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LAND COVER MAPPING AND CROP PHENOLOGY OF POTOHAR REGION, PUNJAB, PAKISTAN

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Agriculture a major source of food and fibre affects the natural land cover and in turn is affected by climatic factors like temperature and precipitation patterns beside other factors. The soil temperature and moisture, wind, relative humidity and crop water requirements also affect the crop growth. Local farming practices also alter the natural landscape structure and biodiversity in croplands. This study was conducted with the objective to find out seasonality trend and to determine the land cover classification in Potohar region using Normalized Difference Vegetation Index (NDVI). Moreover, random points throughout the study area were selected in order to detect the vegetation index pattern in different land cover types. For land cover classification and acquiring seasonality trend, crop growth patterns were determined by phenological phases of a particular crop. Land cover was classified with standard Level 1 Terrain-corrected (L1T) orthorectified images from Landsat 8 from years 2012 to 2016. Seven land cover classes within the study area were identified namely; agriculture, grasses, forest, shrubs/tall herbs, bare soil, built-up and water bodies. Moreover, the seasonality trend over the study was found related to different land cover classifications using 959 sample plots with 97.81% accuracy. The phase trend analysis determined the change in vegetation cover during the years under study, which was correlated to precipitation patterns in Potohar. The NDVI pattern was highly fluctuating in agricultural land cover due to seasonal crop growth but it remained stable throughout the year in forest covers. Urban land cover was found to have high impact on nearby vegetation as it was related to change in land cover type, which affected the climate of the area. Climate being a vital deriving force, affected precipitation patterns of the rain-fed (*barani*) land which in turn shifted the seasonal growth of various agricultural crops.
Keywords: Agriculture, crop phenology, land cover maps, NDVI, *barani* (rain-fed), seasonality trend

INTRODUCTION

The understanding of dynamics that influence the land use and land cover change (LULC) are imperative for ensuring food security and to address the challenges associated with global climatic changes. The synchronization of societal goals and tripartite linkages among social, ecological and economic domains are essential to achieve the goals of sustainable development (Engstrom *et al.,* 2016; Hegazy and Kaloop, 2015). Land use and land cover are two interchangeable terminologies, where, land cover is described as the physical characteristic of the earth's surface and land use as the way in which that characteristic is used by humans. Land cover are classified into two broad categories i.e. natural (vegetation, forests, shrubs and grasses, water bodies, bare soil etc.) and man-made/human-transformed which reflect anthropogenic interventions in natural environment for economic activities include agricultural lands, settlements etc. (Rawat and Kumar, 2015).

The climate of an area is a product and dependent upon the cumulative behaviour of land use/ land cover types and human interaction in a contextual setting. The vegetative cover of a geographic region help us to decipher the causation and impacts of climate change. In this connection, the role and behaviour of agricultural land cover is unique. It not only contribute in food provisioning but also serve as a natural sink for greenhouse gases such as carbon dioxide (CO_2). It covers more than one third of the land on earth in the form of pastures and croplands. Keeping in view the increasing rate of population, it is vital information to know that only 10% of increase in agricultural land is taking place which makes the unavailability of food for about one billion people globally (Pongratz *et al.,* 2008; Engstrom *et al.,* 2016; Qin *et al.,* 2015). Land cover change can be detected by studying vegetation phenology. Phenology is the study of periodic events in the life cycle of living species (Vina *et al.,* 2004; Sakamoto *et al.,* 2010). An efficient method for assessment of vegetation phenology is the use of satellite derived vegetation indices including Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) (Gong *et al.,* 2015). Landsat 8 provides an efficient source of phenology assessment in the area like Pakistan having diverse crops. Sensors of the satellite i.e., Operational Land Imager (OLI) with nine bands and Thermal Infrared Sensor (TIRS) with two thermal bands provide the resolution of about 30 m (Jia *et al.,* 2014) which is an accurate resolution for phenological assessment of large as well as small crop lands like that of Potohar region.

The geographic area of Pakistan is about 80 million hectares (Mha), of which 18 Mha is irrigated and dry land farming is practiced on 12 Mha. The *barani* (rainfed) areas of Punjab cover about 7 Mha and are home to over 19 million people. This is equivalent to about 40% of the total area of the Pakistan Punjab (Oweis and Ashraf, 2012). These areas, however, contribute less than 10% to total agricultural production and depend solely on the rainfall. In addition to a food source for the citizens of the country, agriculture is also a very important economic sector of Pakistan contributing about 21% in GDP. An important subsector of agriculture is cropland constituting 39.6% of agriculture and which has a share of about 8.3% in GDP (Khan *et al.,* 2016). The major share (76%) is contributed by Punjab (Rashid *et al.,* 2014). Kazmi and Rasul (2009) hypothesised that the underestimated *barani* land (rainfed area) of Potohar plateau is capable to significantly contribute in the economy of Pakistan because more than 1200 kg/acre wheat is grown in the area which shows its potential to lower import load.

Productivity of Potohar is reported to be decreased about 2.5 to 7 times due to over grazing and removal of vegetation for purpose of obtaining fuel wood. Habitat degradation is the obvious consequence of this event as water erosion effects the agro ecosystems. The vegetation cover can be recovered by increase in precipitation (Gong *et al.,* 2015).

Land cover mapping of a region is an important task in order to determine the ongoing changes in LULC over time. Land cover mapping helps us determine whether a certain sector either agriculture or urban requires proper planning and management. The study of crop phenology help us to determine changes in the climate of the area as the climate of the region directly affects the agricultural lands. Data about crop phenology relate to food security of an area.

The main objectives of the present study were to develop land cover maps for determining area under agricultural land cover, analyze the seasonal trend of Potohar region from 2012-2016 and to find out correlation between precipitation and NDVI.

MATERIALS AND METHODS

***Study area*:** The study area chosen for the present study was Potohar plateau, Pakistan and includes major portion of districts Attock, Chakwal, Islamabad, Jhelum and Rawalpindi (Fig. 1). The region lies between Indus River and the Jhelum River and stretches from the salt range northward to the foot hills of Himalayas (approximately 32.5°N to 34.0°N Latitude and 72°E to 74°E Longitude). The total area of this region is approximately 13,000 km^2 with elevation from sea level fluctuating between 305 - 610 m. It has highly undulating topography and erratic rainfall pattern. The climate of the area is semi-arid to humid. Out of total, about 80% rain falls during July to October (Sarwar *et al.,* 2014). The summer temperature ranges between 15^{o}C and 40^{o}C while the range of winter temperature is generally between 4 and 25^{o}C but it can occasionally drop. Around 994 thousand hectares area of Potohar plateau is being cultivated (GoP, 2016). About 4% of the cultivated land is irrigated while 96% is dependent on rain (Majeed *et al.*, 2010). The major crops grown in the area include wheat (*Triticum vulgare*), maize (*Zea mays*), barley (*Hordeum vulgare*), sorghum (*Sorghum bicolor*), millets (*Panicum miliaceum*), lentils (*Lens culinary*), gram (*Cicer arietinum*), groundnut (*Arachis hypogaea*) and brassica (*Brassica rapa*).

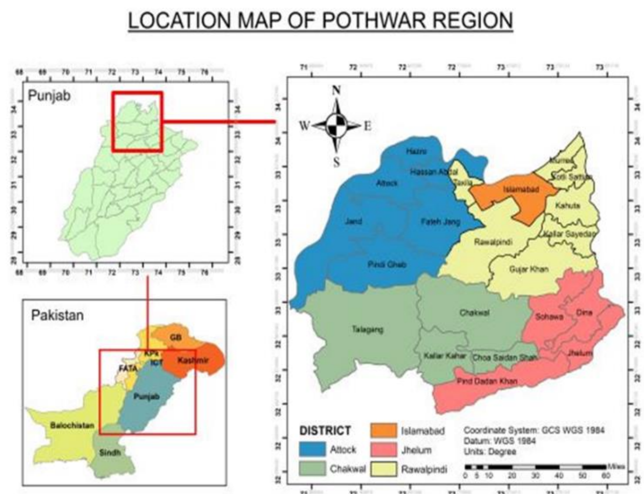

Figure 1. Location map of the study area.

***Land cover mapping and phenology*:** In order to map land cover and trends in land surface phenology of the croplands, Landsat 8 satellite data was used. All the data analyses were carried out in Google Earth Engine (GEE) platform. The dataset used was calibrated top-of-atmosphere (TOA) reflectance (Collection 1 Tier 1) from Landsat 8 imagery. The reflectance is calculated on the calibration coefficients defined by Chander *et al*. (2009). The study area is covered by World Referencing System (WRS) path 150 and row 37. For developing land cover an image acquired 17th March 2017 was used (landsat ID: LC08_L1TP_150037_20170317_20170328_01_T1) that contained <1% cloud cover. All the available imagery (n=77) was used for the analysis of land surface phenology trends. The selected images from year 2012 to 2016 were processed using Earth Engine API.

***Cloud removal*:** Some of the acquired data becomes inaccurate due to presence of cloud cover over the study area which hinders the satellite assessment of the region. It is termed as noise in the data. Such regions were masked by removing clouds. In this study, all these bad observations were masked using Landsat 8 quality assessment band

(Scaramuzza *et al.,* 2012; Roy *et al.,* 2014). The masked correction of bad observations is classified in four levels including “not determined” (Algorithm did not determine the status of this condition), “no” (0–33% confidence), “maybe” (34–66% confidence), and “yes” (67–100% confidence) (Dong *et al.,* 2016). We used the 67–100% confidence level to exclude all the potential bad observation effects from clouds and cirrus. It helped to obtain 97.8% accuracy of results.

***Spectral indices*:** The time series of Landsat TOA image collection was used to calculate three vegetation indices, including NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index) and MNDWI (Modification of Normalized Difference Water Index). The spectral indices were calculated using following equations:

$$\mathrm{NDVI}\left(\frac{B5-B4}{B5+B4}\right);\ldots\ldots\ldots\ldots\ldots\text{eq (1)}$$

$$\mathrm{NDWI}\left(\frac{B3-B5}{B3+B5}\right);\ldots\ldots\ldots\ldots\ldots\text{eq (2)}$$

$$\mathrm{MNDWI}\left(\frac{B5-B4}{B5+B4}\right),\ \mathrm{MNDWI}\left(\frac{B3-B7}{B3+B7}\right)\ldots\ldots\text{eq (3)}$$

Gaps in the original NDVI were filled using linear and harmonic regression models.

***Linear regression*:** Google Earth Engine contains a variety of methods for performing linear regression. Linear regression model gives the fitted values out of original NDVI values in a linear trend. Linear model only describes the trend on the values being increasing or decreasing over a certain period of time. The linear trend was calculated in Earth Engine using the following equation:

$$pt = \beta 0 + \beta 1t + et\ldots\ldots\ldots\ldots\text{eq (4)}$$

Where, pt is NDVI at time, t is time and et is random error. The missing data in the original NDVI were filled using this model. This was shown as the fitted value in the graph. Linear regression equation was used in the script in order to show the increasing and decreasing trend for NDVI value.

***Harmonic regression*:** In order to extract the phase and amplitude using windowed fourier analysis for seasonal trend analysis, a script was developed in Earth Engine Code editor whereby the equation of harmonic regression was incorporated along with linear regression trend. The number of harmonic cycle taken was two. This equation of harmonic regression is as follows;

$$Y=\beta_0+cT+\sum_{i=1}^{n} A_i \mathrm{Sin}\left(\frac{2\pi i}{s}T\right)+\varphi_i \qquad \ldots\text{eq (5)}$$

Where Y is the NDVI, β0 is an offset, c is the trend, Ai is the amplitude of the *i*th oscillation, φi is the phase component of the *i*th oscillation, s is the fundamental frequency and T is the time-dependent variable. The peak of annual greenness was represented by the amplitude while the timing of the peak NDVI value was represented by phase.

***Seasonal trend analysis*:** Seasonal trend analysis is a two stage process to describe seasonal NDVI cycle. First stage dealt with obtaining amplitude 0 (mean annual greenness) and amplitude 1 (peak of annual greenness) by performing harmonic regression on each pixel of 5- year NDVI time series with temporal window of one year. Phase 0 and phase 1 were obtained in the second stage relevant to amplitude 0 and amplitude 1. Values for phase image ranges from 0 to 359 degrees and after every 30 degrees a change of one calendar month is represented (Eastman *et al.*, 2009). The equation utilized in script for seasonal trend analysis is expressed as follows;

$$y = \alpha_0 \sum\nolimits_n \left\{a_n \sin\left(\frac{2\pi nt}{T}\right) + b_n \cos\left(\frac{2\pi nt}{T}\right)\right\} + e \qquad \text{eq (6)}$$

Where, t is time, T is the interval of time-series, n is a harmonic multiplier, e is an error term, α_0 is the series mean and a_n and b_n are regression parameters.

***Digital image classification*:** To classify the land cover of Potohar, complex pixels of satellite image containing multiple spectral bands and range of millions of colours, were classified into definite number of classes. Earth engine classifier package handled the pixels using CART classifier to generate land cover maps. It fundamentally separated the forest and non-forest areas.

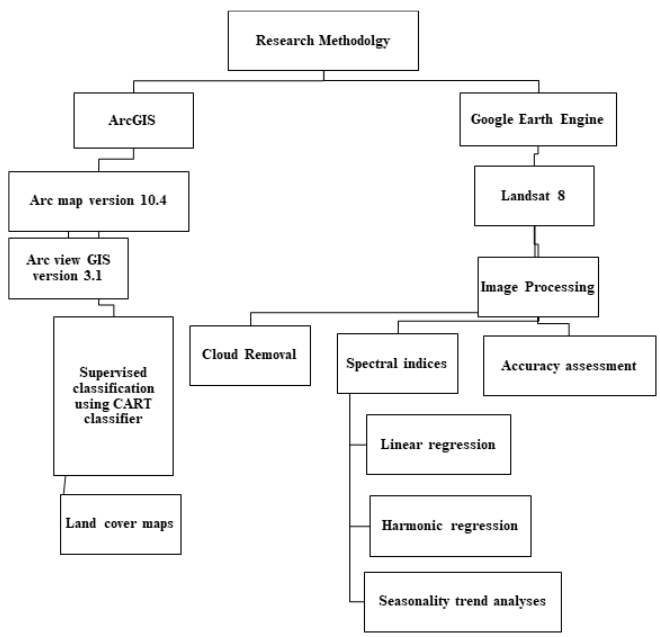

Figure 2. Schematic flow of the methodology.

RESULTS AND DISCUSSION

***Land cover classification*:** The supervised classification of satellite images of Potohar distinguished seven types of land cover. Figure 3 illustrates these types along with the area covered by each land cover type. Land cover types identified included agriculture, grasses, tree/forest, shrubs/tall herbs, bare soil/rocks, built-up and water bodies. Some of the area remained unclassified due to research time and resource constraints.

Area that each of the land type covered was calculated separately for five districts of Potohar namely Chakwal, Attock, Rawalpindi, Jhelum and Islamabad. Percentage of the area covered in each district is mentioned in Table 1 while Figure 4 shows the same in kilometre square (km^2).

Table 1. List of land cover distribution (in percentage) in districts of Potohar in year 2017.

Land cover types	Islam-abad	Attock	Chak-wal	Jhelum	Rawal-pindi
Agriculture	37.32%	69.17%	68.65%	37.35%	38.52%
Grasses	16.42%	7.88%	7.46%	14.38%	16.13%
Trees/Forests	19.85%	16.11%	17.03%	30.78%	29.45%
Shrubs/Tall herbs	13.81%	2.69%	3.10%	5.69%	10.94%
Bare soil/Rocks	3.01%	1.05%	1.35%	5.79%	1.58%
Built-up	8.94%	2.76%	2.25%	5.55%	3.29%
Water	0.66%	0.35%	0.17%	0.45%	0.09%

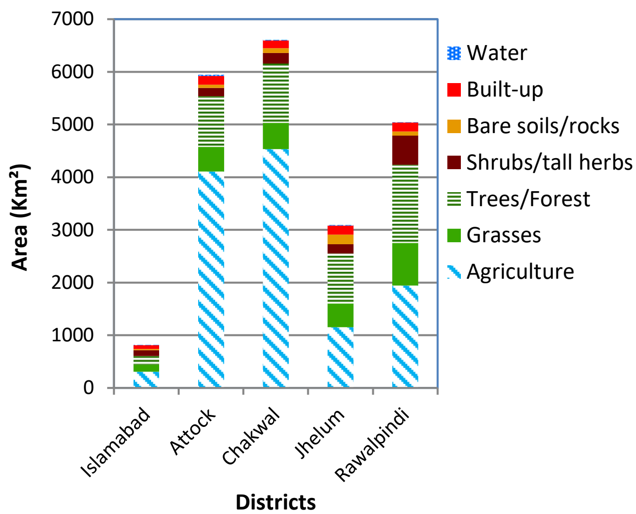

Figure 4. Illustration of Land cover distribution in each district of Potohar Region in kilometre square (Km^2) in year 2017.

***Accuracy assessment*: The overall accuracy of the land cover map was 97.81% with value 0.971 for Kappa quotient, and 0.9903 was the maximum possible un-weighted Kappa given the observed marginal frequencies. At 0.95 confidence interval upper values in both methods 1 and 2 were 0.9832 and lower values were 0.9586. Both the accuracies, 'Producer and User', were greater than 94% for all the land cover classes except for class 'grasses' that have producer accuracy 91.61% as shown in Table 2.**

***Seasonal trend analysis*: The first harmonic cycle indicates the first half of the year (from January to June) in terms of phase 1 and the second harmonic cycle indicates the latter half of the year (from July to August) in terms of phase 2. Figure 5 visualizes phase 1 trend analysis while Figure 6 illustrates this trend over agricultural land.**

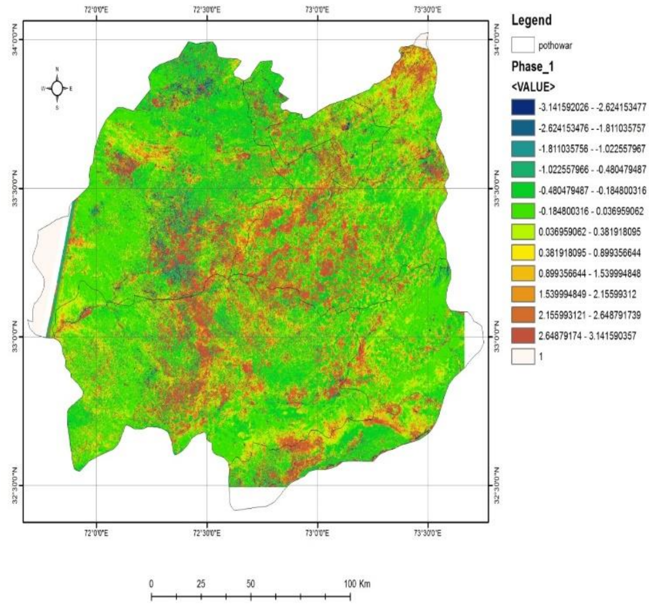

Figure 5. Map of Potohar region illustrating phase 1 trend analysis (2012 - 2016).

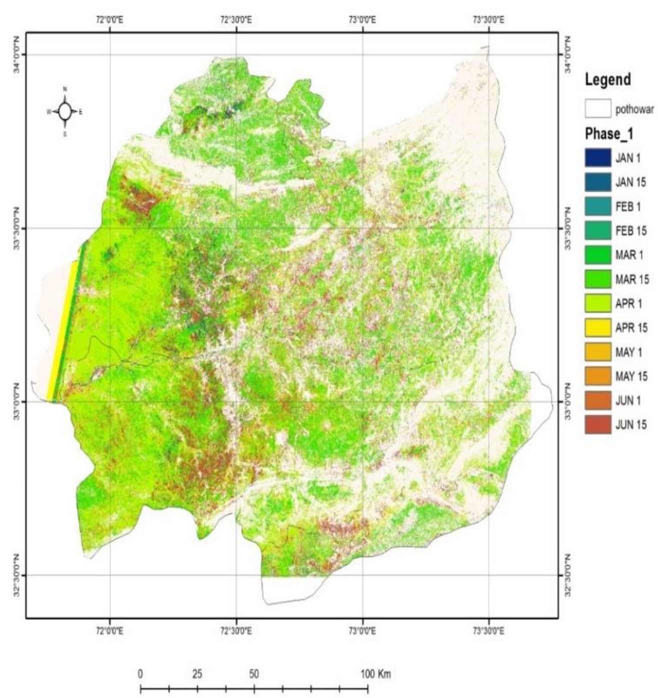

Figure 6. Map of Potohar region illustrating phase 1 trend over agricultural land cover (2012 - 2016).

Phase 2 trend is shown in Figure 7 & 8. The shades of the resulted phase maps illustrate months of the year. The colour codes for each month of phase 1 and phase 2 are mentioned in Tables 3 & 4.

Table 2. Error matrix for land cover classification showing accuracy assessment of the results in terms of user accuracy, producer accuracy and overall accuracy with Kappa=0.971.

Land cover	1	2	3	4	5	6	7	Total	Useraccuracy
1. Agriculture	340	8	0	0	1	0	0	349	97.42%
2. Grasses	6	142	1	0	0	0	0	149	95.30%
3. Trees/Forest	0	5	264	0	0	0	0	269	98.14%
4. Shrubs/Tall Herbs	0	0	0	88	0	0	0	88	100.00%
5. Bare Soil/Rocks	0	0	0	0	19	0	0	19	100.00%
6. Built-up	0	0	0	0	0	47	0	47	100.00%
7. Water	0	0	0	0	0	0	38	38	100.00%
Total possible	346	155	265	88	20	47	38		
Omissions	6	13	1	0	1	0	0		
Commissions	9	7	5	0	0	0	0		
Correctly Classified	340	142	264	88	19	47	38		
Producer Accuracy	98.27%	91.61%	99.62%	100.00%	95.00%	100.00%	100.00%		Overall Accuracy = 97.81%

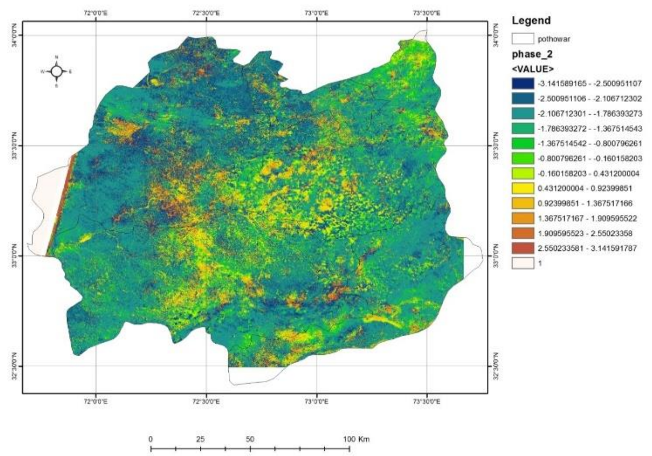

Figure 7. Map of Potohar region illustrating phase 2 trend analysis (2012 - 2016).

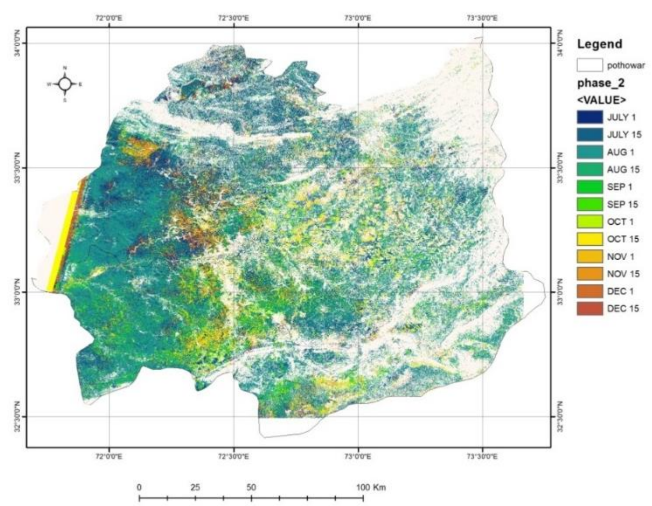

Figure 8. Map of Potohar region illustrating phase 2 trend over agricultural land cover (2012 - 2016).

Table 3. List of colour codes with their identical description for phase 1.

Colour Identity	Description
Dark Blue	peak beginning of January
Moderate Blue	Middle of January
Light Blue	peak beginning of February
Sea Green	Middle of February
Dark Green	peak beginning of March
light green	Middle of March
Lime Green	peak beginning of April
Bright Yellow	Middle of April
Orange	peak beginning of May
Dark Orange	Middle of May
moderate Brown	peak beginning of June
Maroon	Middle of June

Table 4. List of colour codes with their identical description for phase 2.

Colour Identity	Description
Dark Blue	peak beginning of July
Moderate Blue	Middle of July
Light Blue	peak beginning of August
Sea Green	Middle of August
Dark Green	peak beginning of September
light green	Middle of September
Lime Green	peak beginning of October
Bright Yellow	Middle of October
Orange	peak beginning of November
Dark Orange	Middle of November
moderate Brown	peak beginning of December
Maroon	Middle of December

Overall seasonality of the area is shown in Figure 9. In simple RGB model crop phenology of different land covers in the study area is displayed. This phenological trend is shown via graphs in Figures 10-15 using random points throughout the study area.

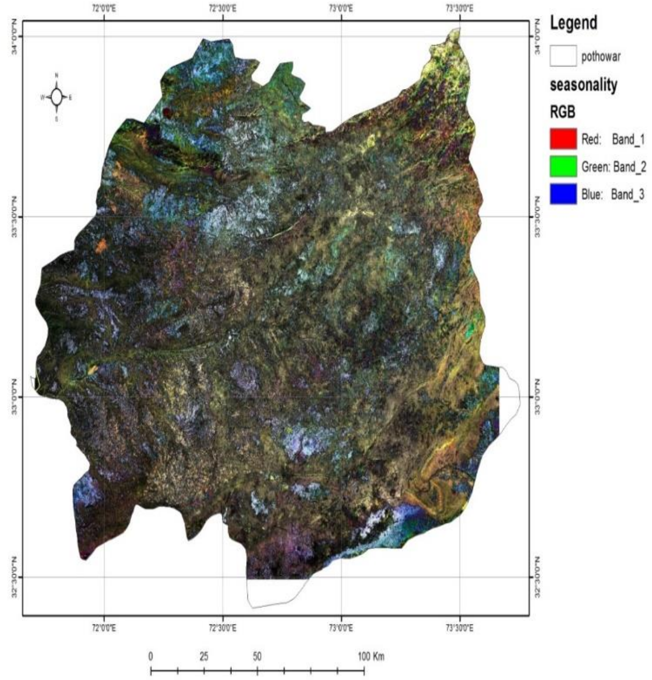

Figure 9. Map of Potohar region illustrating seasonality trend analysis (2012 - 2016).

***Precipitation correlation*:** The productivity of Potohar region was correlated with precipitation as it is a *barani* area. Figure 16 displays the change in productivity immediately after precipitation. In Figure 17, map of correlation lag 17 is displayed which shows the change in NDVI 17 days after the precipitation. Similarly in Figure 18, lag 30 map shows the change 30 days later.

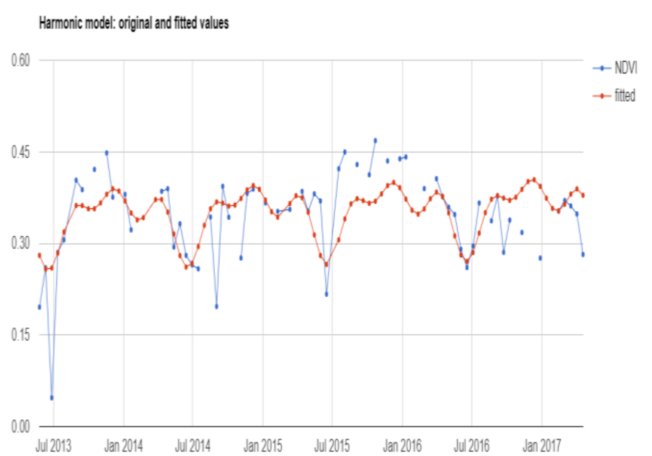

Figure 10. Illustration of phenological trend in forest cover near Attock district.

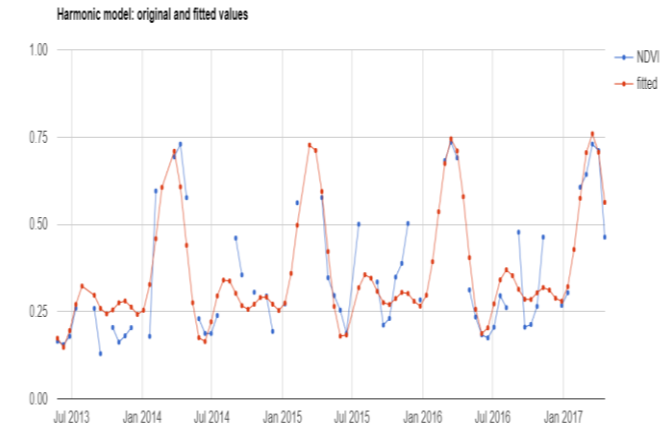

Figure 11. Illustration of phenological trend in agricultural field in Chakwal district.

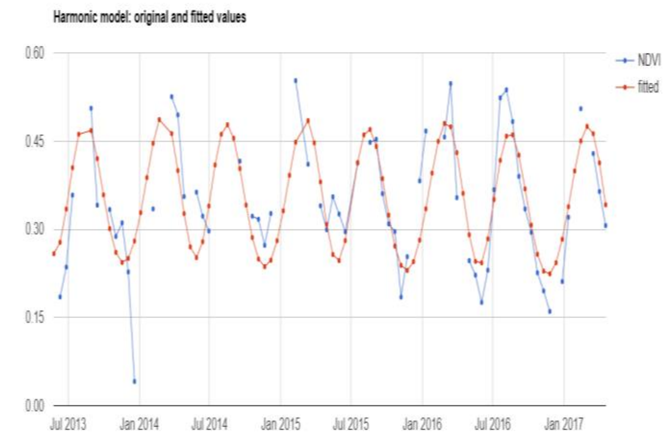

Figure 12. Illustration of phenological trend in crop field of Jhelum district.

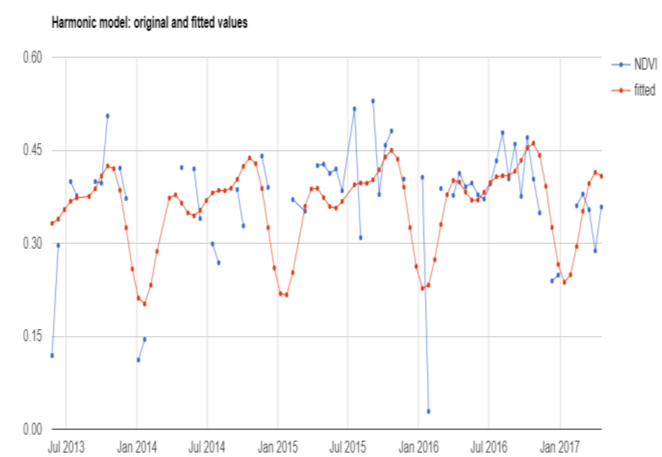

Figure 13. Illustration of phenological trend in evergreen forest at foothills of Himalayas.

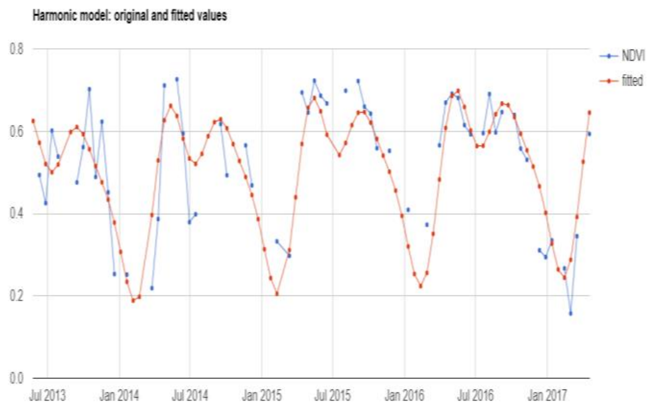

Figure 14. Illustration of phenological trend in forest near Rawal Lake, Islamabad.

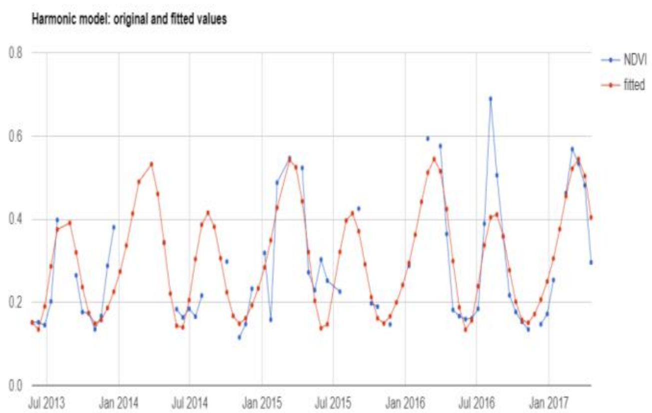

Figure 15. Illustration of NDVI trend in urban built-up of Rawalpindi district.

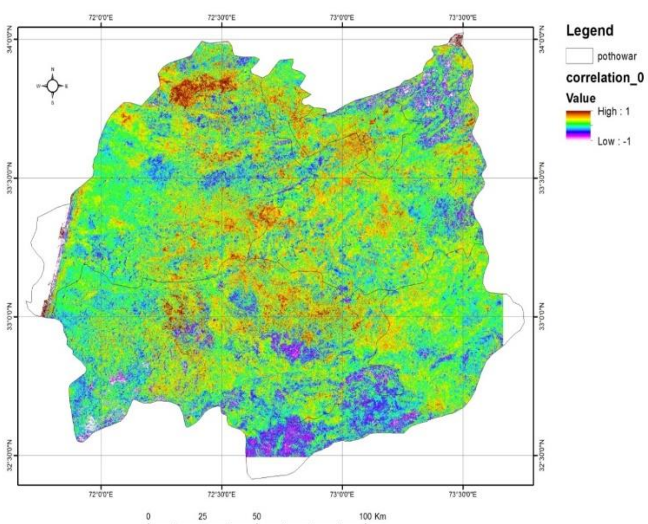

Figure 16. Map illustrating precipitation correlation at lag 0 with changing NDVI.

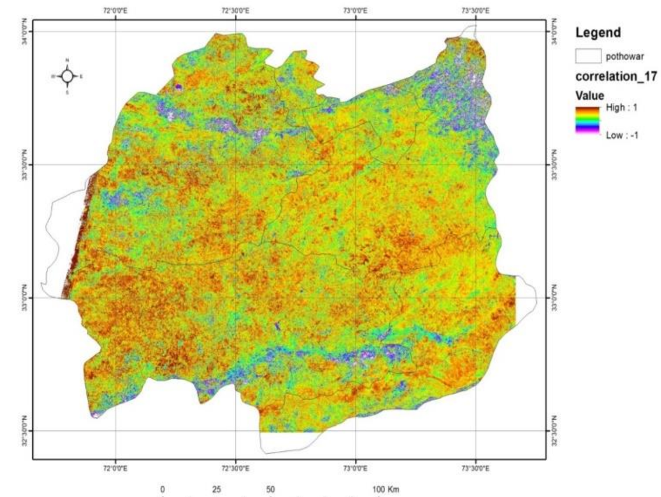

Figure 17. Map illustrating precipitation correlation at lag 17 with changing NDVI.

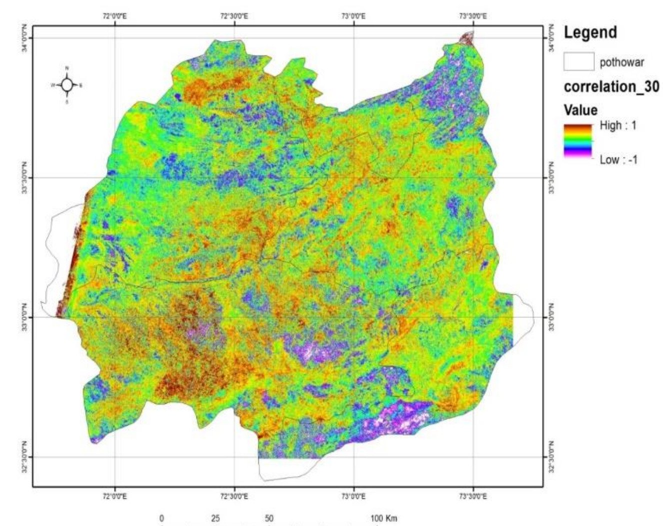

Figure 18. Map illustrating precipitation correlation at lag 30 with changing NDVI.

To characterize seasonal trend and crop phenology of Potohar region, satellite-derived time-series data was utilized. A very interesting crop phenology trend was found to be obtained in Figures 5 & 6. A negative NDVI value describes an early season of the year indicated by blue colour, while, red colour in the map having positive NDVI values indicate the peak of the season (Fig. 5). In Figure 6, first harmonic cycle completing in June shows the phenology of a crop which possibly has a harvest time period in March or April as most of the study area was represented in green which shows a mean NDVI value. Wheat crop is an abundant crop in Potohar which possibly describes the obtained NDVI value for March and April (Kazmi and Rasul, 2006). The similar trend is followed in Figures 7 & 8, whereas, in July the early season

Annexure 1. Showing the codes (JAVA Script) and procedural measures adopted for data acquisition and processing.

Processing	Code

Image processing
Satellite data Acquisition
Year: 2012-2016
Bands Used: 1, 2, 3, 4, 5 & 7
Worldwide Reference System: WRS 2: 150/37
	//Landsat Data
	VarNAME=ee.imageCollection('LANDSAT/LC8_L1T_TOA')
	.filterData('2012-01-01');
	.filter(ee.Filter.eq('WRS_PATH', 150));
	.filter(ee.Filter.eq('WRS_ROW', 37y));
	//Band Selection
	var bands = ['B1','B2','B3','B4','B5','B7'];

Cloud Removal	var image = ee.ImageCollection('LANDSAT/LC8_L1T_TOA')
	//selected year cloud remove
	.sort('CLOUD_COVER')
	.map(maskClouds)

Spectral Indices
NDVI $\left(\frac{B5-B4}{B5+B4}\right)$;…………eq (1)
NDWI $\left(\frac{B3-B5}{B3+B5}\right)$;………...eq (2)
MNDWI $\left(\frac{B3-B7}{B3+B7}\right)$……..…eq (3)
	
	var ndvi = image.normalizedDifference(['B4','B5']);
	var ndwi = image.normalizedDifference(['B3','B5']);
	var mndwi = image.normalizedDifference(['B3','B7']);

Land Cover Classification	var trainingImage = ee.Image([image.select('B1'),
	image.select('B2'),
	image.select('B3'),
	image.select('B4'),
	image.select('B5'),
	image.select('B7'),
	ndbi.rename('ndbi'),
	ndvi.rename('ndvi'),
	mndwi.rename('mndwi'),
	Map.centerObject(roi);
	Map.addLayer(trainingImage,vizParams,'True-color composite',false);
	Map.addLayer(trainingImage,{'bands':['ndvi','ndbi','mndwi'],
	'min':-1,'max':1},'NDXI composite',false);
	/*
	//Classification starts Here
	print(trainingImage);
	// Image classification
	var predictionBands = trainingImage.bandNames();
	print(predictionBands);
	var trainingFeatures = agriculture //1
	.merge(grasses) //2
	.merge(trees) //3
	.merge(shrubs) //4
	.merge(bare) //5
	.merge(builtup) //6
	.merge(water); //8
	var classifierTraining = trainingImage
	.select(predictionBands)
	.sampleRegions({collection: trainingFeatures,
	properties: ['landcover'],
	scale: 30
	});
	// train the classifier
	var classifier = ee.Classifier.cart().train({
	features: classifierTraining,
	classProperty: 'landcover',
	inputProperties: predictionBands
	});

Accuracy Assessment on the basis of classification	print(classifier.explain());
	var confusionMatrix = classifier.confusionMatrix()
	var accuracy = confusionMatrix.accuracy()
	print(confusionMatrix,accuracy);

Linear regression formulation	ee.Reducer.linearFit()
Export result for further image processing	Export.image.toDrive({ image: classified, description: 'classified_image', scale: 30, region: roi });

shows negative NDVI trends indicating the sowing of a crop. The other intermediate shades between blue and red indicate the presence of other minor crops.

Crop phenology study was conducted to determine the start and end of seasons of various crops in Potohar and their relation with the land cover and precipitation. Random points taken from the study area revealed the patterns of vegetation in various land cover types. A sub-tropical deciduous forest in Attock sheds its leaves in the start of dry season so as to retain water to survive in harsh weather conditions and drought. The seasonal trend didn't show a very high change in NDVI showing the stable nature of the forest cover. The agricultural field in Chakwal shows crop phenology by exhibiting changes in NDVI. Wheat has the harvesting period from March to May during which it shows decrease in NDVI value and then in sowing period from October to November, it shows high increase in NDVI. The other minor fluctuations show the presence of grasses in the field. The crop field of Jhelum displays the phenologies of wheat and maize in the area indicating high increase in NDVI in November till March for wheat and from July till October or November for maize crop. An evergreen forest on the foothills of Himalaya was taken as the comparison between NDVI of deciduous and evergreen forest. Evergreen forest indicated a very minor fluctuation in NDVI throughout the year with decreasing trend in winters due to snow cover. Forest vegetation near Rawal Lake was taken to determine the relation of water body with the changing NDVI. The trends in NDVI show increase, only minor, in value during monsoon and winter rains when lake is filled by the precipitation and decrease in values in dry seasons. Near urban areas of Rawalpindi, the vegetation either consists of grasses or they may be small private crop fields showing negligible change in NDVI.

In Figures 16, 17 and 18, the productivity of the crops is correlated with precipitation. The areas having positive values indicate that the increase in precipitation increases the productivity. Such areas are arid having water scarcity and dependant on precipitation as water source. Those having negative correlation show that the productivity decreases as the precipitation increases while those having zero values for correlation mean, it is not dependant on precipitation. In Figure 17, map of correlation lag 17 is displayed, which shows the change in NDVI 17 days after the precipitation. Similarly in Figure 18, lag 30 map shows the change 30 days later. Lag 17 maps indicated high correlation in dense agricultural lands and forest covers near urban settings showing human induced changes in the area. Lag 30 maps indicated the high values of correlation for agricultural lands and moderate for urban settings. Correlation values for forest covers in moist environments remained low while for arid and dry climatic regions like Attock, precipitation seemed to have high impact. Mishra and Chauhdary (2014) also discussed in their study about the precipitation correlation with seasonality analysis showing increase in brownness due to changing precipitation patterns due to anthropogenic activities.

***Conclusion*:** The underlying goal of this research was to evaluate the seasonality shift and land cover classes in Potohar. Using the refined resolution of Landsat 8 (30m), the vegetation indices were studied for an assessment of land cover activity based on time series trend analysis. The long term seasonality trend helped to monitor and identify the factors which are responsible for land cover changes in Potohar. The results have shown the seasonality shift based on land cover change with the accuracy of Kappa= 0.9781. The vegetation alongwith the urban setting had shown shift in the values of NDVI, while the forest cover away from urban area had quite stable seasonality trend. The agricultural land, however, showed different NDVI trends for different crops depending upon their start of season. On the basis of these results, it is incurred that, vegetation in different land cover types is dependent upon the prevailing environment in the particular land cover type. Land use and land change is highly associated with the changing environment especially in the context of climate change.

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