest temperature (Malik *et al.*, 2019). Cotton crops are ideal for this region because it requires 4-5 months of uniform high temperature (28-43 °C) while optimal air temperature for its proper vegetative growth requires temperature in range of 21-29 °C (Singh *et al.*, 2007; Bange *et al.*, 2008).

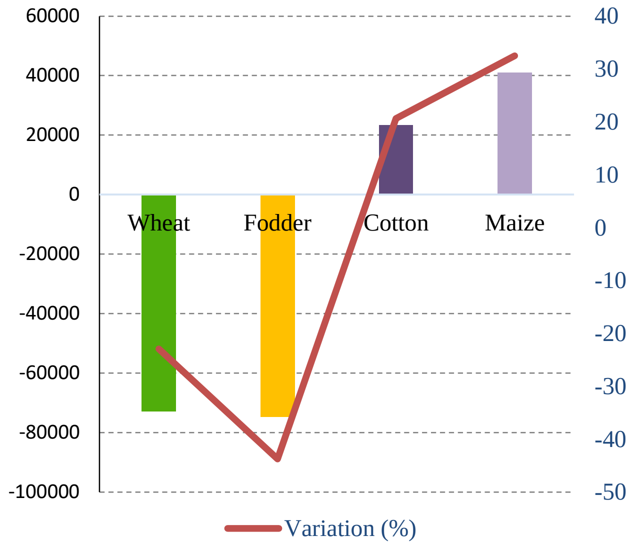

Figure 6. Graph of results output difference in between NDVI and Classified Results.

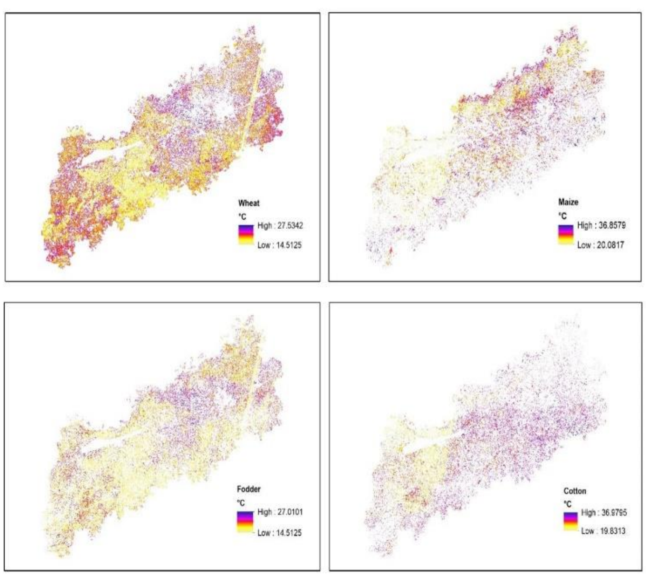

Figure 7. Crop land surface temperature (°C).

Here, in this research the temperature variations of observed crops with the help of sample data also studied. Graph in Figure 8 illustrates the temperature variations with respect to observed crops based on their signatures. All field samples in this research were choose of better and healthy crop grown area and the signatures also showed the temperature ranges for each crop but in this study much higher and homogenous NDVI range was selected. Then, identified the temperature for that NDVI's in observed sample data to analyze the crop health/growth. In this research, results revealed that if the training samples were used to extract the value of LST for wheat crop then it shows that the overall surface temperature range varying from 17.25 to 23.26 °C. Furthermore, 61 % signatures lie between 18.67 to 21.25 °C where the observed NDVI values were found much higher with respect to others. In the case of fodder crop the observed temperature of training samples ranges from 17.56 to 22.98 °C and 56 % signature's temperature lies in between 19.21 to 21.05 °C for healthier crops. Although the surface temperature results of cotton and maize crop were between 25.92- 32.21 °C and 24.31 - 33.35 °C respectively. But for cotton crop temperature from 27.75 to 30.59 °C had better NDVI range with respect to others in sample observations. Moreover, in the observation of maize 58 % signature lies between 27.57 - 30.21 °C where NDVI showed the good crop condition as per the pixel value of signature.

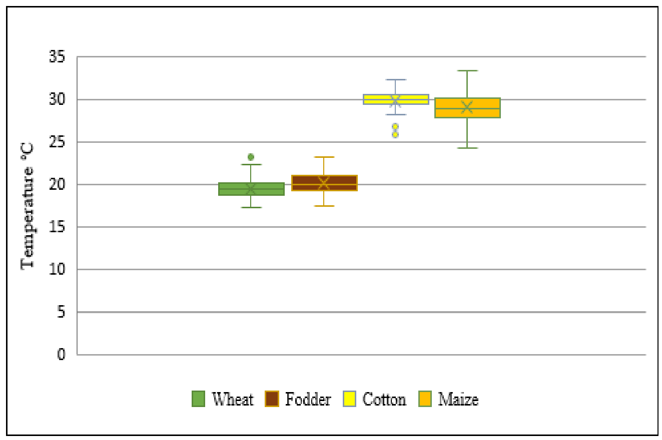

Figure 8. Crops temperature ranges on the basis of field training data.

The assessed temperature from training samples for each crop were analyzed and found motivating results. After that the assessment of relative temperature for observed peak NDVI value range applied according to each crops mask on extracted temperature results. The results showed that 61 % signature had better NDVI for wheat and 56 % fodder and 58 % for maize. Furthermore, the temperature ranges 18.67 to 21.25 °C, 19.21 to 21.05 °C, 27.57 - 30.21 °C and 27.75 to 30.59 °C were applied on wheat, fodder, maize and cotton crop mask area, respectively. These observed ranges were based upon the healthy crop area signatures of the observed AOI. This region had better range of NDVI values on observed sample locations. The results showed that similarity of observed temperature range was found over 93.71 % area of wheat, 58.57 % of fodder, 37.85 % of maize and 32.03 % of cotton crop. Moreover, the indicator like NDVI performed perfectly during early season of crop but sometimes it did not, for stressed vegetation in their later stage.

Hence, based on the field data collected in above mentioned area very high percentage of wheat crop was perceived. The Figure 9 shows the crop health/growth, where blue color indicates the healthy/peak stage of crop area in acres. According to the observation of National Agromet Centre, Pakistan (NAMC, 2020) the wheat peak growth season fall in February-March and August -September are considered as peak months for maize and cotton crops that's why the composites were prepared for said months. The results of this study showed that crop growth and health stage that can be monitored with the help of remote sensing datasets. The other area of crop which does not fall in the said temperature range, it may indicate the different growing stage of respective crop because the sowing time in observed region is not same. It absolutely depends upon the farmers when the crop land available and also fertile for the cultivation.

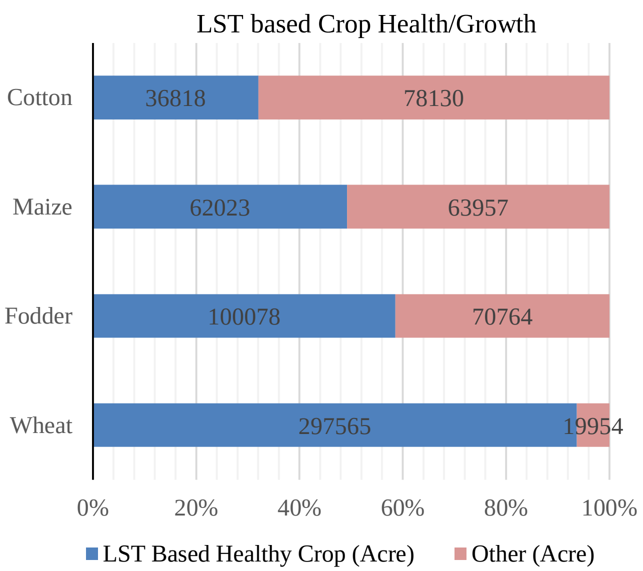

Figure 9. Crop Land Surface temperature based crop health/growth assessment Graph

***Accuracy assessment and results comparison*:** Confusion matrix is known method for accuracy assessment of classification (Congalton, 1991) and its accuracy is based upon the comparison of reference and classified data (Comber *et al.*, 2012). Although, in this research, confusion matrix method was used for accuracy assessment in which "0" shows the worst accuracy and "1" shows the highest accuracy. Accuracy assessment for classification by using random forest algorithm compared with the training sample. As 80 % field signature has been used for supervised classification and 20 % signature used for the accuracy assessment purpose, thus the results established the scenario that the wheat, cotton, maize and fodder has 84, 80, 81 and 71 % accuracies respectively. Figure 10 is showing the difference and comparison of result accuracy by visualizing the study area. It can be witnessed that the Chichawatni forest has been identified in NDVI results which could not have considered as a crop. NDVI signature based ranges mixed up the vegetation in cotton, maize and fodder too and it cannot much suitable for crops with respect to random forest algorithm based classification.

Figure 10 is also showing; the zones that have been identified for better visualization. Zone-A and B are showing the variation in between classified and NDVI results. The wheat crop is much dense in Zone-B that is the mixing crop area. The NDVI results are not able to differentiate the mixing area of crop on the basis of field data that is used in this research. Furthermore, the results of fodder, maize and cotton showed the drastic change in the observations. The forest covered area has also showed as crop covered area in NDVI outcomes. Zone-C and E indicate the area of classified crop at the other hand the Zone-D and F showing the area of NDVI outcome that the forest cover showed as crop in Zone-D and F. Although, the changes in Zone-G and H were also observed and it showed no crop area but their cultivation of maize exists. The forest covered area has been shown as crop in resultant map**.**

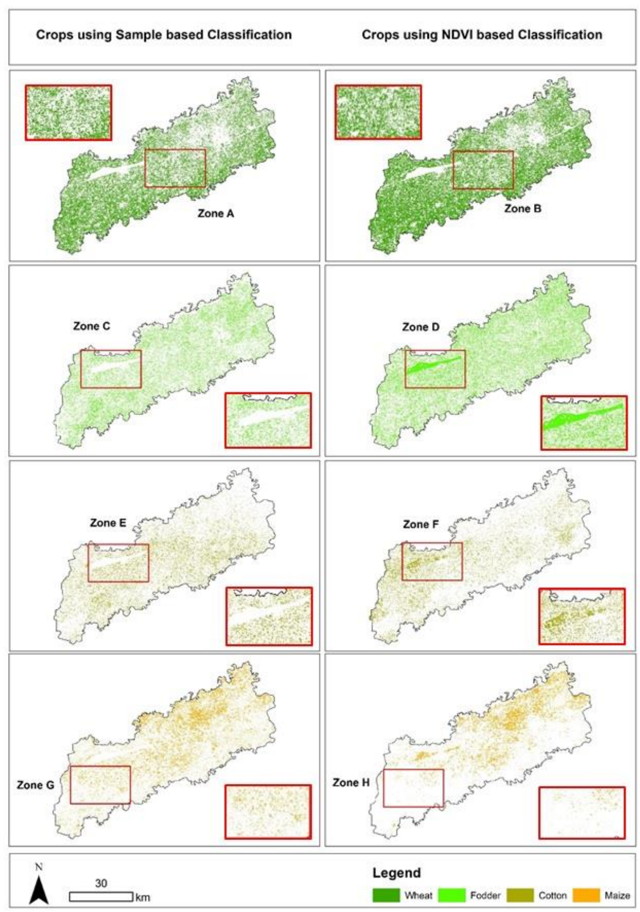

Figure 10. Comparison of NDVI and classified results difference for observed agricultural crops

DISCUSSIONS

The current study revealed the best fit technique for crop observation in the observed area with comparative methods. The overall observation of both methods that used for crop classification the supervised method was much efficient with respect to another one. Akbari *et al.*, (2020) used random forest classifier for crop types classification on Sentinel-2 satellite imagery. In the observed region the harvesting and cultivation time are not same; crops are cultivated when the farmer land is available throughout the season. The analysis of satellite remote sensing data is a cost-effective way to map up-to-date crops for larger areas at different scales (Matton *et al.*, 2015). The NDVI based crop growth was also observed in this research and the cultivation time varies in the study area which might affect the harvesting time for each crop. Usually, vegetation monitoring by remotely sensed data are carried out using vegetation indices. These mathematical transformations help the analyst in assessments of spectral contribution of green plants to multi-spectral observations (Maselli, 2004). The health of crop was evaluated by examining the NDVI and the crop stress/stage was also observed by using the surface temperature ranges. Therefore, the decrease in NDVI shows the water stress or early/later stage of crop (Thapa *et al.*, 2019). Therefore, the LST and NDVI output showed the results that were much reliable. Precise measurement of LST depends on the surface emissivity which mainly depends upon the stages of plant development (Heinemann *et al.*, 2020). The vegetation condition and growth stage has also been observed using crop NDVI phenology (Hu *et al.*, 2020) which has negative correlation with LST. The relation of increase in LST showed that the decrease in vegetation. Rehman *et al.* (2015) found increasing trend of LST in the Keti Bandar area, Indus delta, Pakistan with decreasing area of vegetation. Ahmad *et al.* (2018) observed the maize anticipation in Faisalabad Pakistan by using LST and NDVI relation by identifying the stress. The overall results of current research showed the technicality of method that were used to enhance the results intimation in the study area with usable supporting data. Random forest was fast and efficient with respect to other classifier due to its affluence of stoutness and parameterization (Pelletier *et al.*, 2016; Vuolo *et al.*, 2018). Moreover, the observations of this research also shown that the results of RF were much reliable under the experiential parameters in the region of experimentation. The results also revealed that the LST and NDVI has strong relationship in crop growth stages assessment. If the temperature rises the value of NDVI will dramatically decrease.

***Conclusion*:** This research analysis showed that the supervised classification method has better accuracy than the signature based NDVI extraction for crop cover identification. Wheat, cotton, maize and fodder had 84, 80, 81 and 71 % accuracies respectively which were perceived using random forest classifier. NDVI is an explicit way of crop identification, but random forest is an implicit way of crop identification. As implicitly using a lot of features perhaps concerning biological, physical and semantic features. Although, it showed -22.94%, -43.72%, 20.61% and 32.49 % variations in wheat, fodder, cotton and maize crop when the results of both adopted techniques were compared. The mentioned variations showing the NDVI based estimated area not well justifiable and similar to the supervised classification method results. The supervised classification method with field data is much better for crops identification with respect to the other one which is discussed above because resultant data was much refined to NDVI based results. The relation of LST and NDVI in the study area was very interesting and it will be helpful for crop growth assessment. The wheat crop condition was much satisfying with respect to other observed crop. In future, it might be helpful to acquire healthier outcomes for relevant department in meaningful way. The acquired methods and findings of this study are technically practical and experimental that would be highly recommended for concern departments to enhance the efficiency of results in time and cost efficient ways. This research will also help specially, in those area, where different crops are cultivated in same time especially in the regions similar to Pakistan.

***Authors Contribution Statement*:** Danish Raza designed the study methodology, processed, analyzed the data and conducted research. Hong SHU supervised the overall work and helped in technical findings. Sami Ullah Khan helped in data analysis while Muhsan Ehsan, Urooj Saeed, Hasnat Aslam, Rana Waqar Aslam and Muhammad Arshad helped in data collection. All authors proof-read the article.

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