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Landsat Based Multitemporal Approach for Wheat Mapping in Semi-arid Region of Punjab, Pakistan

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ABSTRACT

Conventional ways of crop area and production estimation such as area list frame are not designed for pre-harvest results, while requiring huge human, logistics and financial resources. An alternative method that can provide pre-harvest crop statistics is the need of the time. Data available from satellite monitoring of the earth has promising application in pre-harvest crop statistics. However, accuracy of information derived for heterogenous cropping systems and small land holding agriculture using multitemporal satellite data needs to be evaluated. We used multitemporal Landsat imagery for our research study that were available free of cost for pre-harvest wheat area estimation in Faisalabad. Different bands and indices of multitemporal Landsat imagery was used as input variables into random forest algorithm for wheat classification. The estimated results were then validated through accuracy assessment using field survey. Landsat-based wheat area estimated is within 0.6% of our sample-based reference estimate. The findings was 14% lesser as compared to official recorded disclosed by Punjab province. Overall accuracy of wall-to-wall wheat map was 86% (SE = 1.6).

Introduction

Changing weather patterns due to climate change result in decline in wheat yield in Pakistan. Food security issues arising from variation in winter weather pattern might adversely affect majority of population in Pakistan. Conventional list frame ways are in use in Pakistan for crop area and production estimation. Conventional method is not only time consuming but also requires significant monetary and technical human resources (Yang et al., 2017). The conventional methods are used in Punjab for area and crop estimation but the results of these surveys are not helpful in deciding supply and demand for the year of crop production. Therefore, remote sensing data is more appropriate for stability between supply and demand and thus addressing the food security concerns.

The medium resolution satellite observations provide cost-effective opportunities for consistent crop monitoring and mapping (Song et al., 2017). For modelling crop yield, researcher usually applied Moderate Resolution Imaging Spectroradiometer (MODIS) over large areas from (Anderson et al., 2016). Crop mapping is constantly confronted by diverse in cropping systems, diverse land holding sizes and cultural constrain. Wheat crop in Punjab is cultivated under sole, mixed and inter cropping system i.e. sole wheat, mixed wheat cultivation in guava, mango and citrus orchards. Some other crops such as chickpea (gram), lentils and clover (fodder) are also grown during wheat growing season. Crop identification with satellite imagery in such heterogenous cropping systems can be improved using multiple sources (Fermont and Benson 2011). Multi-temporal Landsat data improve map accuracy and reliability of estimated crop area.

Data collection and characterization of satellite imagery at the field through survey for results validation are useful for accuracy assessment. The purpose of this research is assessment of wheat area employing multitemporal Landsat imagery with in-situ data and identification of the most important input variable for wheat classification using random forest algorithm under heterogenous cropping system.

Methodology

Study area

The Faisalabad district, the 2nd most populated district and located in the central Punjab with an area of 580,961 ha was selected as study site (Figure 1). The study area represent heterogeneous cropping system under semiarid climate (Cheema et al. 2006). In Faisalabad, the farmers have small land holdings. About 70 percent of annual rainfall in Faisalabad is the result of summer monsoons (Cheema et al. 2006).

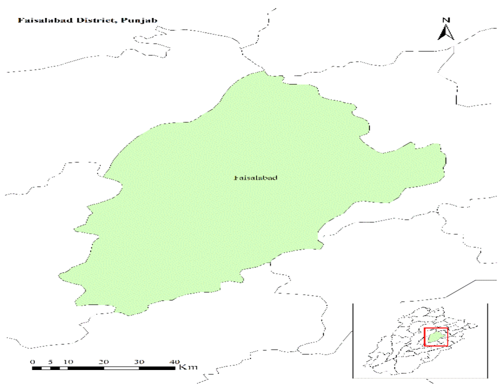

Figure 1: ***Faisalabad district in Punjab***

Table 1: Total number of images (Landsat) processed in wheat season 2015-16

Satellite	Path/row			
	149/038	**149/039**	**150/038**	**150/039**
Landsat 7	Jan 11, 2016	Jan 11, 2016	Feb 03, 2016	Feb 03, 2016
	Jan 27, 2016	Jan 27, 2016	Feb 19, 2016	Feb 19, 2016
	Feb 12, 2016	Feb 12, 2016	Mar 06, 2016	Mar 06, 2016
	Feb 28, 2016	Feb 28, 2016	Mar 22, 2016	Mar 22, 2016
	Mar 15, 2016	Mar 15, 2016		
	Mar 31, 2016	Mar 31, 2016		
Landsat 8	Jan 03, 2016	Jan 03, 2016	Jan 10, 2016	Jan 10, 2016
	Feb 04, 2016	Feb 04, 2016	Feb 27, 2016	Feb 27, 2016
	Feb 20, 2016	Feb 20, 2016	Mar 14, 2016	Mar 14, 2016
	Mar 07, 2016	Mar 07, 2016	Mar 30, 2016	
	Mar 23, 2016	Mar 23, 2016		

Preparation of input data set and selection of training areas

Crop calendar for wheat crop in Faisalabad show sowing in early November to December almost each year. Landsat multitemporal data from January to March, 2016 was used for wheat crop area and yield estimation. Table 1 shows 37 downloaded images from USGS website with two paths and rows (149/038, 149/039, 150/038 and 150/039) covering the study area.

We included corresponding bands of The bands including Red, Green, NIR SWR 2 and SWIR of Landsat 8 OLI and Landsat 7 ETM+ and 2 indices i.e., Normalized Difference Vegetation Index (NDVI) shown in equation 1 and Normalized Difference Water Index (NDWI) (Rodríguez-Garlito et al., 2023) shown in equation 2 below as input data set. Shorter wavelength blue band was not included in input data due to its sensitivity to aerosol. The pixels with cloud cover were removed using cloud mask provided by NASA for each image. Scan line corrections were used for Landsat 7 ETM+ images and Top of Atmosphere (TOA) reflectance were calculated for each band of Landsat. Using methods from Hansen et al., (2013) we normalized the data for surface reflectance.

$$NDVI = \frac{NIR - Red}{NIR + Red} (Equation 1)$$

$$NDWI = \frac{SWIR1 - Red}{SWIR1 + Red} (Equation 2)$$

In equation 1 & 2, NIR represent Near Infrared and SWIR1 represent Shortwave Infrared bands, respectively. Ranked metrics were derived from stack of all corresponding bands and indices of multitemporal images (Landsat 7 ETM+ & Landsat 8 OLI). Relevant phenological information has been determined through metrics for mapping land cover. Multitemporal images were organized in uphill order. We calculated percentiles i.e, 10, 25, 50, 75, 90, 100 (minimum) and mean were calculated for each variable (2 indices NDVI and NDWI and 5 bands). The layers are arithmetic sources of pixels having best quality. We adopted the methodology of Hansen et al. (2013) for 56 layers that consisted of 4 scene footprints and they were mosaiced for covering Faisalabad district.

False color composite (FCC) was used for capturing phenological variations and crop diversity, visual image interpretation. Images of SWIR1, NIR and Red were verified by different information sources such as (a) variation in crop phenology and peak growing season from multitemporal images (b) Google Earth^{TM} imagery of high resolution and (c) labeling of random field plots during field visit other than ground truthing sampling pixels. Training data comprise of assigning wheat and non-wheat labels to a small number of pixels (7217 pixels in this study) as compared to total number of pixels for classification.

Table 2: Accuracy for wheat and Non-Wheat area

	Reference			**Errors %**		**Accuracies % (SE)**		
Map	**Wheat**	**Non-wheat**	**Sample total**	**Commission**	**Omission**	**Users**	**Producers**	**Overall**
Wheat	0.38	0.07	0.45	15.0	15.5	85.0 (2.2)	84.5 (1.9)	86 (1.4)
Non-wheat	0.07	0.48	0.55	12.7	12.3	87.3 (1.8)	87.7 (1.6)	
Map total	0.453	0.547	1.00					

Classification with Random Forest algorithm

To match the training data to the Landsat metrics, we applied Random Forest (RF) algorithm to develop wheat and non-wheat land covers. Wheat and non-wheat special signatures are used to develop model which were recorded and calibrated with manually labelled wheat and non-wheat training pixels of 56 layers of Landsat metrics. A study by Ok et al., (2012) looked at how well different classification methods performed against one another and found that accuracy of the Random Forest method was eight percent more accurate than the Maximum Likelihood Classification method (MLC). It is useful to compare the performances of various classification methods, including RF, Decision Tree, and Rule Based Classifiers, among others. They have recommended the use of the RF method as a result of their investigations. Many researchers (Ok et al. 2012; Saini & Gosh, 2018) have advocated for the use of RF for crop classification. As a result, in this study, the RF method was chosen as a classifier for the data.

The training data set is divided in to multiple random samples with the help of RF (Mishina, et al., 2015). To set rules for data classification (tree), two third of each random sample are used. Nodes may be either root nodes or terminal nodes. Node basically refer to a point where data is separated into identical sets through entropy measure. The left over part of the sample is called “Out of Bag” (OOB). 500 trees were produced within each RF algorithm for classification of data. Compared to individual trees, multiple trees avoids overfitting.

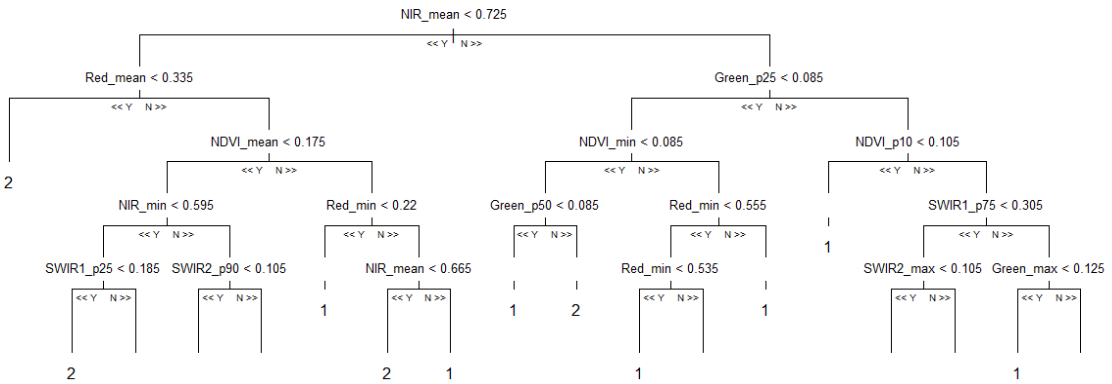

Figure 2: Structure of one Random Forest Tree and its classification mechanism; “1” and “2” represents Wheat and Non wheat pixels, respectively

During development of each tree, randomly selected seven variables out of 56 variables were sampled as candidates at each splitting node and specified one variable to minimize the impurity among training pixels of wheat and non-wheat based on Gini index (Wang et al., 2022). Different number of variables were used in each tree varied from 24 to 49. The classification structure of first tree is presented in figure 2.

The relative importance of variables can be obtained through Out of bag (OOB). Average accuracy was determined for all the trees. RF model was used to find out the wheat & non-wheat area mapping and area estimation. To validate the map accuracy, field sample data (figure 2) were overlaid on wheat map (figure 3) and analyzed by confusion matrix (table 2).

Sampling strategy for ground truthing and accuracy assessment

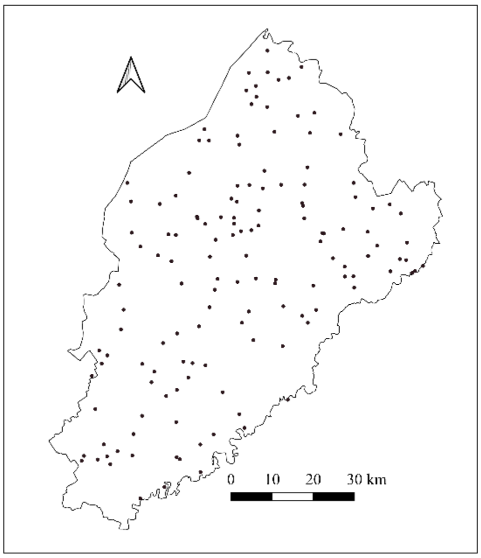

Figure 3: ***Georeferenced random samples (568) collected in winter season 2015-16***

As a uniformly heterogenous cropping system with effective size of wheat field as +42 ha was found throughout the study area in winter growing (rabi) season, simple random sampling design, was applied for ground truthing. Simple random sampling design is suitable for uniform population and geospatial extents without clustering with each sample having equal chance of selection. A total of 568 samples (Landsat pixels) were selected in Faisalabad district. Three weeks prior to harvest, we recorded randomly selected pixels as georeferenced field samples during ground truthing. Sample pixels were visited and manually estimated the wheat coverage percentage e.g. 10%, 20%, 30%, ….100% was manually estimated for each sample pixel. Mean of all sample pixels for wheat coverage percentage was calculated and used to derive the total wheat area for Faisalabad district.

Faisalabad wheat area = Total area of Faisalabad district x Mean of all sample pixels for wheat coverage percentage

We also used unbiased and random field samples, collected during ground truthing to: (a) validate the wheat map derived with Landsat imagery using error matrix and (b) calculated an error matrix for map accuracy.

Results

Comparison of sample-based estimate with CRS estimate and map accuracy

We estimated 263,193±16473 ha (95% confidence interval) of wheat in Faisalabad district using our field-based sample dataset. This estimate is 14% lower than the official recorded estimation of 300,810 ha by CRS and 0.6% higher than 261,667 ha derived from Landsat map (figure 4). Sample area validates the area of Landsat map and therefore are in agreement to each other. To validate the map accuracy, a confusion matrix was derived through comparison of field data to map data for each of the sample pixel (table 2).

We calculated an overall map accuracy of 86% (SE = 1.4%). Accuracy level for wheat and non-wheat area were 85% (SE = 2.2%) and 87% (SE = 1.8%), respectively. Accuracies for wheat and non-wheat area were 85% (SE = 1.9%) and 88% (SE = 1.6%), respectively (Table 2).

Variable Importance for wheat classification

All percentiles (NDVI) are imperative for wheat classification. However, to differentiate wheat area from non-wheat, minimum NDVI is of utmost importance. Average value of mean decrease accuracy of all percentiles of SWIR1, NIR, SWIR2, Green, NDWI and Red ranked as respectively less important variables to each other for wheat classification (Figure 5).

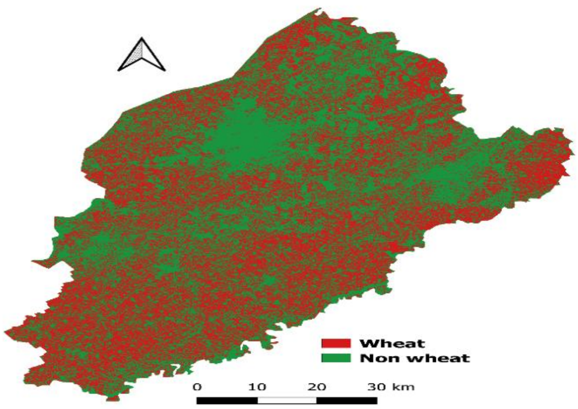

Figure 4: ***Wheat map of Faisalabad district developed with multi-temoral Landsat imagery for rabi season 2015-16.***

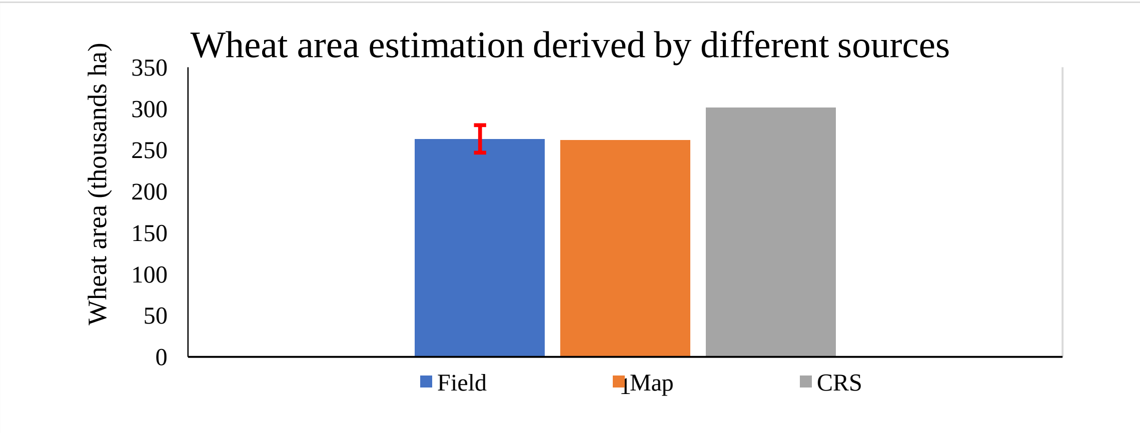

Figure 5: ***Estimation of wheat area through different methods***

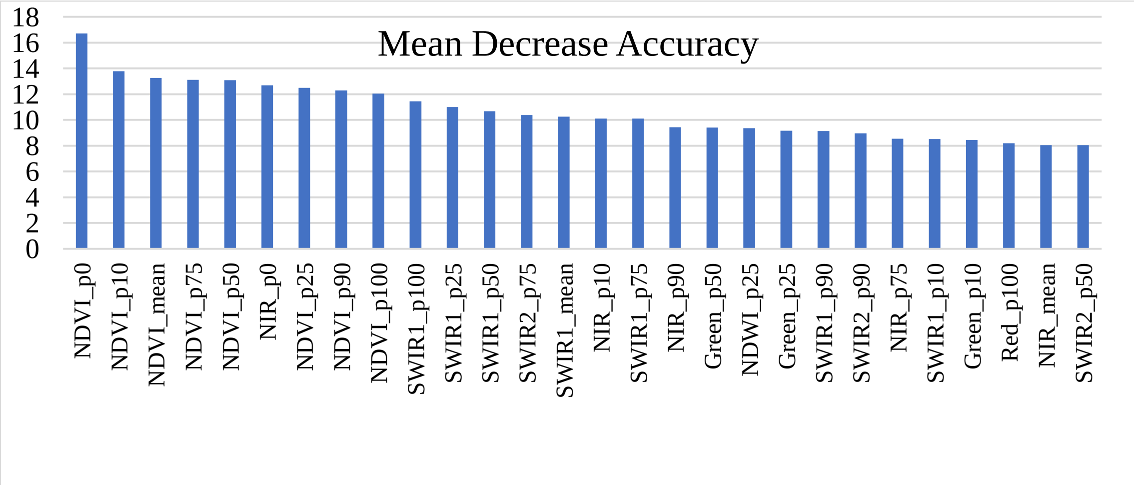

Figure 6: ***Decrease Accuracy (Mean) of 28 variables***

Discussion

Results indicated that the commission error (15%) was a bit low than the omission error (15.5%) for wheat. The non-wheat's commission error was 12.7%, which was higher than the omission error of 12.3%. Error difference showed that some non-wheat area was also considered as part of wheat area. Lower estimate of map-based wheat area (261,667 ha) than sample-based estimate (263,197 ha) verifies the results of commission and omission errors. CRS estimate (300,810 ha) is established by calculating the area (acres) under wheat cultivation in the concerned sample village. This strengthens the view that CRS estimate of wheat area would be higher as compared to the wheat area classified through wall-to-wall map and sample-based estimate.

The commission error was solely due to the clover (a fodder for livestock feeding) as it synchronizes with wheat growing period. Its spectral signatures are very much similar to wheat crop, which makes its discrimination difficult from wheat crop (Song et al., 2016).

NDVI is the proportion of difference and sum of red bands and NIR (equation 1). Plant canopies absorb red and reflect NIR due to chlorophyll and moisture content present in the plant body, respectively. Each crop contains specific proportion of chlorophyll and moisture content which makes NDVI is the most important variable for classification having specific range for each crop at specific time. Wheat crop has unique planting window (November and December) which makes minimum NDVI is the most important variable for classification recorded in the month of January at initial growth stages of wheat crop while all other crops present in the field at this time were not at their initial stages. This research will increase the capability of policy maker for in time management of crop commodity.

Conclusion

This study concluded a wheat mapping methodology with the heterogeneous cultivation system using multitemporal Landsat images using RF algorithm. RF classifier was successfully used for classification of multitemporal Landsat imagery with a greater number of input variables. It captures the temporal characteristics of wheat and prepares a map with 86% accuracy. For classifying the wheat area under heterogenous cropping system, NDVI is extremely important variable due to its higher vegetation sensitivity. The study presents a reliable and less resources utilization methodology for the timely estimation of the wheat area for the policy making to avoid the food insecurity.

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