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Spectral Characteristics and Mapping of Rice Fields using Multi-Temporal Landsat and MODIS Data: A Case of District Narowal

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Abstract- Availability of remote sensed data provides powerful access to the spatial and temporal information of the earth surface. Real-time earth observation data acquired during a cropping season can assist in assessing crop growth and development performance. As remote sensed data is generally available at large scale, rather than at field-plot level, use of this information would help to improve crop management at broad-scale. Utilizing the Landsat TM/ETM+ ISODATA clustering algorithm and MODIS (Terra) the normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) datasets allowed the capturing of relevant rice cropping differences. In this study, we tried to analyze the MODIS (Terra) EVI/NDVI (February, 2000 to February, 2013) datasets for rice fractional yield estimation in Narowal, Punjab province of Pakistan. For large scale applications, time integrated series of EVI/NDVI, 250-m spatial resolution offer a practical approach to measure crop production as they relate to the overall plant vigor and photosynthetic activity during the growing season. The required data preparation for the integration of MODIS data into GIS is described with a focus on the projection from the MODIS/Sinusoidal to the national coordinate systems. However, its low spatial resolution has been an impediment to researchers pursuing more accurate classification results and will support environmental planning to develop sustainable land-use practices. These results have important implications for parameterization of land surface process models using biophysical variables estimated from remotely sensed data and assist for forthcoming rice fractional yield assessment.

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SPECTRALCHARACTERISTICSANDMAPPINGOFRICEFIELDSUSINGMULTI-TEMPORALLANDSATANDMODISDATAACASEOFDISTRICTNAROWAL

Strictly as per the compliance and regulations of:

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I. Introduction

Remote sensing dataset offers unique possibilities for spatial and temporal characterization of the changes. The fundamental requirement is the availability of different dates of satellite imagery which permits continuous monitoring of change and environmental developments over time (Lu et al., 2004; Nasr and Helmy, 2009; Ahmad, 2012b; Ahmad et al., 2013). RS sensor is a key device that captures data about an object or scene remotely. Since objects have their unique spectral features, they can be identified from RS imagery according to their unique spectral characteristics (Xie, 2008; Ahmad and Shafique, 2013; Ahmad et al., 2013). A good case in vegetation mapping by using RS technology is the spectral radiances in the red and near-infrared (NIR) regions, in addition to others (Ahmad et al., 2013). The radiances in these regions could be incorporated into the spectral vegetation indices (VI) that are directly related to the intercepted fraction of photosynthetically active radiation (Asrar et al., 1984; Galio et al., 1985; Xie, 2008; Ahmad and Shafique, 2013; Ahmad et al., 2013). The spectral signatures of photosynthetically and non-photosynthetically active vegetation showed obvious difference and could be utilized to estimate forage quantity and quality of grass prairie (Beeri et al., 2007; Xie, 2008; Ahmad and Shafique, 2013).

RS is the technology that can give an unbiased view of large areas, with spatially explicit information distribution and time repetition, and has thus been widely used to estimate crop yield and offers great potential for monitoring production, yet the uncertainties associated with large-scale crop yield (Quarmby et al., 1993; Báez-González et al., 2002; Doraiswamy et al., 2003; Ruecker et al., 2007; Ahmad and Shafique, 2013a) estimates are rarely addressed (Ahmad et al., 2013).

RS dataset of better resolution at different time interval helps in analyzing the rate of changes as well as the causal factors or drivers of changes (Dai and Khorram, 1999; Ramachandra and Kumar, 2004; Ahmad, 2012b). Hence, it has a significant role in planning at different spatial and temporal scales. Change detection in agricultural planning helped in enhancing the capacity of local governments to implement sound environmental management (Prenzel and Treitz, 2004; Ramachandra and Kumar, 2004; Ahmad, 2012b). This involves development of spatial and temporal database and analysis techniques. Efficiency of the techniques depends on several factors such as classification schemes, modelling, spatial and

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spectral resolution of RS data, ground reference data and also an effective implementation of the result (Ramachandra and Kumar, 2004; Ahmad, 2012b). Natural resources in the arid environment are declining in productivity and require special attention, and if the ecological condition persists, a further decline in resources may result in land degradation (Babu et al., 2011).

Preprocessing of satellite datasets prior to vegetation extraction is essential to remove noise (Schowengerdt, 1983; Ahmad and Shafique, 2013) and increase the interpretability of image data (Campbell, 1987; Schowengerdt, 2006; Ahmad and Shafique, 2013). The ideal result of image preprocessing is that all images after image preprocessing should appear as if they were acquired from the same sensor (Hall et al., 1991; Xie, 2008; Ahmad and Shafique, 2013). Image preprocessing commonly comprises a series of operations, including but not limited to bad lines replacement, radiometric correction, geometric correction, image enhancement and masking although variations may exist for images acquired by different sensors (Schowengerdt, 1983; Campbell, 1987; Xie, 2008; Ahmad and Shafique, 2013). Long-term observations of remotely sensed vegetation dynamics have held an increasingly prominent role in the study of terrestrial ecology (Budde et al., 2004; Prasad et al., 2007; Ouyang et al., 2012; Ahmad, 2012a).

The development of long-term data records from multi-satellites/multi-sensors is a key requirement to improve our understanding of natural and human-induced changes on the Earth and their implications (NRC, 2007; Miura et al., 2008; Ahmad, 2012c). A major limitation of such studies is the limited availability of sufficiently consistent data derived from long-term RS (Ouyang et al., 2012; Ahmad, 2012a; Ahmad et al., 2013). The benefit obtained from a RS sensor, largely depends on its spectral resolution (Jensen, 2005; Ahmad, 2012a; Ahmad et al., 2013), which determines the sensor's capability to resolve spectral features of land surfaces (Fontana, 2009; Ahmad, 2012a; Ahmad et al., 2013). One of the key factors in assessing vegetation dynamics and its response to climate change is the ability to make frequent and consistent observations (Thomas and Leason, 2005; Ouyang et al., 2012; Ahmad, 2012a; Ahmad et al., 2013).

Landsat ETM+ has shown great potential in agricultural mapping and monitoring due to its advantages over traditional procedures in terms of cost effectiveness and timeliness in availability of information over larger areas (Murthy et al., 1998; Rahman et al., 2004; Adia and Rabiu, 2008; Ahmad, 2012d) and ingredient the temporal dependence of multi-temporal image data to identify the changing pattern of vegetation cover and consequently enhance the interpretation capabilities. Integration of multi-sensor and multi-temporal satellite data effectively improves the temporal attribute and the accuracy of results (Adia and Rabiu, 2008; Ahmad, 2012d).

The MODIS (Terra) NDVI (Rouse et al., 1973) and EVI (Liu and Huete, 1995; Justice et al., 1998; Huete et al., 1999) datasets provide unique opportunities for monitoring terrestrial vegetation conditions at regional and global scales (Yang et al., 1997; Piao et al., 2006; Ahmad, 2012a; Ahmad et al., 2013), and has widely been used in research areas of net primary production (Potter et al., 1993; Paruelo et al., 1997; Piao et al., 2006; Ahmad, 2012a; Ahmad et al., 2013), vegetation coverage (Tucker et al., 1991; Myneni et al., 1997; Los et al., 2001; Zhou et al., 2001; Piao et al., 2003; Piao et al., 2006; Ahmad, 2012a; Ahmad et al., 2013), biomass (Myneni et al., 2001; Dong et al., 2003; Piao et al., 2006; Ahmad, 2012a; Ahmad et al., 2013), and phenology (Reed et al., 1994; Moulin et al., 1997; Piao et al., 2006; Ahmad, 2012a; Ahmad et al., 2013).

Multi-year time series of EVI/NDVI can reliably measure yearly-changes in the timing of the availability of high-quality vegetation. The biological significance of NDVI indices should be assessed in various habitat types before they can be widely used in ecological studies (Hamel et al., 2009; Ahmad, 2012a). The premise is that the NDVI is an indicator of vegetation health, because degradation of ecosystem vegetation, or a decrease in green, would be reflected in a decrease in NDVI value (Hamel et al., 2009; Meneses-Tovar, 2011; Ahmad, 2012a). The NDVI has the potential ability to signal the vegetation features of different eco-regions and provides valuable information as a RS tool in studying vegetation phenology cycles at a regional scale (Guo, 2003; Ahmad, 2012a).

The NDVI is established to be highly correlated to green-leaf density and can be viewed as a proxy for above-ground biomass (Tucker and Sellers, 1986; Ahmad, 2012e). The NDVI is the most commonly used index of greenness derived from multispectral RS data (USGS, 2010; Ahmad, 2012e), and is used in several studies on vegetation, since it has been proven to be positively correlated with density of green matter (Townshend et al., 1991; Huete et al., 1997; Huete et al., 2002; Debien et al., 2010; Ahmad, 2012e). The NDVI provides useful information for detecting and interpreting vegetation land cover it has been widely used in RS studies (Dorman and Sellers, 1989; Myneni and Asrar, 1994; Gao, 1996; Sesnie et al., 2008; Karaburun, 2010; Ahmad, 2012f; Ahmad and Shafique, 2013a; Ahmad et al., 2013).

The NDVI is chlorophyll sensitive; the EVI (Liu and Huete, 1995; Justice et al., 1998; Huete et al., 1999; Ahmad et al., 2013) is more responsive to canopy structural variations, including canopy type, plant physiognomy and canopy architecture (Gao et al., 2000; Huete et al., 2002; Ahmad et al., 2013). The two VIs complement each other in global vegetation studies and improve upon the detection of vegetation changes and extraction of canopy biophysical parameters (Huete et al., 1999; 2002; Ahmad et al., 2013).

a) Study Area:

The District Narowal (Figure 1; 2) lies in the Punjab province of Pakistan from 31° 55' to 32° 30' North latitude and 74° 35' to 75° 21' East longitude. The district is bounded on the north-west by Sialkot district, on the north by Jammu State, on the east by Gurdaspur district (India) and on the south by Amritsar district (India) and Sheikhupura district (GOP, 2000).

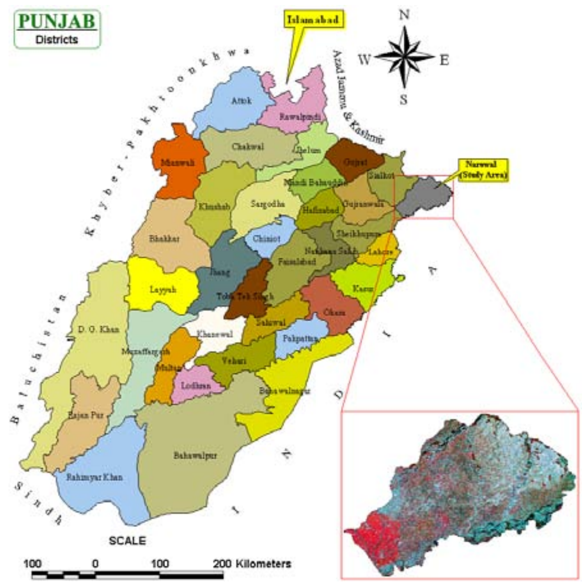

Figure 1 : Location Map of the Study Area

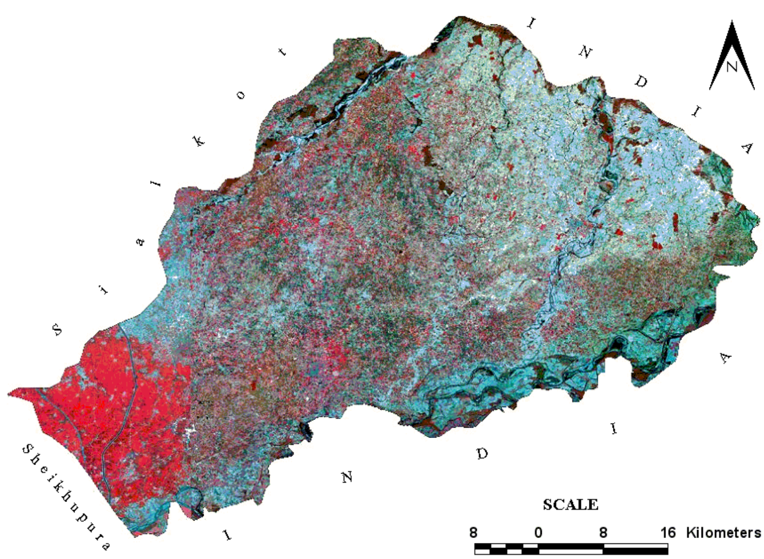

Figure 2 : Narowal - Landsat ETM+ 30th September, 2001 image *Source: http://glovis.usgs.gov/*

b) Physical Features:

The general aspect of the district is a plain slopping down from the uplands at the base of the Himalayas to the level country to the south-west (Figure 3), and the general altitude is 266 meters above sea level (GOP, 2000; Shah, 2007).

Bounded on the south-east by the river Ravi, the district is fringed on the either side by a line of fresh alluvial soil, about which rise the low banks that form the limits of the river bed. At about a distance of 24 km from Ravi, another stream, the Dake which rises in the Jammu hills traverses the district. The district is practically a level plain. Its north-eastern boundary is at a distance of about 32 km from the outer line of the Himalayas, but the foot-hills stop short of the district and its surface is level plain broken only by the river Ravi, by the Aik and Dake streams and a few *nullahs* that are little more than drainage channels. The general slope as indicated by the lines of drainage is from north-east to south-west (GOP, 2000).

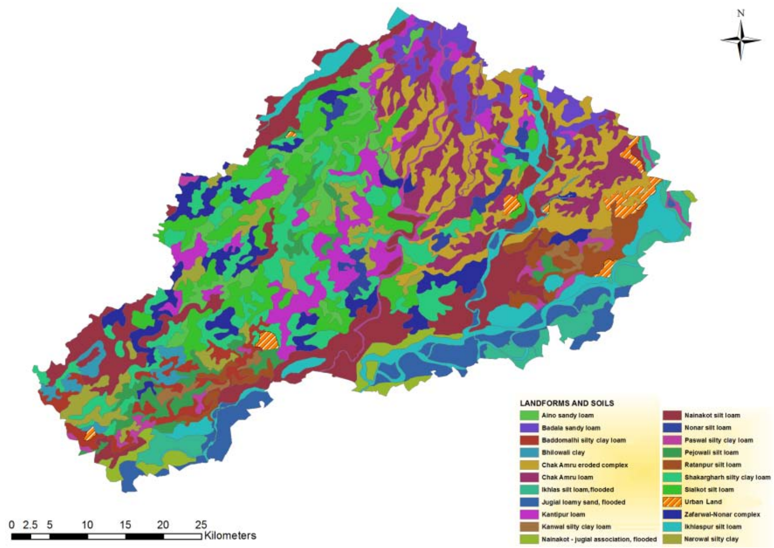

Figure 3 : Landforms and Soils, Narowal District *Source: After Shah, 2007*

II. Research Design and Methods

In this research, Landsat TM/ETM+ (path 148, row 38; path 149, row 38) scenes of 30th September, 2001 and 2nd November, 2010 was used to detect and identify the rice-pixels and paddy cropped areas in Narowal. The fundamental steps are: image registration and image enhancement (Macleod and Congalton, 1998; Mahmoodzadeh, 2007; Al-Awadhi et al., 2011). The scene was corrected and geo-referenced using projection UTM, zone 43 and datum WGS 84.

To monitor the cultivated land under different environmental conditions, RS has been approved the best technology (Heller and Johnson, 1979; Eckhardt et al., 1990; Pax-Lenney et al., 1996; DeFries et al., 1998; Lobell et al., 2003; Thenkabail et al., 2005; Alexandridis et al., 2008; Ozdogan and Gutman, 2008; Thenkabail et al., 2009; Ozdogan et al., 2010). RS provides synoptic coverage of paddy/rice fields with temporal frequencies sufficient to assess growth, maturity, and ripening (Ozdogan and Gutman, 2008; Ozdogan et al., 2010). Satellite dataset is time-consuming and less costly than traditional statistical surveys. This makes particularly valuable for inventories of crop land/crop growth for monitoring, evaluation and assessment (Ozdogan et al., 2010) in developing countries like Pakistan.

Image amplification of satellite dataset also include latest computerized methodologies (Keene and Conley, 1980; Thiruvengadachari, 1981; Kolm and Case, 1984; Haack et al., 1998; Ozdogan et al., 2010). The studies benefit from the strong spectral separation of paddy/rice fields from other crops and fallow land in the visible and NIR portions of the EMS (Ozdogan et al., 2010). Image classification of satellite dataset is useful because the analysis time is shorter and cost associated with mapping is lower. Familiar methods include multi-stage classification (Thelin and Heimes, 1987; El-Magd and Tanton, 2003; Ozdogan et al., 2010), supervised clustering (Kauth and Thomas, 1976; Thelin and Heimes, 1987; Eckhardt et al., 1990; Ozdogan et al., 2010), and density slicing with thresholds (Manavalan et al., 1995; Starbuck and Tamayo, 2007; Ozdogan et al., 2006; Ozdogan et al., 2010). The multi-stage procedure involves classification of land cover at increasingly refined categorical levels following the concept that paddy/rice fields are subclass of cultivated lands, which themselves belong to vegetated landscapes (Ozdogan et al., 2010). As in image augmentation, digital image classification benefits from spectral transformations (Kauth and Thomas, 1976; Eckhardt et al., 1990; Pax-Lenney et al., 1996; Ozdogan et al., 2006; Starbuck and Tamayo, 2007; Ozdogan et al., 2010). In particular, the NDVI proves to be indispensible for identifying crop lands in local scale studies.

The use of the NDVI would comprise direct inclusion into a categorization algorithm as an input feature (Ozdogan et al., 2010). Using dataset from multiple time periods, the prejudice procedure is based on the different spectral responses of crops according to their phenological evolution (Abuzar et al., 2001; Ozdogan et al., 2010). A number of studies have established that using spectral information from two successive seasons in a crop-year is sufficient to identify the paddy/rice fields. However, for each season, the estimates require multiple datasets (Abuzar et al., 2001; Ozdogan et al., 2006; Ozdogan et al., 2010). This is because single-date analysis in visible cropping intensity often does not take into account planting dates that vary from year to year. Therefore, multi-temporal analysis has greater potential to define paddy/rice fields (Akbari et al., 2006; Ozdogan et al., 2010). Eventually, the results of classification are restricted upon the temporal and spatial variability of the spectral signature of the land cover type in question, so suitable datasets must be available for the temporal approach to provide a complete inventory of all crops (Ozdogan et al., 2010).

RS studies of vegetation normally use specific wavelengths selected to provide information about the vegetation present in the area from which the radiance data emanated. These wavelength regions are selected because they provide a strong signal from the vegetation and also have a spectral contrast from most background resources (Tucker and Sellers, 1986). The wavelength region located in the VIS–NIR transition has been shown to have high information content for vegetation spectra (Collins, 1978; Horler et al., 1983; Broge and Leblanc, 2000). The spectral reflectance of vegetation in this region is characterized by very low reflectance in the red part of the spectrum followed by an abrupt increase in reflectance at 700–740 nm wavelengths (Broge and Leblanc, 2000). This spectral reflectance pattern of vegetation is generally referred to as the 'red edge'. The red edge position is likewise well correlated with biophysical parameters at the canopy level, but less sensitive to spectral noise caused by the soil background and by atmospheric effects (Baret et al., 1992; Demetriades-Shah et al., 1990; Guyot et al., 1992; Mauser and Bach, 1994; Broge and Leblanc, 2000).

Leaf water content governs the reflectance properties beyond 1000 nm, but has practically no effect on the spectral properties in the VIS and NIR regions (Broge and Leblanc, 2000). In fact, chlorophyll concentration was sufficient to absorb nearly all of the blue and red radiation. Reflectance in the green (550 nm) and red-edge (715 nm) bands increase significantly as chlorophyll concentration decrease (Daughtry et al., 2000). Variations of leaf dry matter content affects canopy reflectance by increasing or decreasing the multiple intercellular scattering of the NIR rays. However, for practical RS applications, this effect can be assumed to be negligible, because within-crop variations of leaf dry matter content is very stable (Broge and Leblanc, 2000). Soil compaction negatively affects crop growth characteristics (Lowery and Schuler, 1991; Kulkarni and Bajwa, 2005; Ahmad et al., 2013), yield (Johnson et al., 1990; Kulkarni and Bajwa, 2005; Ahmad et al., 2013), and root distribution and development (Taylor and Gardner, 1963; Unger and Kaspar, 1994; Kulkarni and Bajwa, 2005; Ahmad et al., 2013). However, bare soil reflectance may be affected by the impact of tillage practices and moisture content (Barnes et al., 1996; Kulkarni and Bajwa, 2005; Ahmad et al., 2013). The wavelengths detected as responsive to soil compaction were close to each other, they might had similar information about the vegetation vigor. In the red portion of spectrum, the wavelengths ranged from 620 to 700 nm (Thenkabail et al., 2000; Kulkarni and Bajwa, 2005; Ahmad et al., 2013).

The NDVI assumed the most common vegetation index used throughout the history of satellite data applications. The NDVI represents the absorption of photosynthetic active radiation and hence is a measurement of the photosynthetic capacity of the canopy (Rouse et al., 1973; Woomer et al., 2004). The NDVI is computed following the equation:

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}}$$

Where, ρ_{NIR} and ρ_{Red} are the surface bidirectional reflectance factors for their respective MODIS bands. The NDVI is referred to as the 'continuity index' to the existing 20+ year NOAA-AVHRR derived NDVI (Rouse et al., 1973; Ahmad, 2012c) time series (Moran et al., 1992; Verhoef et al., 1996; Jakubauskas et al., 2001; Huete et al., 2002; Zoran and Stefan, 2006; USGS, 2010; Ahmad, 2012c), which could be extended by MODIS data to provide a longer term data record for use in operational monitoring studies (Chen et al., 2003; Ahmad, 2012c). The NDVI has been established to be highly correlated to green-leaf density, absorbed fraction of photosynthetically active radiation and above-ground biomass and can be viewed as a surrogate for photosynthetic capability (Asrar et al., 1984; Tucker and Sellers, 1986; Propastin and Kappas, 2009).

The NDVI values range from -1 to +1; because of high reflectance in the NIR portion of the EMS, healthy vegetation is represented by high NDVI values between 0.1 and 1 (Liu and Huete, 1995; USGS, 2008; 2010; Ahmad, 2012a; Ahmad et al., 2013). On the contrary, non-vegetated surfaces such as water bodies yield negative values of NDVI because of the electromagnetic absorption property of water. Bare soil areas represent NDVI values which are closest to 0 due to high reflectance in both the visible and NIR portions of the EMS (Townshend, 1992; Ahmad, 2012a; Ahmad et al., 2013).

The EVI is an 'optimized index' designed to enhance the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Liu and Huete, 1995; Justice et al., 1998; Huete et al., 1999; Ahmad, 2012c). The EVI is computed following the equation:

$$\mathrm{EVI} = \mathrm{G} \times \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{C1} \times \mathrm{RED} - \mathrm{C2} \times \mathrm{Blue} + \mathrm{L})}$$

Where NIR/RED/Blue are atmospherically-corrected or partially atmosphere corrected (Rayleigh and ozone absorption) surface reflectances, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are; L=1, C1 = 6, C2 =

7.5, and G (gain factor) = 2.5 (Liu and Huete, 1995; Justice et al., 1998; Huete et al., 1999; Huete et al., 2002; Karnieli and Dall'Olmo, 2003; Huete, 2005; Gao and Mas, 2008; Ahmad, 2012c).

The MODIS has been supplying a continuous data stream since 2000, lending to comprehensive time series analysis of the global terrestrial environment (Grogan and Fensholt, 2013). Of the available POES datasets, the MODIS reflectance products are favored among many in the research community with a focus on monitoring regional to global vegetation dynamics. The MODIS has a number of advantages when compared to other moderate-to-course resolution sensors, including superior spatial resolution, a broad spectral range (visible to mid-infrared), and superior geolocational accuracy (Wolfe et al., 2002; Grogan and Fensholt, 2013). One additional attraction to the MODIS dataset is the detailed description of data quality accompanying the products in the form of quality flags, including indicators of cloud cover, cloud shadow, aerosol loading and sensor-solar geometry for both the surface reflectance products (Vermote et al., 2011; Grogan and Fensholt, 2013) and the derived Vegetation Index (VI) composites (Solano et al., 2010; Grogan and Fensholt, 2013).

The MODIS (Terra) EVI/NDVI (MOD13Q1) data products for research area were acquired, in this case data were downloaded from the Land Processes Distributed Active Archive Center (LPDAAC). Tile number covering this area is h24v05, reprojected from the Integerized Sinusoidal projection to a Geographic Lat/Lon projection, and Datum WGS84 (GSFC/NASA, 2003; Ahmad, 2012a; 2012b; Ahmad et al., 2013). A gapless time series of MODIS (Terra) EVI/NDVI composite raster data from February, 2000 to February, 2013 with a spatial resolution of 250 m (Table 1) was utilized for calculation of the rice fractional yield. The datasets provide frequent information at the spatial scale at which the majority of human-driven land cover changes occur (Townshend and Justice, 1988; Verbesselt et al., 2010; Ahmad, 2012a; Ahmad et al., 2013). MODIS products are designed to provide consistent spatial and temporal comparisons between different global vegetation conditions that can be used to monitor photosynthetic activity and forecast crop yields (Vazifedoust et al., 2009; Cheng and Wu, 2011; Ahmad et al., 2013). Details documenting the MODIS (Terra) EVI/NDVI compositing process and Quality Assessment Science Data Sets can be found at NASA's MODIS web site (MODIS, 1999; USGS, 2008; Ahmad et al., 2013). This study explored the suitability of the MODIS (Terra) EVI/NDVI (MOD13Q1) pixels obtained from a paddy/rice cultivated area, Naina Kot over thirteen years (February, 2000 to February, 2013), to explore rice fractional yield (Mulianga et al., 2013).

Table 1 : MODIS (Terra) bands used in this research study

Bandwidth specifications (nm)	Band 1: 620–670
	Band 2: 841–876
Spatial resolution (m)	250
Radiometric resolution (bits)	12
Time window	16-days

ERDAS imagine 2014 and ArcGIS 10.1 software were used for the application of the NDVI model to detect the paddy/rice cropped area and calculation for Landsat TM/ETM+ (path 148, row 38; path 149, row 38) images of 30th September, 2001 and 2nd November, 2010 respectively. The supervised classification was applied upon the image for the estimation of the paddy cropped area. Calculation of paddy crop growth stages (transplanting to maturity and further ripening) using MODIS (Terra) EVI/NDVI pixel values of the selected 11 villages; Bara Manga, Becochak, Boora Dala, Budha Dhola, Fattu Chak, Gumtala, Lalian, Naina Kot, Nathoo Kot, Pherowal, and Talwandi Bhindran were carried out and linear forecast trendline was plotted to identify the variations in the rice fractional yield dataset of Naina Kot from February, 2000 to February, 2013. Standard multispectral image processing techniques were generally developed to classify multispectral images into broad categories of surface condition (Shippert, 2004; Ahmad, 2012; Ahmad et al., 2013).

The importance of the NDVI index may vary according to habitat nature (Pettorelli et al., 2005; Hamel et al., 2009; Ahmad and Shafique, 2013a; Ahmad et al., 2013). The NDVI is successful as a vegetation measure is that it is sufficiently stable to permit meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity (Choudhury, 1987; Jakubauskas et al., 2002; Chen et al., 2006; Zoran and Stefan, 2006; Nicandrou, 2010; Ahmad, 2012a; 2012b; 2012c). The strength of the NDVI is in its ratio concept (Moran et al., 1992; Ahmad, 2012a), which reduces many forms of multiplicative noise present in multiple bands (Chen et al., 2002; Nicandrou, 2010; Ahmad, 2012a; 2012b). RS provides a viable source of data from which updated land-cover information can be extracted efficiently and cheaply in order to invent and monitor these changes effectively (Mas, 1999; Ahmad and Shafique, 2013a; Ahmad et al., 2013).

Supervised classification which is a part of post classification comparison technique or direct classification method. This approach is based on the natural groupings of the spectral properties of the pixels which are usually selected by the RS software without any influence from the users (Al-Awadhi et al., 2011; Ahmad et al., 2013). Satellite dataset offers unique possibilities for spatial and temporal characterization of the changes. The basic requirement is the availability of different dates of imagery which permits continuous monitoring of change and environmental developments over time (Ayman and Ashraf, 2009; Ahmad and Shafique, 2013).

The EVI/NDVI pixel values were used to calculate fractional yield (Shinners and Binversie, 2007; Ahmad et al., 2013) from February, 2000 to February, 2013. The NDVI pixel values showed theoretical yield and EVI pixel values showed actual yield. The fractional yield is computed following the equation:

$$\text{Fractional Yield} = \frac{\text{Actual Yield}}{\text{Theoretical Yield}} \text{ x } 100$$

Phenology is the study of the times of recurring natural phenomena. One of the most successful of the approach is based on tracking the temporal change of a vegetation index such as NDVI or EVI. The evolution of vegetation index exhibits a strong correlation with the typical green vegetation growth stages. The results (temporal curves) can be analyzed to obtain useful information such as the start/end of vegetation growing season (Gao and Mas, 2008; Ahmad, 2012a; 2012b; Ahmad and Shafique, 2013).

Vegetation phenology derived from RS is important for a variety of applications (Hufkens et al., 2010; Ahmad, 2012b). Vegetation phenology can provide a useful signal for classifying vegetated land cover (Dennison and Roberts, 2003; Ahmad, 2012b). Changes in vegetation spectral response caused by phenology can conceal longer term changes in the landscape (Hobbs, 1989; Lambin, 1996; Dennison and Roberts, 2003; Ahmad, 2012b). Multi-temporal data that captures these spectral differences can improve reparability of vegetation types over classifications based on single date imagery (DeFries et al., 1995; Ahmad, 2012b).

III. Results

The vegetation phenology is important for predicting ecosystem carbon, nitrogen, and water fluxes (Baldocchi et al., 2005; Richardson et al., 2009; Chandola et al., 2010; Ahmad, 2012a), as the seasonal and interannual variation of phenology have been linked to net primary production estimation, crop yields, and water supply (Aber et al., 1995; Jenkins et al., 2002; Chandola et al., 2010; Ahmad, 2012a).

The application of the NDVI (Rouse et al., 1973; Tucker, 1979; Ahmad, 2012a) in ecological studies has enabled quantification and mapping of green vegetation with the goal of estimating above ground net primary productivity and other landscape-level fluxes (Wang et al., 2003; Pettorelli et al., 2005; Aguilar et al., 2012; Ahmad, 2012a).

The NDVI has been widely used for vegetation monitoring primarily for its simplicity. It is conceived as the normalized difference between the minimum peak of reflectance in the red wavelength and the maximum reflectance in the NIR domain: the higher the index value the better the vegetation conditions in terms of both biomass amount and vegetation health (Daughtry et al., 2000; Haboudane et al., 2002; Stroppiana et al., 2006).

Vegetation extraction from satellite imagery is the process of extracting vegetation information by interpreting satellite images based on the interpretation elements and association information (Xie, 2008; Ahmad and Shafique, 2013). Hyperspectral vegetation research is still based on multi-spectral indices used as reference or contemporary data. These indices are readily adaptable to hyperspectral data but remain problematic in arid and semi-arid areas (Broge and Leblanc, 2000; McGwire et al., 2000; Frank and Menz, 2003; Ahmad and Shafique, 2013). Hyperspectral data could provide much more possibilities compared with multi-spectral data in detecting and quantifying sparse vegetation because it provides a continuous spectrum across a range in wavelengths (Kumar et al., 2001; Frank and Menz, 2003; Ahmad and Shafique, 2013).

Besides climate alterations leading to changes in the productivity and phenology of natural vegetation (Villalba et al., 1998; Villalba et al., 2003; Baldi et al., 2008; Ahmad, 2012a), direct human drivers such as land uses and land covers changes (Grau et al., 2005; Fearnside, 2005; Huang et al., 2007; Baldi and Paruelo, 2008; Baldi et al., 2008; Ahmad, 2012a), infrastructure enterprises (Canziani et al., 2006; Baldi et al., 2008; Ahmad, 2012a), and urban expansion (Romero and Ordenes, 2004; Pauchard et al., 2006; Baldi et al., 2008; Ahmad, 2012a; Ahmad, 2012f) took place.

Figure 4 shows classified NDVI 2001, Narowal. After rectification, the NDVI model was applied upon Landsat ETM+ image acquired on 30th September, 2001. ArcGIS symbology tool was used to develop NDVI classes and recognize the paddy cropped areas in Narowal. Maximum NDVI, minimum NDVI, mean NDVI and standard deviation is given in Table 2.

Figure 5 shows classified NDVI 2010, Narowal. After rectification, the NDVI model was applied upon Landsat TM image acquired on 2nd November, 2010. ArcGIS symbology tool was used to develop NDVI classes and recognize the paddy cropped areas in Narowal. Maximum NDVI, minimum NDVI, mean NDVI and standard deviation is given in Table 2.

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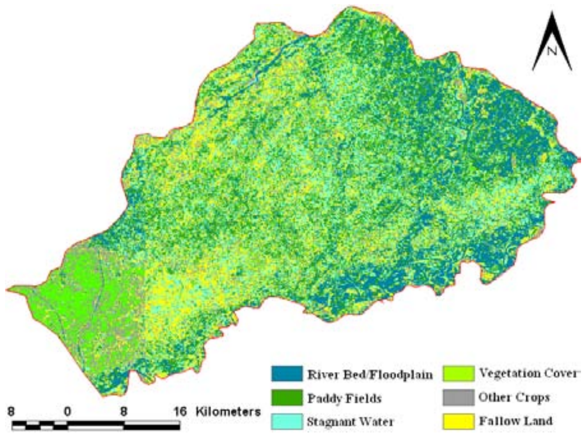

Figure 4 : Classified NDVI 2001, Narowal

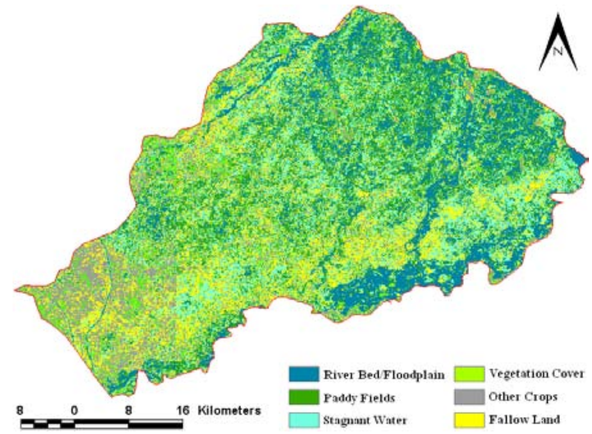

Figure 5 : Classified NDVI 2010, Narowal

Table 2 : NDVI values of Landsat TM/ETM+ image

Image Acquisition Date	Maximum NDVI	Minimum NDVI	Mean NDVI	Standard Deviation
30th September, 2001 (Landsat ETM+)	0.56	-0.42	0.05	0.11
2nd November, 2010 (Landsat TM)	0.65	-0.40	0.13	0.11

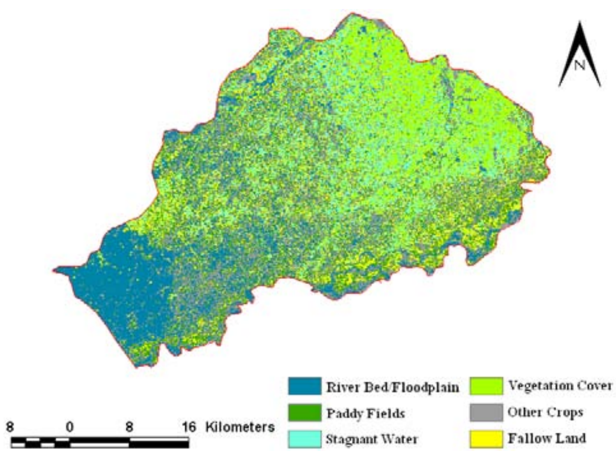

Figure 6 : Supervised Classification 2001

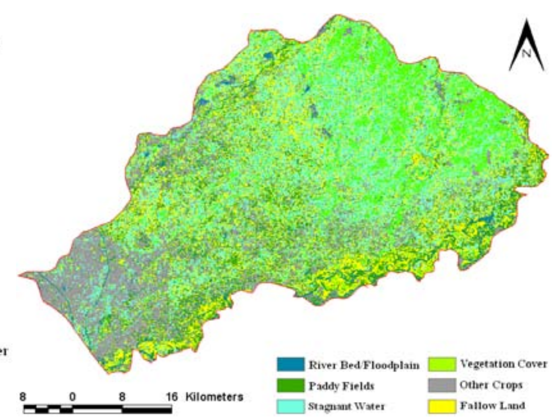

Figure 7 : Supervised Classification 2010

Table 3 : Supervised Classification of Landsat ETM+ image

Image Acquisition Date	Classes	Area (km^2)	Area (%)	Accuracy Assessment (%)
30th September, 2001 (Landsat ETM+)	River Bed/Floodplain	498.69	19.37	87.42
	Paddy Fields	430.88	16.73	85.44
	Stagnant Water	382.97	14.87	87.08
	Vegetation Cover	294.12	11.42	88.45
	Other Crops	565.24	21.95	92.20
	Fallow Land	403.10	15.66	87.29
	SUM	2575	100	-

Figure 6 shows supervised classification 2001, Narowal. The classification was applied upon Landsat ETM+ image acquired on 30th September, 2001. The findings showed that the river bed/floodplain covered the area of 498.69 km^2 (19.37%), paddy fields 430.88 km^2 (16.73%), stagnant water 382.97 km^2 (14.87%), vegetation cover 294.12 km^2 (11.42%), fallow land 403.10 km^2 (15.66%) while other crops covered the area of 565.24 km^2 (21.95%). Accuracy assessment is given in the Table 3.

Table 4 : Supervised Classification of Landsat TM image

Image Acquisition Date	Classes	Area (km²)	Area (%)	Accuracy Assessment (%)
2nd November, 2010 (Landsat TM)	River Bed/Floodplain	481.90	18.71	87.02
	Paddy Fields	400.14	15.53	88.04
	Stagnant Water	359.31	13.95	92.04
	Vegetation Cover	320.48	12.45	85.42
	Other Crops	467.01	18.14	90.20
	Fallow Land	546.16	21.22	87.09
	SUM	2575	100	-

Figure 7 shows supervised classification 2010, Narowal. The classification was applied upon Landsat TM image acquired on 2nd November, 2010. The findings showed that the river bed/floodplain covered the area of 481.90 km^2 (18.71%), paddy fields 400.14 km^2 (15.53%), stagnant water 359.31 km^2 (13.95%), vegetation cover 320.48 km^2 (12.45%), fallow land 546.16 km^2 (21.22%) while other crops covered the area of 467.01 km^2 (18.14%). Accuracy assessment is given in the Table 4.

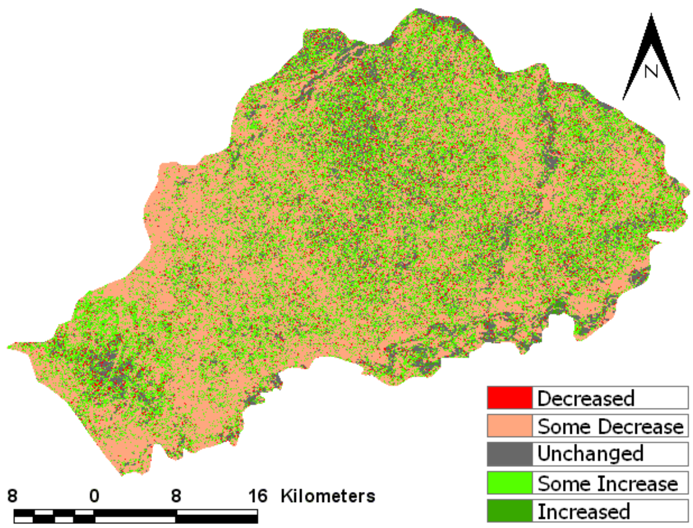

Figure 8 : Image Difference (2001-2010) at Narowal

Table 5 : Image Difference (2001-2010) at Narowal

Classes	During 2001 to 2010		
	Area (km²)	Area (%)	Accuracy Assessment (%)
Decreased	1254.83	48.73	87.31
Some Decrease	840.27	32.64	90.19
Unchanged	133.95	5.20	87.22
Some Increase	336.37	13.06	85.79
Increased	9.58	0.37	92.14
SUM	2575	100	-

Figure 8 shows image difference or change detection (2001-2010) at Narowal. The findings showed that decreased was 1254.83 km^2 (48.73%), some decrease 840.27 km^2 (32.64%), unchanged was 133.95 km^2 (5.20%), some increase 336.37 km^2 (13.06%) while increased was 9.58 km^2 (0.37%). Decreased and some decrease in vegetation cover was much higher as compared to some increase and increased. Accuracy assessment is given in the Table 5.

Detection of change is the measure of the distinct data framework and thematic change information that can direct to more tangible insights into underlying process involving land cover and land-use changes (Singh et al., 2013; Ahmad and Shafique, 2013). Monitoring the locations and distributions of land cover changes is important for establishing links between policy decisions, regulatory actions and subsequent land-use activities (Lunetta et al., 2006;

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Ahmad and Shafique, 2013). Change detection as defined by Hoffer (1978) is temporal effects as variation in spectral response involves situations where the spectral characteristics of the vegetation or other cover type in a given location change over time. Singh (1989) described change detection as a process that observes the differences of an object or phenomenon at different times (Adia and Rabiu, 2008; Ahmad and Shafique, 2013).

Accurate assessment of vegetation response across multiple-year time scales is crucial for analyses of global change (Running and Nemani, 1991; Sellers et al., 1994; Stow, 1995; Justice et al., 1998; Fensholt, 2004; Baugh and Groeneveld, 2006; Ahmad, 2012c), effects of human activities (Moran et al., 1997; Milich and Weiss 2000; Thiam, 2003; Baugh and Groeneveld, 2006; Ahmad, 2012c) and ecological relationships (Baret and Guyot, 1991; Asrar et al., 1992; Begue, 1993; Epiphanio and Huete, 1995; Gillies et al., 1997; Baugh and Groeneveld, 2006; Ahmad, 2012c).

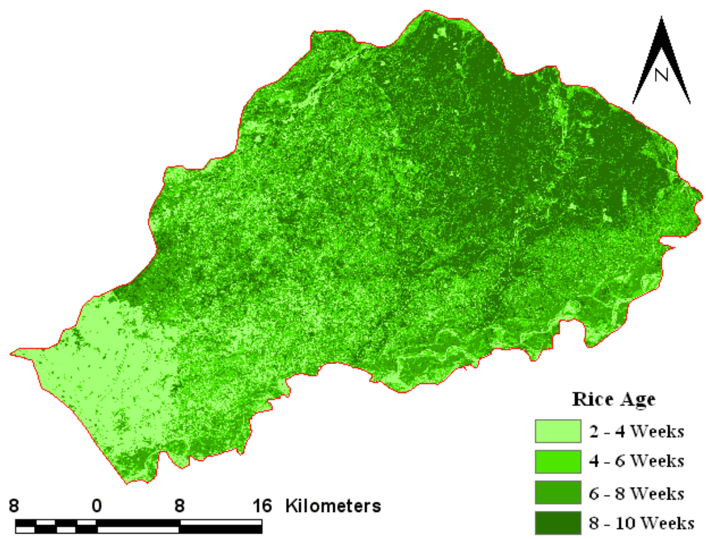

Figure 9 : Paddy/rice fields distribution map of Narowal from the analysis of Landsat ETM+ image

Figure 9 shows paddy/rice fields distribution map of Narowal from the analysis of Landsat ETM+ image using the following Rice Growth Vegetation Index (RGVI) model. In Narowal, especially in early transplanting periods, water environment plays an important role in rice spectral (Nuarsa et al., 2011; Nuarsa et al., 2012). The blue band of Landsat ETM+ has good sensitivity to the existence of water; therefore, the development of RGVI used the B1, B3, B4, and B5 of Landsat ETM+ with the following equation (Nuarsa et al., 2011):

$$RGVI = \frac{(B4+B5+B7) - (B1+B3)}{(B4+B5+B7)}$$

Simplified equation is as follow:

$$RGVI = 1 - \frac{(B1+B3)}{(B4+B5+B7)}$$

Where RGVI is the rice growth vegetation index, and B1, B3, B4, B5, and B7 refer to the band of Landsat ETM+. Theoretically, rice fields in normal conditions are the same, like vegetation in general (Nuarsa et al., 2011). Chlorophyll pigments, present in leaves absorb red light. In the near-infrared portion, radiation is scattered by the internal spongy mesophyll leaf structure, which leads to higher values in near-infrared channels. This interaction between leaves and the light that strikes them is often determined by their different responses in the red and near-infrared portions of reflective light (Niel and McVicar, 2001; Nuarsa et al., 2005; Nuarsa et al., 2011; Nuarsa et al., 2012). In contrast, absorption properties of the middle infrared band cause a low reflectance of rice fields in this channel (Lillesand and Kiefer, 1994; Nuarsa et al., 2011).

RS has been widely applied and recognized as a powerful/effective tool in detecting land use and land cover changes (Nuarsa et al., 2011). Landsat satellite images have 8 bands, including a thermal and a panchromatic band. In visible, near-infrared and middle infrared regions, Landsat ETM+ has 30-m spatial resolution. However, in thermal and panchromatic regions, spatial resolutions are 60 m and 15 m, respectively (Nuarsa et al., 2005; Nuarsa et al., 2011). This study used both visible and reflectance infrareds (Band-1 - 5 and band-7) of Landsat ETM+ (Nuarsa et al., 2011). Although the Landsat ETM+ used in this study had the SLC off, considerations of better spatial, spectral, and temporal resolution of these images made it relevant to use. With 16 days of temporal resolution, Landsat ETM+ was the ideal satellite image for rice monitoring (Nuarsa et al., 2011; Nuarsa et al., 2012).

The visible band of Landsat ETM+ (Band 1, Band 2, and Band 3) showed a weak exponential relationship to rice age; however, the reflective infrared band of Landsat ETM+ (Band 4 and B5) and the Rice Growth Vegetation Index (RGVI) showed a strong exponential relationship to rice age (Nuarsa et al., 2005; Nuarsa et al., 2011; Nuarsa et al., 2012). Use of vegetation indexes to monitor and map rice field gives better results than use of a single band of Landsat ETM+. RGVI is a better vegetation index to describe rice age than existing vegetation indexes (Nuarsa et al., 2011) like EVI. Paddy/rice fields have specific land cover properties. Rice land coverage changes during the rice life circle. In irrigated rice fields of Narowal, almost all land coverage is dominated by water during the plantation period. As the rice ages, rice vegetation coverage grows and reaches a maximum (rice age = 2½ months) and then gradually decreases until harvest time (Shao et al., 2001; Nuarsa et al., 2005; Nuarsa et al., 2011).

Figure 10 shows time-series phenology metrics for Bara Manga district Narowal. In this profile MODIS (Terra) EVI/NDVI 250 m data products for the period February 2000 to February 2013 at 16-days interval was evaluated. The NDVI value in February 2000 (start) was 0.79 and the NDVI value in February 2013 (end) was 0.66 while EVI pixel value in February 2000 (start) was 5835 and in February 2013 (end) was 3786. The maximum NDVI value (0.87) was recorded in February 2007 while minimum NDVI value (0.05) was in January 2003. The trend analysis (NDVI) showed no change during the entire period. The phenological profile showed the paddy crop growth stages (transplanting to maturity and further ripening) at Bara Manga. The fluctuations in the phenological profile were due to variation in the temperature-precipitation. Variations in vegetation activity have been linked with changes in climates (Los et al., 2001; Tucker et al., 2001; Zhou et al., 2001; 2003; Lucht et al., 2002; Piao et al., 2003; Ahmad, 2012a).

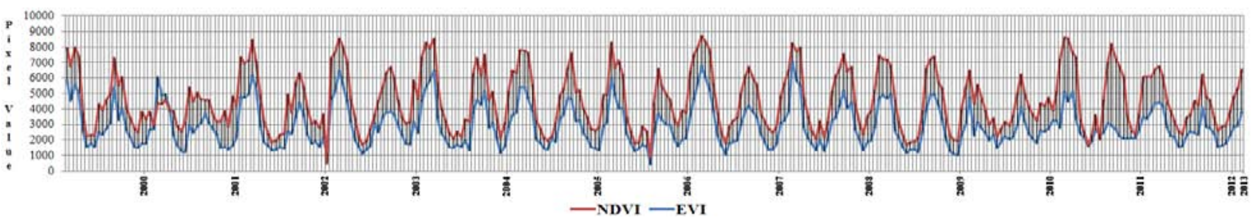

Figure 10 : Time series phenology metrics for Bara Manga *Processed by the author*

Figure 11 shows time-series phenology metrics for Becochak district Narowal. The NDVI value in February 2000 (start) was 0.57 and NDVI value in February 2013 (end) was 0.62; EVI pixel value in February 2000 (start) was 3287 and in February 2013 (end) was 3306. The maximum NDVI value (0.85) was recorded in July 2011 while the minimum NDVI value (0.05) was in January 2003. Liu and Huete (1995) integrated atmospheric resistance and background effects in NDVI to enhance vegetation signals in high biomass regions and proposed EVI (Ahmad, 2012c).

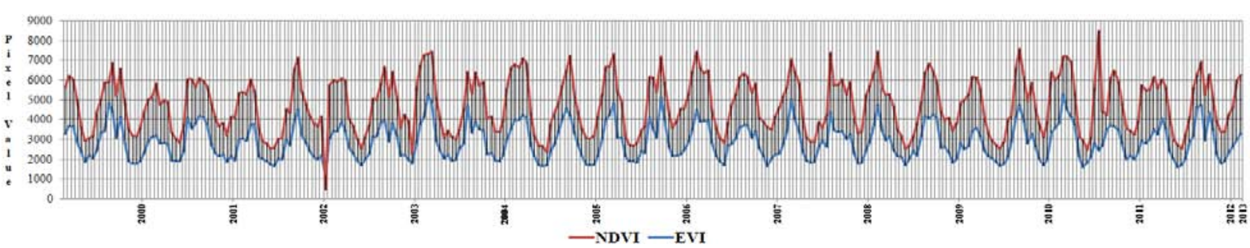

Figure 11 : Time series phenology metrics for Becochak *Processed by the author*

Figure 12 shows time-series phenology metrics for Boora Dala district Narowal. The NDVI value in February 2000 (start) was 0.53 and the NDVI value in February 2013 (end) was 0.63 while EVI pixel value in February 2000 (start) was 3375 and in February 2013 (end) was 3441. The maximum NDVI value (0.79) was recorded in March 2011 while minimum NDVI value (0.04) was in January 2003. The EVI differs from NDVI because of endeavor to differentiate atmospheric and background effects (Ahmad, 2012b). The EVI is better to categorize little differences in dense vegetative areas, where NDVI showed saturation (Ahmad and Shafique, 2013).

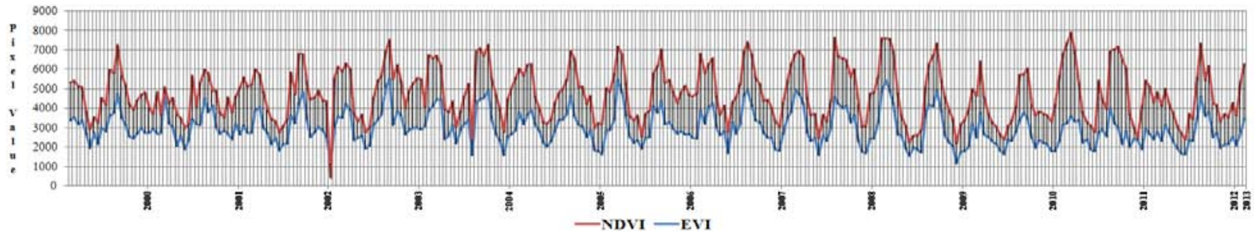

Figure 12 : Time series phenology metrics for Boora Dala *Processed by the author*

Figure 13 shows time-series phenology metrics for Budha Dhola district Narowal. The NDVI value in February 2000 (start) was 0.60 and the NDVI value in February 2013 (end) was 0.73 while EVI pixel value in February 2000 (start) was 3873 and in February 2013 (end) was 2998. The maximum NDVI value (0.83) was recorded in January 2013 while minimum NDVI value (0.04) was in January 2003. The green cover fraction and soil productivity in winter season was much higher as compared to summer season. The phenology metrics showed a clear relationship with the seasonality of rainfall, winter and summer growing seasons (Wessels et al., 2011; Ahmad 2012b; Ahmad and Shafique, 2013). The EVI values are generally lower in order to avoid saturation in high biomass areas (Huete et al., 2002).

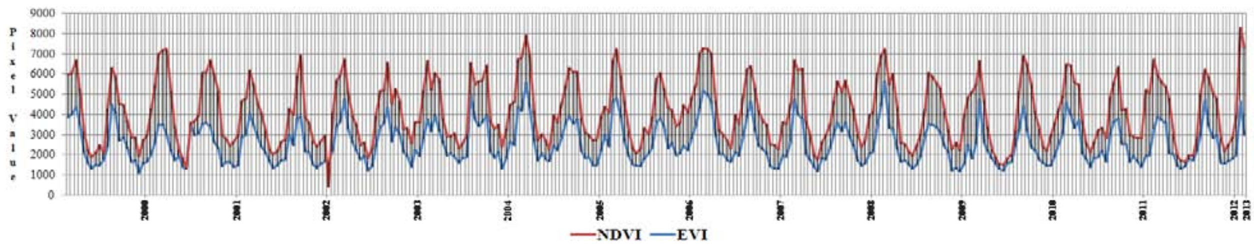

Figure 13 : Time series phenology metrics for Budha Dhola *Processed by the author*

Figure 14 shows time-series phenology metrics for Fattu Chak district Narowal. The NDVI value in February 2000 (start) was 0.46 and the NDVI value in February 2013 (end) was 0.66 while EVI pixel value in February 2000 (start) was 3433 and in February 2013 (end) was 4140. The maximum NDVI value (0.81) was recorded in March 2007 while minimum NDVI value (0.04) was in January 2003. The evolution of vegetation index exhibits a strong correlation with the typical green vegetation growth stages (Zhao et al., 2005; Ahmad, 2012d). The results (temporal curves) can be analyzed to obtain useful information such as the start/end of vegetation growing season. However, RS based phenological analysis results are only an approximation of the true biological growth stages. This is mainly due to the limitation of current space based RS, especially the spatial resolution, and the nature of vegetation index. A pixel in an image does not contain a pure target but a mixture of whatever intersected the sensor's field of view (Gao and Mas, 2008; Ahmad, 2012d).

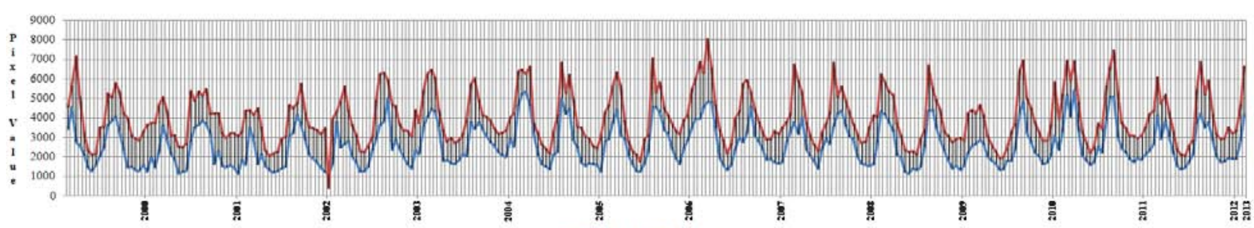

Figure 14 : Time series phenology metrics for Fattu Chak *Processed by the author*

Figure 15 shows time-series phenology metrics for Gumtala district Narowal. The NDVI value in February 2000 (start) was 0.38 and the NDVI value in February 2013 (end) was 0.58 while EVI pixel value in February 2000 (start) was 2453 and in February 2013 (end) was 3450. The maximum NDVI value (0.70) was recorded in August 2011 while minimum NDVI value (0.04) was in January 2003. The NDVI can be used not only for accurate description of vegetation classification and vegetation phenology (Tucker et al., 1982; Tarpley et al., 1984; Justice et al., 1985; Lloyd, 1990; Singh et al., 2003; Los et al., 2005; Ahmad, 2012a) but also effective for monitoring rainfall and drought, estimating net primary production of vegetation, crop growth conditions and crop yield, detecting weather impacts and other events important for agriculture and ecology (Glenn, 2008).

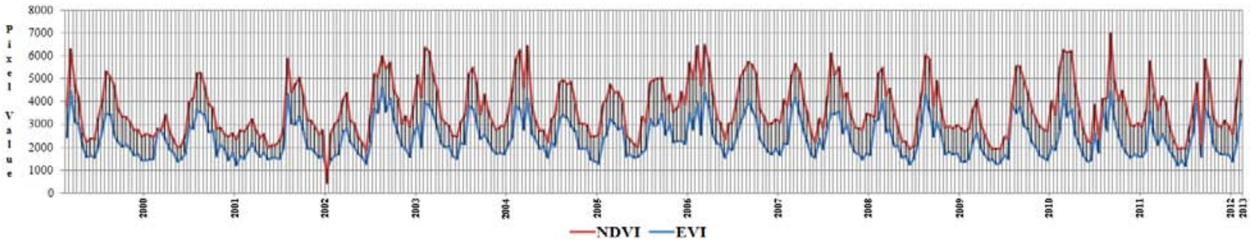

Figure 15 : Time series phenology metrics for Gumtala *Processed by the author*

Figure 16 shows time-series phenology metrics for Lalian district Narowal. The NDVI value in February 2000 (start) was 0.49 and the NDVI value in February 2013 (end) was 0.50 while EVI pixel value in February 2000 (start) was 3291 and in February 2013 (end) was 3001. The maximum NDVI value (0.85) was recorded in August 2010 while minimum NDVI value (0.04) was in January 2003. The application of the NDVI (Rouse et al., 1973; Tucker, 1979; Ahmad, 2012a) in ecological studies has enabled quantification and mapping of green vegetation with the goal of estimating above ground net primary productivity and other landscape-level fluxes (Wang et al., 2003; Pettorelli et al., 2005; Aguilar et al., 2012; Ahmad, 2012a).

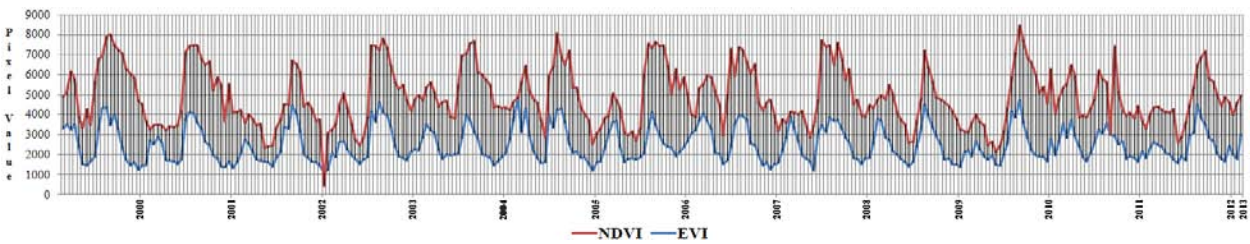

Figure 16 : Time series phenology metrics for Lalian *Processed by the author*

Figure 17 shows time-series phenology metrics for Naina Kot district Narowal. The NDVI value in February 2000 (start) was 0.80 and the NDVI value in February 2013 (end) was 0.66 while EVI pixel value in February 2000 (start) was 3524 and in February 2013 (end) was 3576. The maximum NDVI value (0.83) was recorded in September 2005 while minimum NDVI value (0.05) was in January 2003. The NDVI suppresses differential solar illumination effects of slope and aspect orientation (Lillesand and Kiefer, 1994; Sader et al., 2001; Ahmad and Shafique, 2013a) and helps to normalize differences in brightness values when processing multiple dates of imagery (Singh, 1986; Lyon et al., 1998; Sader et al., 2001; Ahmad and Shafique, 2013a).

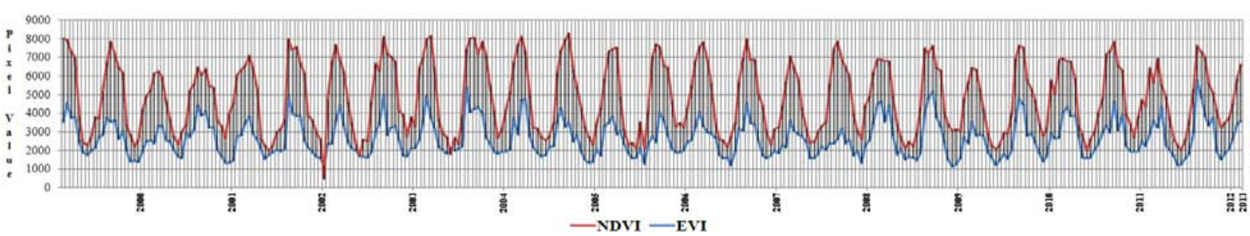

Figure 17 : Time series phenology metrics for Naina Kot *Processed by the author*

Figure 18 shows time-series phenology metrics for Nathoo Kot district Narowal. The NDVI value in February 2000 (start) was 0.60 and the NDVI value in February 2013 (end) was 0.77 while EVI pixel value in February 2000 (start) was 3944 and in February 2013 (end) was 5073. The maximum NDVI value (0.78) was recorded in March 2012 while minimum NDVI value (0.05) was in January 2003. RS provides a key means of measuring and monitoring phenology at continental to global scales and vegetation indices derived from satellite data are now commonly used for this purpose (Nightingale et al., 2008; Tan et al., 2008; Ahmad, 2012e; Ahmad, 2012f). Changes in the phenological events may therefore signal important year-to-year climatic variations or even global environmental change (Botta et al., 2000; Jolly et al., 2005; Hashemi, 2010; Ahmad, 2012e; Ahmad, 2012f).

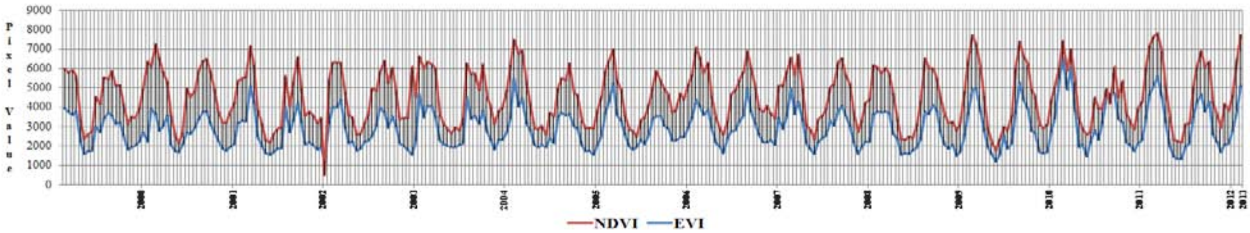

Figure 18 : Time series phenology metrics for Nathoo Kot *Processed by the author*

Figure 19 shows time-series phenology metrics for Pherowal district Narowal. The NDVI value in February 2000 (start) was 0.69 and the NDVI value in February 2013 (end) was 0.74 while EVI pixel value in February 2000 (start) was 4758 and in February 2013 (end) was 4289. The maximum NDVI value (0.80) was recorded in March 2012 while minimum NDVI value (0.04) was in January 2003. RS change detection techniques can be broadly classified as either pre or post classification change methods. Pre-classification methods can further be characterized as being spectral or phenology based (Lunetta et al., 2006; Ahmad and Shafique, 2013). As the use of space and computer technology developed, humankind has a great advantage of produce this much important research projects with the help of technology in an easier, more accurate way within less time than other ways. As a result, all these can have a very effective role in helping the country to increase the amount and the quality of agricultural products (Ahmad, 2012c). The use of vegetation indices, in general, takes into account mostly the green living vegetation (Cyr et al., 1995; Ahmad, 2012c).

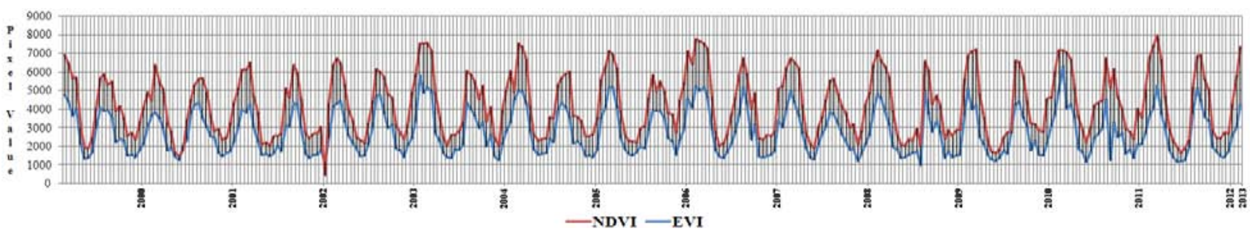

Figure 19 : Time series phenology metrics for Pherowal *Processed by the author*

Figure 20 shows time-series phenology metrics for Talwandi Bhindran district Narowal. The NDVI value in February 2000 (start) was 0.65 and the NDVI value in February 2013 (end) was 0.37 while EVI pixel value in February 2000 (start) was 4620 and in February 2013 (end) was 1722. The maximum NDVI value (0.79) was recorded in March 2005 while minimum NDVI value (0.04) was in January 2003. The NDVI is the most commonly used of all the VIs tested and its performance, due to non-systematic variation as described by Huete and Liu (1994) and Liu and Huete (1995). The soil background is a major surface component controlling the spectral behaviour of vegetation (Ahmad and Shafique, 2013). Although vegetation indices, such as the soil-adjusted (Huete, 1988) vegetation indices, considerably reduce these soils effects, estimation of the vegetation characteristics from the indices still suffers from some imprecision, especially at relatively low cover, if no information about the target is known (Rondeaux et al., 1996; Ahmad and Shafique, 2013).

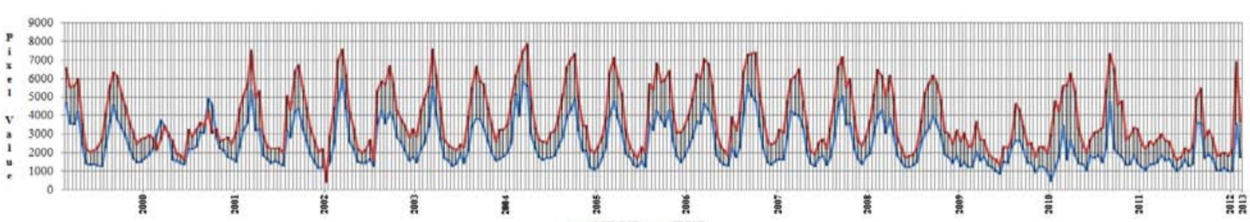

Figure 20 : Time series phenology metrics for Talwandi Bhindran *Processed by the author*

Table 6 : MODIS (Terra) EVI/NDVI and Fractional Yield dataset of Naina Kot

Image Acquisition (Month/Year)	EVI Pixel Value	NDVI Pixel Value	Fractional Yield (%)	Image Acquisition (Month/Year)	EVI Pixel Value	NDVI Pixel Value	Fractional Yield (%)
Feb. 2000	3524	8008	44.01	Feb. 2007	4061	7586	53.53
May 2000	1775	2289	77.54	May 2007	1590	2557	62.18
Aug. 2000	3516	7839	44.85	Aug. 2007	4531	7971	56.84
Nov. 2000	1411	2874	49.10	Nov. 2007	1585	3025	52.40
Feb. 2001	2363	6118	38.62	Feb. 2008	3564	7055	50.52
May 2001	1677	2332	71.91	May 2008	1602	2447	65.47
Aug. 2001	3847	6021	63.89	Aug. 2008	2607	7832	33.29
Nov. 2001	1687	3317	50.86	Nov. 2008	1984	3079	64.44
Feb. 2002	3415	6524	52.35	Feb. 2009	4595	6857	67.01
May 2002	1782	1957	91.06	May 2009	1491	2121	70.30
Aug. 2002	3988	7373	54.09	Aug. 2009	4786	7202	66.45
Nov. 2002	1904	3596	52.95	Nov. 2009	1485	3416	43.47
Feb. 2003	3506	7671	45.70	Feb. 2010	3510	6422	54.66
May 2003	1669	1707	98.12	May 2010	1205	2068	58.27
Aug. 2003	4981	8101	61.49	Aug. 2010	4740	7610	62.29
Nov. 2003	1699	3922	43.32	Nov. 2010	1816	3405	53.33
Feb. 2004	4858	7968	60.97	Feb. 2011	3994	6968	57.32
May 2004	2133	1792	119.03	May 2011	1602	1961	81.70
Aug. 2004	4214	8057	52.30	Aug. 2011	2929	7303	40.08
Nov. 2004	1937	4090	47.36	Nov. 2011	1951	3409	57.23
Feb. 2005	2863	7701	37.18	Feb. 2012	3559	5639	63.11
May 2005	1684	2324	61.82	May 2012	1206	2283	52.83
Aug. 2005	3252	7920	41.06	Aug. 2012	4804	7263	66.14
Nov. 2005	1497	3240	46.20	Nov. 2012	1500	3205	46.80
Feb. 2006	3481	7309	47.63	Feb. 2013	3576	6584	54.31
May 2006	1578	2434	64.83				
Aug. 2006	2441	7710	31.66				
Nov. 2006	1907	3292	57.93				

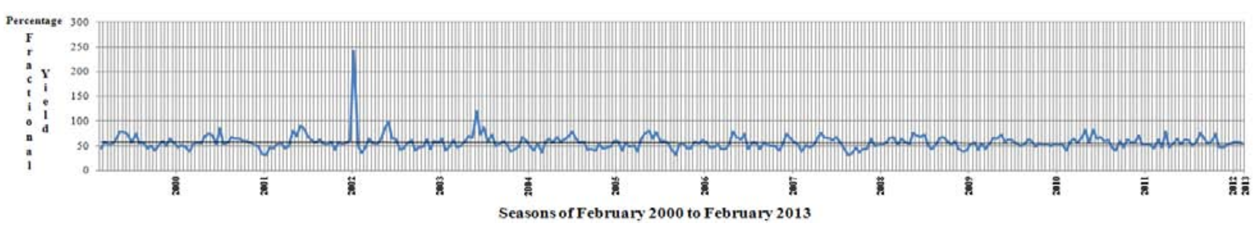

Figure 21 : Linear forecast trendline for the dataset of Naina Kot

Linear forecast trendline was plotted upon the fractional yield dataset of Naina Kot (Table 6; Figure 21) to investigate the general trend. Linear forecast trendline showed that fractional yield at Naina Kot was smooth during the entire period. The findings showed that January 2003 was the driest month during the entire period; February 2000 to February 2013. Heavy amount of fertilizer was used for crop growth and soil productivity.

IV. Discussion and Conclusions

RS datasets and techniques have already proven to be relevant to many requirements of crop inventory and monitoring (Haboudane et al., 2002). At the present, there is an increased interest in precision farming and the development of smart systems for agricultural resource management; these relatively new approaches aim to increase the productivity, optimize the profitability, and protect the environment. In this context, image-based RS technology is seen as a key tool to provide valuable information that is still lacking or inappropriate to the achievement of sustainable and efficient agricultural practices (Moran et al., 1997; Daughtry et al., 2000; Haboudane et al., 2002).

RS provides a key means of measuring and monitoring phenology at continental to global scales and vegetation indices derived from satellite data are now commonly used for this purpose (Nightingale et al., 2008; Tan et al., 2008; Ahmad, 2012a; 2012f). The study also identified several data acquisition and processing issues that warrant further investigation. Studies are under way to assess the importance of coordinating and timing field data collection and image acquisition dates as a means of improving the strength of the relationships between image and land condition trend analysis (Senseman et al., 1996; Ahmad, 2012c) ground-truth data. Recent literature has shown that the narrow bands may be crucial for providing additional information with significant improvements over broad bands in quantifying biophysical characteristics of paddy/rice crop (Thenkabail et al., 2000).

RS of agricultural resources is based on the measurement of the electromagnetic energy reflected or emitted from the Earth surface as a result of the energy matter interaction. RS data interpretation and processing aim to derive vegetation biophysical properties from its spectral properties (Stroppiana et al., 2006).

Spectral-based change detection techniques have tended to be performance limited in biologically complex ecosystems due, in larger part, to phenology-induced errors (Lunetta et al., 2002; Lunetta et al., 2002a; Lunetta et al., 2006; Ahmad and Shafique, 2013). An important consideration for land cover change detection is the nominal temporal frequency of remote sensor data acquisitions required to adequately characterize change events (Lunetta et al., 2004; Lunetta et al., 2006; Ahmad and Shafique, 2013). Ecosystem-specific regeneration rates are important considerations for determining the required frequency of data collections to minimize errors. As part of the natural processes associated with vegetation dynamics, plants undergo intra-annual cycles. During different stages of vegetation growth, plants' structure and associated pigment assemblages can vary significantly (Lunetta et al., 2006; Ahmad and Shafique, 2013).

Validation is a key issue in RS based studies of phenology over large areas (Huete, 1999; Schwartz and Reed, 1999; Zhang et al., 2003; 2004; Ahmad, 2012d). While a variety of field programs for monitoring phenology have been initiated (Schwartz, 1999; Zhang et al., 2003; 2004; Ahmad, 2012d), these programs provide data that is typically specie-specific and which is collected at scales that are not compatible with coarse resolution RS observations.

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