Global Journal of human-social science: b
Geography, Geo-Sciences, Environmental Disaster Management
Volume 14 Issue 6 Version 1.0 Year 2014
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 2249-460x & Print ISSN: 0975-587X

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

By Farooq Ahmad, Qurat-ul-ain Fatima, Hira Jannat Butt, Shahid Ghazi, Sajid Rashid Ahmad, Ijaz Ahmad, Shafeeq-Ur-Rehman, Rao Mansor Ali Khan, Abdul Raoof, Samiullah Khan, Farkhanda Akmal, Muhammad Luqman, Ahmad Raza & Kashif Shafique

University of the Punjab, New Campus, Lahore, Pakistan

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.

Keywords: *EVI, Landsat TM/ETM+, land-use, multi-temporal, multi-spectral, NDVI, Pakistan.*

GJHSS-B Classification : *FOR Code: 300899*

Strictly as per the compliance and regulations of:

© 2014. Farooq Ahmad, Qurat-ul-ain Fatima, Hira Jannat Butt, Shahid Ghazi, Sajid Rashid Ahmad, Ijaz Ahmad, Shafeeq-Ur-Rehman, Rao Mansor Ali Khan, Abdul Raoof, Samiullah Khan, Farkhanda Akmal, Muhammad Luqman, Ahmad Raza & Kashif Shafique. This is a research/review paper, distributed under the terms of the Creative Commons Attribution-Noncommercial 3.0 Unported License http://creativecommons. org/licenses/by-nc/3.0/), permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

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

Farooq Ahmad [α], Qurat-ul-ain Fatima [σ], Hira Jannat Butt [ρ], Shahid Ghazi [ω], Sajid Rashid Ahmad [¥], Ijaz Ahmad [§], Shafeeq-Ur-Rehman [χ], Rao Mansor Ali Khan [ν], Abdul Raoof [Θ], Samiullah Khan [¢], Farkhanda Akmal [€], Muhammad Luqman [£], Ahmad Raza [Ω] & Kashif Shafique [Ψ]

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.**

Keywords: EVI, Landsat TM/ETM+, land-use, multi-temporal, multi-spectral, NDVI, Pakistan.

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

Author α: Department of Geography, University of the Punjab, New Campus, Lahore, Pakistan. e-mail: drylandpk@yahoo.com
Author σ ρ: GIS Centre, PUCIT, University of the Punjab, Lahore, Pakistan.
Author ω ¥ § χ ν Θ ¢ € £ Ω: Institute of Geology, University of the Punjab, New Campus, Lahore, Pakistan.
Author ψ: Forman Christian College (A Chartered University), Lahore, Pakistan.

© 2014 Global Journals Inc. (US)

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

© 2014 Global Journals Inc. (US)

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).

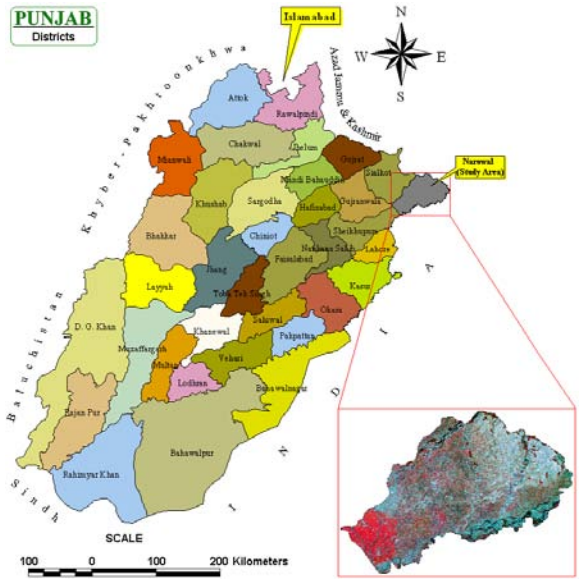

Figure 1 : Location Map of the Study Area

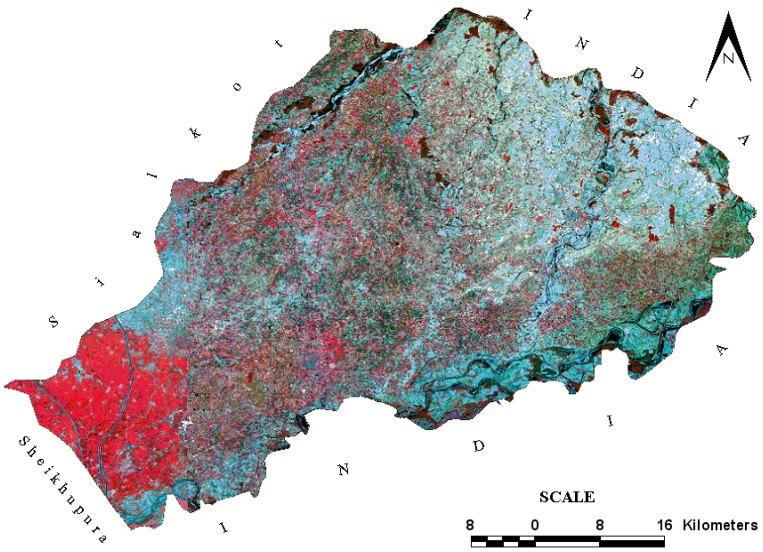

Figure 2 : Narowal - Landsat ETM+ 30th September, 2001 image *Source: http://glovis.usgs.gov/*

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).

© 2014 Global Journals Inc. (US)

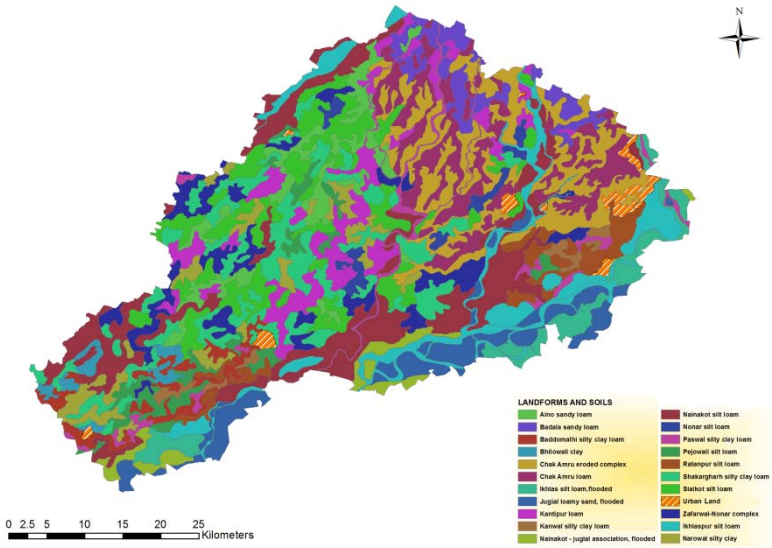

Figure 3 : Landforms and Soils, Narowal District *Source: After Shah, 2007*

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

© 2014 Global Journals Inc. (US)

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:

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

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:

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

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 =

© 2014 Global Journals Inc. (US)

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

© 2014 Global Journals Inc. (US)

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.

© 2014 Global Journals Inc. (US)

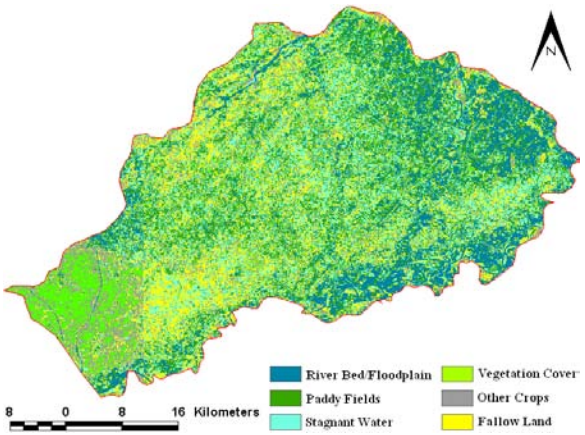

Figure 4 : Classified NDVI 2001, Narowal

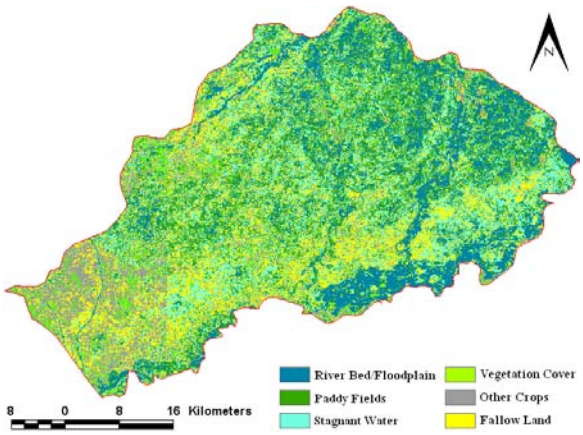

Figure 5 : Classified NDVI 2010, Narowal

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

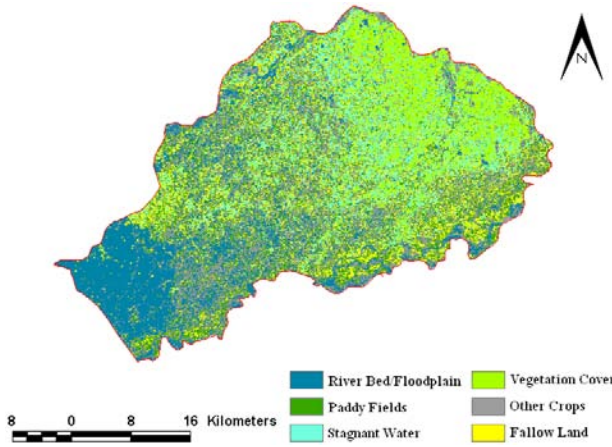

Figure 6 : Supervised Classification 2001

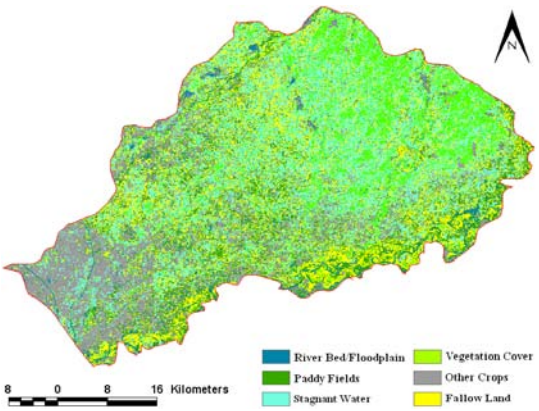

Figure 7 : Supervised Classification 2010

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.

© 2014 Global Journals Inc. (US)

Table 4 : Supervised Classification of Landsat TM image

Image Acquisition Date	Classes	Area (km^2)	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.

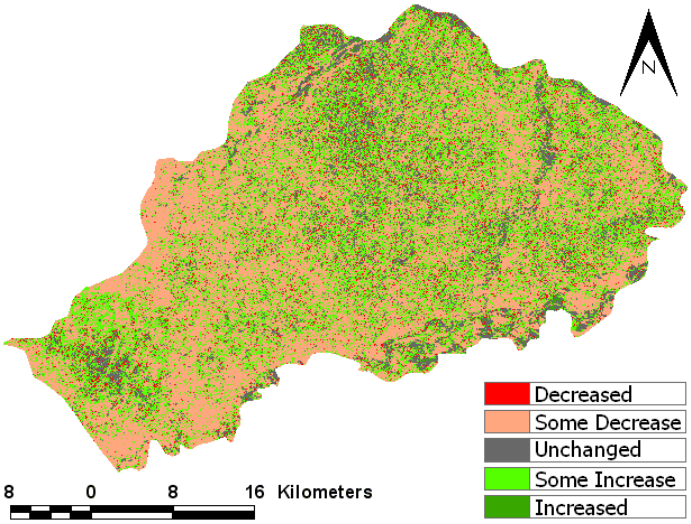

Figure 8 : Image Difference (2001-2010) at Narowal

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

Classes	During 2001 to 2010		
	Area (km^2)	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;

© 2014 Global Journals Inc. (US)

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).

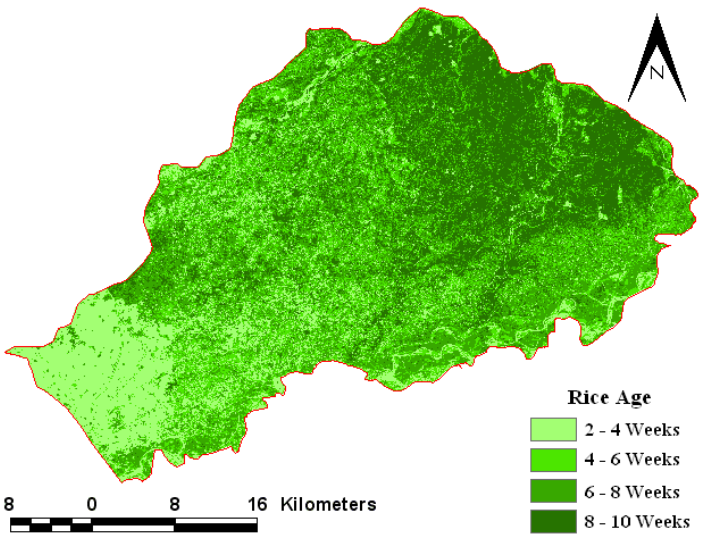

Figure 9 : Paddy/rice fields distribution map of Narowal from the analysis of Landsat ETM+ image

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,

© 2014 Global Journals Inc. (US)

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).

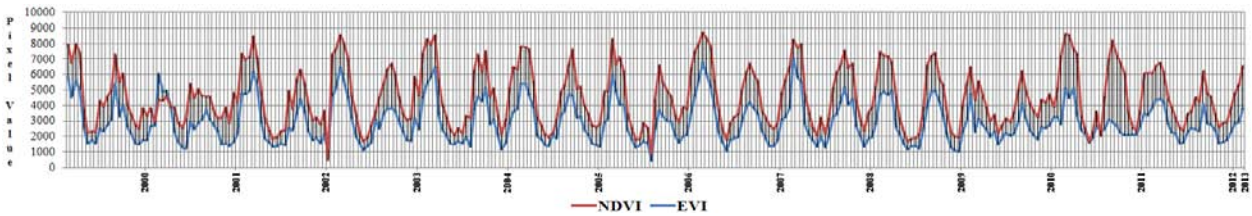

Figure 10 : Time series phenology metrics for Bara Manga *Processed by the author*

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).

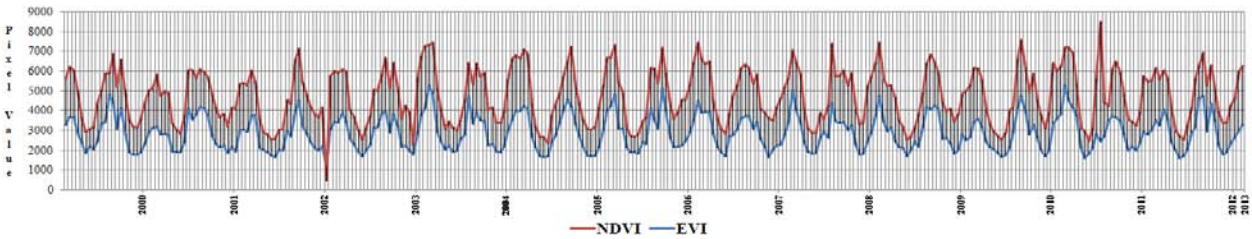

Figure 11 : Time series phenology metrics for Becochak *Processed by the author*

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).

© 2014 Global Journals Inc. (US)

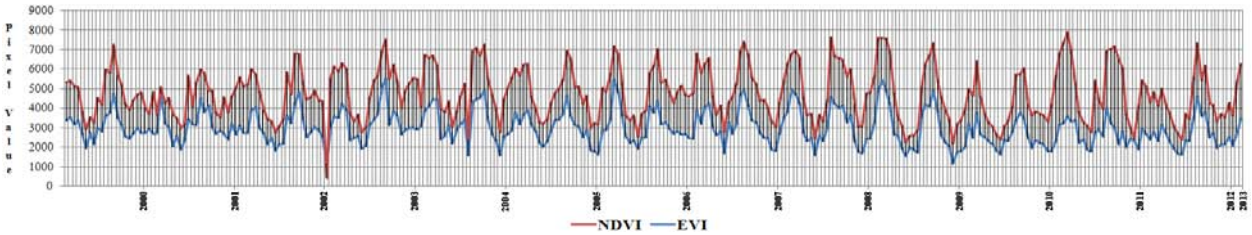

Figure 12 : Time series phenology metrics for Boora Dala *Processed by the author*

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).

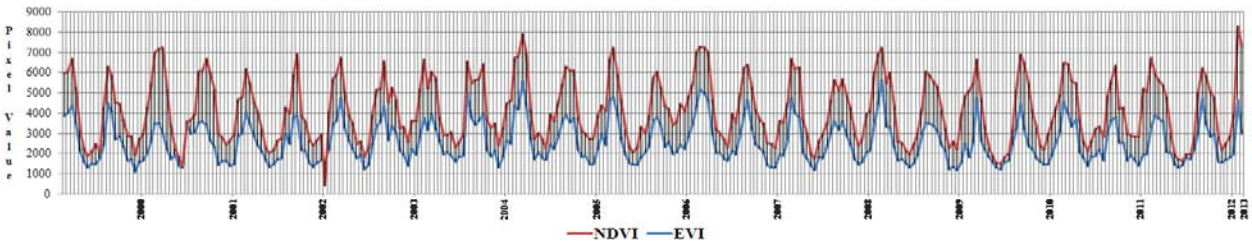

Figure 13 : Time series phenology metrics for Budha Dhola *Processed by the author*

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).

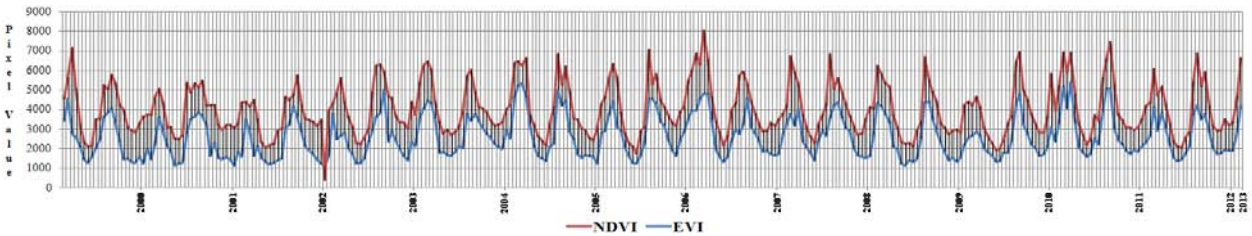

Figure 14 : Time series phenology metrics for Fattu Chak *Processed by the author*

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).

© 2014 Global Journals Inc. (US)

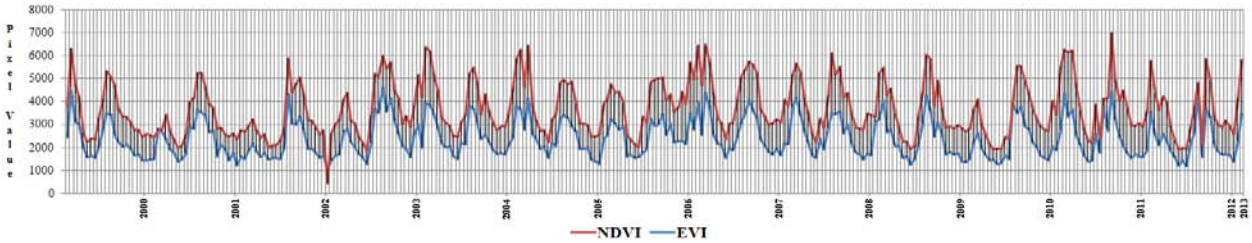

Figure 15 : Time series phenology metrics for Gumtala *Processed by the author*

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).

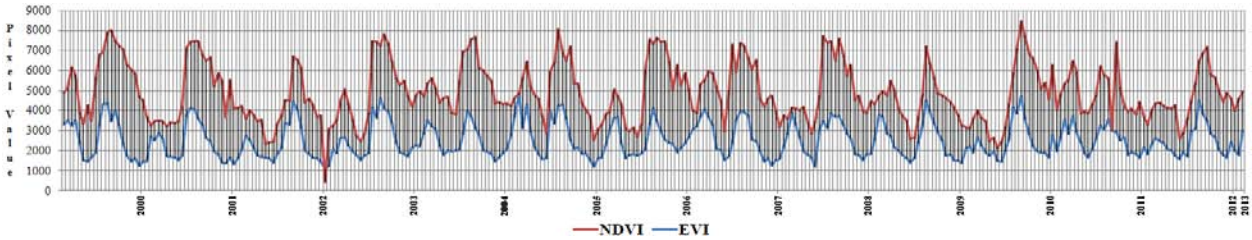

Figure 16 : Time series phenology metrics for Lalian *Processed by the author*

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).

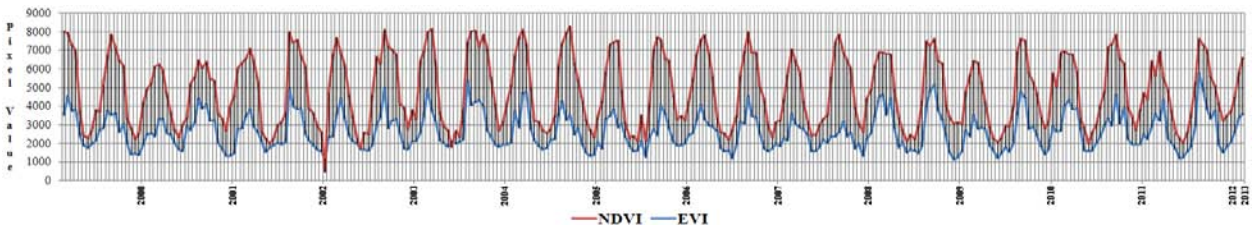

Figure 17 : Time series phenology metrics for Naina Kot *Processed by the author*

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).

© 2014 Global Journals Inc. (US)

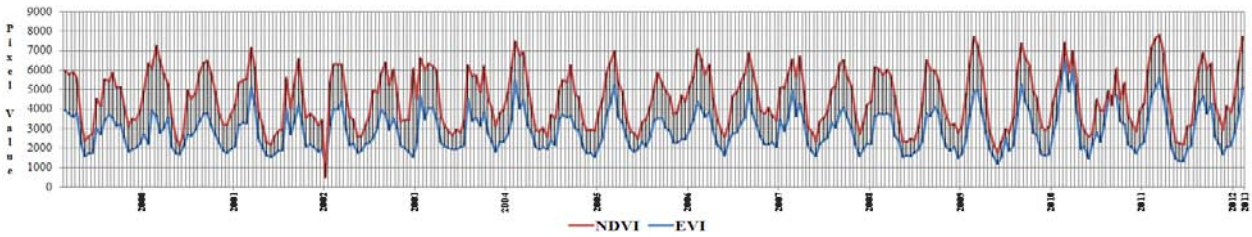

Figure 18 : Time series phenology metrics for Nathoo Kot *Processed by the author*

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).

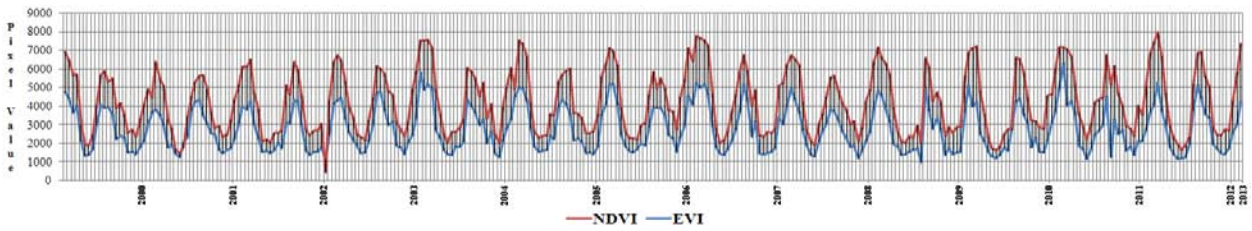

Figure 19 : Time series phenology metrics for Pherowal *Processed by the author*

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).

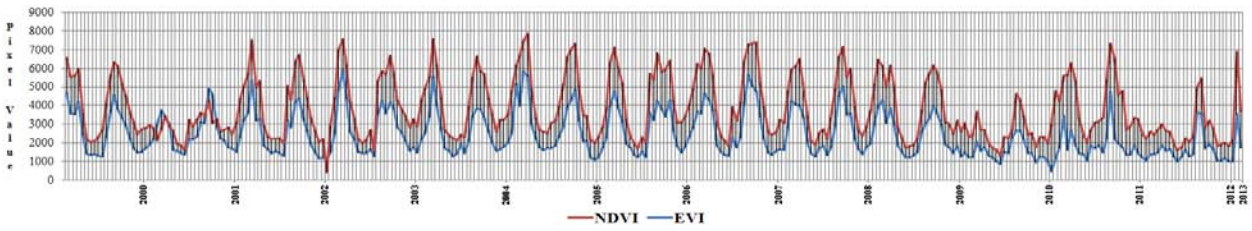

Figure 20 : Time series phenology metrics for Talwandi Bhindran *Processed by the author*

© 2014 Global Journals Inc. (US)

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				

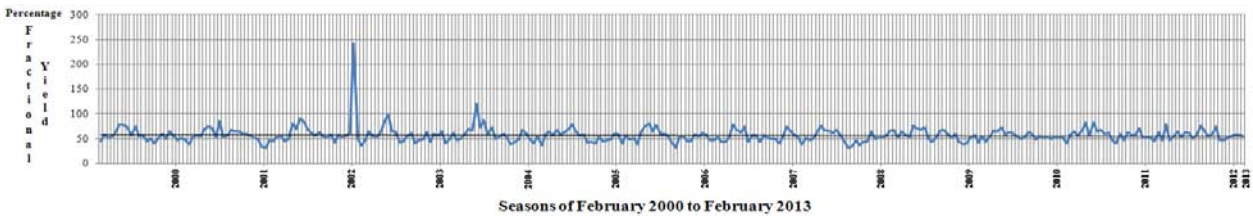

Figure 21 : Linear forecast trendline for the dataset of Naina Kot

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

© 2014 Global Journals Inc. (US)

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.

References Références Referencias

1. Aber, J.D., Ollinger, S.V., Federer, C.A., Reich, P.B., Goulden, M.L., Kicklighter, D.W., Melillo, J.M. and Lathrop, R.G. (1995). Predicting the effects of climate change on water yield and forest production in the northeastern United States. Climate Research, Vol. 5, pp.207-222.
2. Abuzar, M., McAllister, A. and Morris, M. (2001). Classification of seasonal images for monitoring irrigated crops in a salinity-affected area of Australia. International Journal of Remote Sensing, Vol. 22(5), pp.717-726.
3. Adia, S.O. and Rabiu, A.B. (2008). Change detection of vegetation cover, using multi-temporal remote sensing data and GIS techniques. In: Proceedings of Map India, 6-8 February 2008. URL: http://gisdevelopment.net/application/environment/ffm/adia.htm. (Accessed on September 16, 2011).
4. Ahmad, F. (2012). Pixel Purity Index algorithm and n-Dimensional Visualization for ETM+ image analysis: A case of District Vehari. Global Journal of Human Social Science: Arts and Humanities, Vol. 12(15), pp.23-32.
5. Ahmad, F. (2012a). Phenologically-tuned MODIS NDVI-based time series (2000-2012) for monitoring of vegetation and climatic change in North-Eastern Punjab, Pakistan. Global Journal of Human Social Science: Geography & Environmental Geo-Sciences, Vol. 12(13), pp.37-54.
6. Ahmad, F. (2012b). A review of remote sensing data change detection: Comparison of Faisalabad and Multan Districts, Punjab Province, Pakistan. Journal of Geography and Regional Planning, Vol. 5(9), pp.236-251.
7. Ahmad, F. (2012c). Spectral vegetation indices performance evaluated for Cholistan Desert. Journal of Geography and Regional Planning, Vol. 5(6), pp.165-172.
8. Ahmad, F. (2012d). Landsat ETM+ and MODIS EVI/NDVI data products for climatic variation and agricultural measurements in Cholistan Desert. Global Journal of Human Social Science: Geography & Environmental Geo-Sciences, Vol. 12(13), pp.1-11.
9. Ahmad, F. (2012e). NOAA AVHRR NDVI/MODIS NDVI predicts potential to forest resource management in Çatalca district of Turkey. Global Journal of Science Frontier Research: Environment & Earth Sciences, Vol. 12(3), pp.29-46.
10. Ahmad, F. (2012f). NOAA AVHRR satellite data for evaluation of climatic variation and vegetation change in the Punjab Province, Pakistan. Journal of Food, Agriculture & Environment, Vol. 10(2), pp.1298-1307.
11. Ahmad, F. and Shafique, K. (2013). Detection of change in vegetation cover using multi-spectral and multi-temporal information for District Sargodha. Global Journal of Human Social Sciences: Geography & Environmental Geo-Sciences, Vol. 13(1), pp.17-26.
12. Ahmad, F. and Shafique, K. (2013a). Land degradation pattern using geo-information technology for Kot Addu, Punjab Province, Pakistan. Global Journal of Human Social Sciences: Geography & Environmental Geo-Sciences, Vol. 13(1), Version 1.0, pp.1-16.

© 2014 Global Journals Inc. (US)

13. Ahmad, F., Shafique, K., Ahmad, S.R., Rehman, S.-Ur., Khan, R.M.A. and Raoof, A. (2013). The utilization of MODIS and Landsat TM/ETM+ for cotton fractional yield estimation in Burewala. Global Journal of Human Social Science: Geography, Geo-Sciences, Environmental Disaster Management, Vol. 13(7), pp.21-42.
14. Aguilar, C., Zinnert, J.C., Polo, M.J. and Young, D.R. (2012). NDVI as an indicator for changes in water availability to woody vegetation. Ecological Indicators, Vol. 23, pp.290-300.
15. Akbari, M., Mamanpoush, A.r., Gieske, A., Miranzadeh, M., Torabi, M. and Salemi, H.R. (2006). Crop and land cover classification in Iran using Landsat 7 imagery. International Journal of Remote Sensing, Vol. 27(19), pp.4117-4135.
16. Al-Awadhi, T., Al-Shukili, A. and Al-Amri, Q. (2011). The use of remote sensing & geographical information systems to identify vegetation: The case of Dhofar Governorate (Oman). URL: http://www.isprs.org/proceedings/2011/ISRSE-34/211104015Final00239.pdf. (Assessed on September 10, 2011).
17. Alexandridis, T.K., Zalidis, G.C. and Silleos, N.G. (2008). Mapping irrigated area in Mediterranean basins using low cost satellite Earth Observation. Computers and Electronics in Agriculture, Vol. 64(2), pp.93-103.
18. Asrar, G., Fuch, M. and Kanemasu, E.T. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. Agronomy Journal, Vol. 76, pp.300-306.
19. Asrar, G., Myneni, R.B. and Choudhury, B.J. (1992). Spatial heterogeneity in vegetation canopies and remote sensing of absorbed photosynthetically active radiation: A modeling study. Remote Sensing of Environment, Vol. 41, pp.85-103.
20. Ayman, H.N. and Ashraf, K.H. (2009). Integration of Misrsat-1 and SPOT-2 data for quantitative change detection applications. ICGST-GVIP Journal, Vol. 9(5), pp.53-59.
21. Babu, D.B.S., Tummalapalli, P.K., Rao, V.M. and Muralikrishna, I.V. (2011). Generation of action plans for sustainable agriculture development for rain shadow regions using GIS technology. International Journal of Earth Sciences and Engineering, Vol. 4(6), pp.323-329.
22. Báez-González, A.D., Chen, P.Y., Tiscareño-López, M. and Srinivasan, R. (2002). Using satellite and field data with crop growth modeling to monitor and estimate corn yield in Mexico. Crop Science, Vol. 42(6), pp.1943-1949.
23. Baldi, G., Nosetto, M.D., Aragón, R., Aversa, F., Paruelo, J.M. and Jobbágy, E.G. (2008). Long-term satellite NDVI datasets: Evaluating their ability to detect ecosystem functional changes in South America. Sensors, Vol. 8, pp.5397-5425.
24. Baldi, G. and Paruelo, J.M. (2008). Land use and land cover dynamics in South American temperate Grasslands. Ecology and Society, Vol. 13(2), Art 6. URL: http://www.ecologyandsociety.org/vol13/iss2/art6/ (Accessed on January 11, 2012).
25. Baldocchi, D.D., Black, T.A., Curtis, P.S., Falge, E., Fuentes, J.D., Granier, A., Gu, L., Knohl, A., Pilegaard, K., Schmid, H.P., Valentini, R., Wilson, K., Wofsy, S., Xu, L. and Yamamoto, S. (2005). Predicting the onset of net carbon uptake by deciduous forests with soil temperature and climate data: a synthesis of FLUXNET data. International Journal of Biometeorology, Vol. 49, pp.377-387.
26. Baret, F. and Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sensing of Environment, Vol. 35, pp.161-173.
27. Baret, F., Jacquemoud, S., Guyot, G. and Leprieur, C. (1992). Modeled analysis of the biophysical nature of spectral shifts and comparison with information content of broad bands. Remote Sensing of Environment, Vol. 41(2-3), pp.133-142.
28. Barnes, E.M., Moran, M.S., Pinter, Jr. P.J. and Clarke, T.R. (1996). Multispectral remote sensing and site-specific agriculture: Examples of current technology and future possibilities. In: Proceedings of the 3rd International Conference on Precision Agriculture, 23-26 June 1996, Minneapolis, Minnesota, USA, pp.843-854.
29. Baugh, W.M. and Groeneveld, D.P. (2006). Broadband vegetation index performance evaluated for a low-cover environment. International Journal of Remote Sensing, Vol. 27(21), pp.4715-4730.
30. Beeri, O., Phillips, R. and Hendrickson, J. (2007). Estimating forage quantity and quality using aerial hyperspectral imagery for northern mixed-grass prairie. Remote Sensing of Environment, Vol. 110, pp.216-225.
31. Begue, A. (1993). Leaf area index, intercepted photosynthetically active radiation, and spectral vegetation indices: A sensitivity analysis for regular-clumped canopies. Remote Sensing of Environment, Vol. 46, pp.45-59.
32. Botta, A., Viovy, N., Ciais, P., Friedlingstein, P. and Monfray, P. (2000). A global prognostic scheme of leaf onset using satellite data. Global Change Biology, Vol. 6(7), pp.709-725.
33. Broge, N.H. and Leblanc, E. (2000). Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll

© 2014 Global Journals Inc. (US)

density. Remote Sensing of Environment, Vol. 76(2), pp.156-172.
34. Budde, M.E., Tappan, G., Rowland, J., Lewis, J. and Tieszen, L.L. (2004). Assessing land cover performance in Senegal, West Africa using 1-km integrated NDVI and local variance analysis. Journal of Arid Environments, Vol. 59(3), pp.481-498.
35. Campbell, J.B. (1987). Introduction to remote sensing, The Guilford Press, New York, p.281.
36. Canziani, G.A., Ferrati, R.M., Rossi, C. and Ruiz-Moreno, D. (2006). The influence of climate and dam construction on the Iberá wetlands, Argentina. Regional Environmental Change, Vol. 6, pp.181-191.
37. Chandola, V., Hui, D., Gu, L., Bhaduri, B. and Vatsavai, R.R. (2010). Using time series segmentation for deriving vegetation phenology indices from MODIS NDVI data. IEEE International Conference on Data Mining Workshops, 13th December 2010, Sydney, Australia. pp. 202-208.
38. Chen, P.Y., Fedosejevs, G., Tiscareño-LóPez, M. and Arnold, J.G. (2006). Assessment of MODIS-EVI, MODIS-NDVI and VEGETATION-NDVI composite data using agricultural measurements: An example at corn fields in western Mexico. Springer, Netherlands, Environmental Monitoring and Assessment, Vol. 119(1-3), pp.69-82.
39. Chen, P.Y., Srinivasan, R., Fedosejevs, G. and Kiniry, J.R. (2003). Evaluating different NDVI composite techniques using NOAA-14 AVHRR data. International Journal of Remote Sensing, Vol. 24, pp.3403-3412.
40. Chen, P.Y., Srinivasan, R., Fedosejevs, G., Báez-González, A.D. and Gong, P. (2002). Assessment of NDVI composite using merged NOAA-14 and NOAA-15 AVHRR data. Geographic Information Sciences, Vol. 8(1), pp.31-38.
41. Cheng, Q. and Wu, X. (2011). Mapping paddy rice yield in Zhejiang Province using MODIS spectral index. Turkish Journal of Agriculture & Forestry, Vol. 35(6), pp.579-589.
42. Choudhury, B.J. (1987). Relationship between vegetation indices, radiation absorption, and net photosynthesis evaluated by sensitivity analysis. Remote Sensing of Environment, Vol. 22, pp.209-233.
43. Collins, W. (1978). Remote sensing of crop type and maturity. Photogrammetric Engineering & Remote Sensing, Vol. 44, pp.43-55.
44. Cyr L, Bonn F and Pesant A (1995). Vegetation indices derived from remote sensing for an estimation of soil protection against water erosion, Ecological Modelling, Vol. 79(1-3), pp.277-285.
45. Dai, X.L. and Khorram, S. (1999). Remotely sensed change detection based on artificial neural networks. Photogrammetric Engineering & Remote Sensing, Vol. 65(10), pp.1187-1194.
46. Daughtry, C.S.T., Walthall, C.L., Kim, M.S., Colstoun, de E.B. and McMurtrey III, J.E. (2000). Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sensing of Environment, Vol. 74(2), pp.229-239.
47. Debien, A., Neerinckx, S., Kimaro, D. and Gulinck, H. (2010). Influence of satellite-derived rainfall patterns on plague occurrence in northeast Tanzania. International Journal of Health Geographics, Vol. 9, pp.1-10.
48. DeFries, R.S., Hansen, M. and Townshend, J.R.G. (1995). Global discrimination of land cover types from metrics derived from AVHRR pathfinder data. Remote Sensing of Environment, Vol. 54(3), pp.209-222.
49. DeFries, R.S., Hansen, M., Townshend, J.R.G. and Sohlberg, R. (1998). Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. International Journal of Remote Sensing, Vol. 19, pp.3141-3168.
50. Demetriades-Shah, T.H., Steven, M.D. and Clark, J.A. (1990). High resolution derivative spectra in remote sensing. Remote Sensing of Environment, Vol. 33(1), pp.55-64.
51. Dennison, P.E. and Roberts, D.A. (2003). The effects of vegetation phenology on endmember selection and species mapping in southern California chaparral. Remote Sensing of Environment, Vol. 87(2-3), pp.295-309.
52. Dong, J., Kaufmann, R.K., Myneni, R.B., Tucker, C.J., Kauppi, P.E., Liski, J., Buermann, W., Alexeyev, V. and Hughes, M.K. (2003). Remote sensing estimates of boreal and temperate forest woody biomass, carbon pools, sources and sinks. Remote Sensing of Environment, Vol. 84, pp.393-410.
53. Doraiswamy, P.C., Hatfield, J.L., Jackson, T.J., Akhmedov, B., Prueger, J. and Stern, A. (2003). Crop conditions and yield simulations using Landsat and MODIS. Remote Sensing of Environment, Vol. 92, pp.548-559.
54. Dorman, J.L. and Sellers, P.J. (1989). A Global climatology of albedo, roughness length and stomatal resistance for atmospheric general circulation models as represented by the simple biosphere model (SiB). Journal of Applied Meteorology, Vol. 28, pp.833-855.
55. Eckhardt, D.W., Verdin, J.P. and Lyford, G.R. (1990). Automated update of an irrigated lands GIS using SPOT HRV imagery. Photogrammetric Engineering & Remote Sensing, Vol. 56, pp.1515-1522.
56. El-Magd, I.A. and Tanton, T.W. (2003). Improvements in land use mapping for irrigated

© 2014 Global Journals Inc. (US)

agriculture from satellite sensor data using a multi-stage maximum likelihood classification. International Journal of Remote Sensing, Vol. 24, pp.4197-4206.
57. Epiphanio, J.C.N. and Huete, A.R. (1995). Dependence of NDVI and SAVI on sun/sensor geometry and its effect on fPAR relationships in Alfalfa. Remote Sensing of Environment, Vol. 51, pp.351-360.
58. Fearnside, P.M. (2005). Deforestation in Brazilian Amazonia: History, rates, and consequences. Conservation Biology, Vol. 19, pp.680-688.
59. Fensholt, R. (2004). Earth observation of vegetation status in the Sahelian and Sudanian West Africa: Comparison of Terra MODIS and NOAA AVHRR satellite data. International Journal of Remote Sensing, Vol. 10, pp.1641-1659.
60. Fontana, F.M.A. (2009). From single pixel to continental scale: using AVHRR and MODIS to study land surface parameters in mountain regions. Ph.D. dissertation, Institute of Geography, University of Bern, Switzerland. URL: http://www.climatestudies.unibe.ch/students/theses/phd/31.pdf. (Accessed on October 15, 2012).
61. Frank, M. and Menz, G. (2003). Detecting seasonal changes in a semi-arid environment using hyperspectral vegetation indices. In: Proceedings of 3rd EARSel Workshop on Imaging Spectroscopy, Herrschingen, Germany, 13-16 May 2003, pp.504-512.
62. Galio, K.P., Daughtry, C.S.T. and Bauer, M.E. (1985). Spectral estimation of absorbed photosynthetically active radiation in corn canopies. Agronomy Journal, Vol. 78, pp.752-756.
63. Gao, B-C. (1996). NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, Vol. 58(3), pp.257-266.
64. Gao, X., Huete, A.R., Ni, W. and Miura, T. (2000). Optical–biophysical relationships of vegetation spectra without background contamination. Remote Sensing of Environment, Vol. 74(3), pp.609-620.
65. Gao, Y. and Mas, J.F. (2008). MODIS EVI as an ancillary data for an object-based image analysis with multi-spectral MODIS data. URL: http://www.isprs.org/proceedings/XXXVIII/4-C1/Sessions/Session5/6590_YGao_Proc_poster.pdf. (Accessed on September 07, 2011).
66. Gillies, R.R., Carlson, T.N., Cui, J., Kustas, W.O. and Humes, K.S. (1997). A verification of the 'triangle' method for obtaining surface soil water content and energy fluxes from remote measurements of the Normalized Difference Vegetation Index (NDVI) and surface radiant temperature. International Journal of Remote Sensing, Vol. 18, pp.3145-3166.
67. Glenn, E.P., Huete, A.R., Nagler, P.L. and Nelson, S.G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. Sensors, Vol. 8, pp.2136-2160.
68. GOP (2000). District census report of Narowal 1998. Population Census Organization, Statistic Division, Government of Pakistan, Islamabad, Pakistan, pp.1-5.
69. Grau, H.R., Gasparri, N.I. and Aide, T.M. (2005). Agriculture expansion and deforestation in seasonally dry forests of north-west Argentina. Environmental Conservation. Vol. 32, pp.140-148.
70. Grogan, K. and Fensholt, R. (2013). Exploring patterns and effects of aerosol quantity flag anomalies in MODIS surface reflectance products in the tropics. Remote Sensing, Vol. 5, pp. 3495-3515.
71. GSFC/NASA (2003). MODIS technical specifications. URL: http://modis.gsfc.nasa.gov/about/specs.html. (Accessed on September 05, 2011).
72. Guo, X. (2003). Relationships between NDVI and climatological variability in the Prairie ecozone of Canada. Prairie Perspectives, Vol.6, pp.32-46.
73. Guyot, G., Baret, F. and Jacquemoud, S. (1992). Imaging spectroscopy for vegetation studies. In: Toselli, F. and Bodechtel, J. (Eds.), Imaging spectroscopy: Fundamentals and prospective applications, Kluwer Academic Press, Dordrecht, pp.145-165.
74. Haack, B., Wolf, J. and English, R. (1998). Remote sensing change detection of irrigated agriculture in Afghanistan. Geocarto International, Vol. 13(2), pp.65-75.
75. Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J. and Dextraze, L. (2002). Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, Vol. 81(2-3), pp.416-426.
76. Hall, F.G., Strebel, D.E., Nickeson, J.E. and Goetz, S.J. (1991). Radiometric rectification: Toward a common radiometric response among multi-date, multi-sensor images. Remote Sensing of Environment, Vol. 35, pp.11-27.
77. Hamel, S., Garel, M., Festa-Bianchet, M., Gaillard, J-M. and Côté, S.D. (2009). Spring Normalized Difference Vegetation Index (NDVI) predicts annual variation in timing of peak faecal crude protein in mountain ungulates. Journal of Applied Ecology, Vol. 46, pp.582-589.
78. Hashemi, S.A. (2010). Evaluating phenological events of shrubs land by AVHRR data. American Journal of Scientific Research, Issue 12, pp.23-31.

© 2014 Global Journals Inc. (US)

79. Heller, R.C. and Johnson, K.A. (1979). Estimating irrigated land acreage from Landsat imagery. Photogrammetric Engineering & Remote Sensing, Vol. 45, pp.1379-1386.
80. Hobbs, R.J. (1989). Remote sensing of spatial and temporal dynamics of vegetation. In: Hobbs, R.J. and Mooney, H.A. (Eds.), Remote Sensing of Biosphere Functioning, Springer-Verlag, New York, pp.203-219.
81. Hoffer, R.M. (1978). Biological and physical considerations in applying computer-aided analysis techniques to remote sensor data. In Remote Sensing: The quantitative approach. Swam PH, Davis SM (Eds), McGraw- Hill, USA, pp.35-98.
82. Horler, D.N.H., Dockray, M. and Barber, J. (1983). The red edge of plant leaf reflectance. International Journal of Remote Sensing, Vol. 4(2), pp.273-288.
83. Huang, C., Kim, S., Altstatt, A., Townshend, J.R.G., Davis, P., Song, K., Tucker, C.J., Rodas, O., Yanosky, A., Clay, R. and Musinsky, J. (2007). Rapid loss of Paraguay's Atlantic forest and the status of protected areas: A Landsat assessment. Remote Sensing of Environment, Vol. 106, pp.460-466.
84. Huete, A.R. (2005). Global variability of terrestrial surface properties derived from MODIS visible to thermal-infrared measurements. In: Proceedings of IGARSS 05 Geoscience and Remote Sensing Symposium, 25-29 July 2005. URL: http://ieeexplore.ieee.org/iel5/10226/32601/01526782.pdf. (Accessed on September 05, 2011).
85. Huete, A.R., Didan, K., Miura, T., Rodriguez, E.P., Gao, X. and Ferreira, L.G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, Vol. 83(1-2), pp.195-213.
86. Huete, A.R., Justice, C.O. and Leeuwen, van W. (1999). MODIS vegetation index (MOD 13) algorithm theoretical basis document version 3. URL: http://modis.gsfc.nasa.gov/data/atbd/atbd_mod13.pdf. (Accessed on September 17, 2011).
87. Huete, A.R., Liu, H.Q., Batchily, K. and Leeuwen, van W. (1997). A comparison of vegetation indices over a global set of TM images for EOS-MODIS. Remote Sensing of Environment, Vol. 59, pp.440-451.
88. Huete, A.R. and Liu, H.Q. (1994). An error and sensitivity analysis of the atmospheric- and soil-correcting variants of the NDVI for the MODIS-EOS. IEEE Transactions on Geoscience and Remote Sensing, Vol. 32, pp.897-905.
89. Huete, A.R. (1988). A soil adjusted vegetation index (SAVI). Remote Sensing of Environment, Vol. 25(3), pp.295-309.
90. Hufkens, K., Friedl, M.A., Richardson, A.D., Milliman, T. and Migliavacca, M. (2010). Vegetation phenology from MODIS/AVHRR/PhenoCam: Scaling and validation possibilities. URL: http://modis.gsfc.nasa.gov/sci_team/meetings/201001/presentations/posters/land/hufkens.pdf. (Accessed on November 10, 2011).
91. Jakubauskas, M.E., David, R. and Kastens, J.H. (2002). Crop identification using harmonic analysis of time-series AVHRR NDVI data. Computers and Electronics in Agriculture, Vol. 37(1-3), pp.127-139.
92. Jakubauskas, M.E., Legates, D.R. and Kastens, J.H. (2001). Harmonic analysis of time-series AVHRR NDVI data. Photogrammetric Engineering & Remote Sensing, Vol. 67(4), pp.461-470.
93. Jenkins, J.P., Braswell, B.H., Frolking, S.E. and Aber, J.D. (2002). Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S. Geophysical Research Letters, Vol. 29(24), pp.54,1-54,4.
94. Jensen, J.R. (2005). Introductory digital image processing: A remote sensing perspective. 3rd Edition, Englewood Cliffs, New Jersey, Prentice-Hall, pp.34-67.
95. Johnson, J.F., Voorhees, W.B., Nelson, W.W. and Randall, G.W. (1990). Soybean growth and yield as affected by surface and subsoil compaction. Agronomy Journal, Vol. 82(5), pp.973-979.
96. Jolly, W.M., Nemani, R. and Running, S.W. (2005). A generalized, bioclimatic index to predict foliar phenology in response to climate. Global Change Biology, Vol. 11, pp.619-632.
97. Justice, C.O., Townshend, J.R.G., Holben, B.N. and Tucker, C.J. (1985). Analysis of the phenology of global vegetation using meteorological satellite data. International Journal of Remote Sensing, Vol. 6, pp.1271-1318.
98. Justice, C.O., Vermote, E., Townshend, J.R.G., DeFries, R.S., Roy, D.P., Hall, D.K., Salomonson, V.V., Privette, J., Riggs, G., Strahler, A., Lucht, W., Myneni, R., Knjazihhin, Y., Running, S., Nemani, R., Wan, Z., Huete, A.R., Leeuwen, van W., Wolfe, R.E., Giglio, L., Muller, J.-P., Lewis, P. and Barnsley, M. (1998). The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research. IEEE Transactions on Geoscience and Remote Sensing, Vol. 36(4), pp.1228-1249.
99. Karaburun, A. (2010). Estimation of C factor for soil erosion modeling using NDVI in Büyükçekmece watershed. Ozean Journal of Applied Sciences, Vol. 3(1), pp.77-85.
100. Karnieli, A. and Dall'Olmo, G. (2003). Remote-sensing monitoring of desertification, phenology, and droughts. Management of Environmental

© 2014 Global Journals Inc. (US)

Quality: An International Journal, Vol. 14(1), pp.22-38.
101. Kauth, R.J. and Thomas, G.S. (1976). The tasseled cap – A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In: Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, 29 June to 01 July, 1976, West Lafayette, IN, USA, pp.41-51.
102. Keene, K.M. and Conley, C.D. (1980). Measurement of irrigated acreage in Western Kansas from LANDSAT images. Environmental Geology, Vol. 3(2), pp.107-116.
103. Kolm, K.E. and Case, H.L. (1984). The identification of irrigated crop types and estimation of acreages from Landsat imagery. Photogrammetric Engineering & Remote Sensing, Vol. 50, pp.1479-1490.
104. Kulkarni, S.S. and Bajwa, S.G. (2005). Spectral response of cotton canopy to soil compaction. Paper Number: 051066, The Society for engineering in agricultural, food, and biological systems, USA, pp.1-19.
105. Kumar, L., Schmidt, K.S., Dury, S. and Skidmore, A.K. (2001). Review of hyperspectral remote sensing and vegetation science. In: Meer, van der F.D. and Jong, de S.M. (Eds.), Imaging spectrometry: Basic Principles and Prospective Applications, Kluwer Academic Press, Dordrecht, pp.111-155.
106. Lambin, E.F. (1996). Change detection at multiple temporal scales - seasonal and annual variations in landscape variables. Photogrammetric Engineering & Remote Sensing, Vol. 62(8), pp.931-938.
107. Lillesand, T.M. and Kiefer, R.W. (1994). Remote Sensing and Image Interpretation. 3rd Edition, John Wiley & Sons, Inc., New York, pp.203-210.
108. Liu, H.Q. and Huete, A.R. (1995). A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Transactions on Geoscience and Remote Sensing, Vol. 33(2), pp.457-465.
109. Lobell, D.B., Asner, G.P., Ortiz-Monasterio, J.I. and Benning, T.L. (2003). Remote sensing of regional crop production in the Yaqui Valley, Mexico: Estimates and uncertainties. Agriculture, Ecosystems and Environment, Vol. 94, pp.205-220.
110. Los, S.O., North, P.R.J., Grey, W.M.F. and Barnsley, M.J. (2005). A method to convert AVHRR normalized difference vegetation index time series to a standard viewing and illumination geometry. Remote Sensing of Environment, Vol. 99(4), pp.400-411.
111. Los, S.O., Collatz, G.J., Bounoua, L., Sellers, P.J. and Tucker, C.J. (2001). Global interannual variations in sea surface temperature and land surface vegetation, air temperature, and precipitation. Journal of Climate, Vol. 14, pp.1535-1549.
112. Lowery, B. and Schuler, R.T. (1991). Temporal effects of subsoil compaction on soil strength and plant growth. Soil Science Society of America Journal, Vol. 55(1), pp.216-223.
113. Lloyd, D. (1990). A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery. International Journal of Remote Sensing, Vol. 11(12), pp.2269-2279.
114. Lu, D., Mausel, P., Brondizios, E. and Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, Vol. 25(12), pp.2365-2407.
115. Lucht, W., Prentice, I.C., Myneni, R.B., Sitch, S., Friedlingstein, P., Cramer, W., Bousquet, P., Buermann, W. and Smith, B. (2002). Climatic control of the high-latitude vegetation greening trend and Pinatubo effect. Science, Vol. 296(5573), pp.1687-1689.
116. Lunetta, R.L., Johnson, D.M., Lyon, J.G. and Crotwell, J. (2004). Impacts of imagery temporal frequency on land-cover change detection monitoring. Remote Sensing of Environment, Vol. 89(4), pp.444-454.
117. Lunetta, R.S., Alvarez, R., Edmonds, C.M., Lyon, J.G., Elvidge, C.D. and Bonifaz, R. (2002). An assessment of NALC/Mexico land-cover mapping results: Implications for assessing landscape change. International Journal of Remote Sensing, Vol. 23(16), pp.3129-3148.
118. Lunetta, R.S., Ediriwickrema, J., Johnson, D.M., Lyon, J.G. and McKerrow, A. (2002a). Impacts of vegetation dynamics on the identification of land-cover change in a biologically complex community in North Carolina USA. Remote Sensing of Environment, Vol. 82, pp.258-270.
119. Lunetta, R.S., Knight, J.F., Ediriwickrema, J., Lyon, J.G. and Worthy, L.D. (2006). Land-cover change detection using multi-temporal MODIS NDVI data. Remote Sensing of Environment, Vol. 105(2), pp.142-154.
120. Lyon, J.G., Yuan, D., Lunetta, R.S. and Elvidge, C.D. (1998). A change detection experiment using vegetation indices. Photogrammetric Engineering & Remote Sensing, Vol. 64(2), pp.143-150.
121. Macleod, R.D. and Congalton, R.G. (1998). A quantitative comparison of change detection algorithms for monitoring eelgrass from remotely sensed data. Photogrammetric Engineering and Remote Sensing, Vol. 64(3), pp.207-216.
122. Mahmoodzadeh, H. (2007). Digital change detection using remotely sensed data for monitoring green space destruction in Tabriz.

© 2014 Global Journals Inc. (US)

International Journal of Environmental Research, Vol. 1(1), pp.35-41.
123. Manavalan, P., Kesavasamy, K. and Adiga, S. (1995). Irrigated crops monitoring through seasons using digital change detection analysis of IRS-LISS 2 data. International Journal of Remote Sensing, Vol. 16(4), pp.633-640.
124. Mas, J-F. (1999). Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing, Vol. 20(1), pp.139-152.
125. Mauser, W. and Bach, H. (1994). Imaging spectroscopy in hydrology and agriculture - determination of model parameters. In: Hill, J. and Mégier, J. (Eds.), Imaging spectrometry - a tool for environmental observations, Kluwer Academic Press, Dordrecht, pp.261-283.
126. McGwire, K., Minor, T. and Fenstermaker, L. (2000). Hyperspectral mixture modeling for quantifying sparse vegetation cover in arid environments. Remote Sensing of Environment, Vol. 72(3), pp.360-374.
127. Meneses-Tovar, C.L. (2011). NDVI as indicator of degradation. Unasylva, Vol. 62(238), pp.39-46.
128. Milich, L. and Weiss, E. (2000). GAC NDVI interannual coefficient of variation (CoV) images: Ground truth sampling of the Sahel along north-south transects. International Journal of Remote Sensing, Vol. 21, pp.235-260.
129. Miura, T., Yoshioka, H. and Suzuki, T. (2008). Evaluation of spectral vegetation index translation equations for the development of long-term data records. In: Proceedings of IEEE International Geoscience & Remote Sensing Symposium, 6-11 July, 2008, Boston, Massachusetts, U.S.A. doi: 10.1109/IGARSS.2008.4779447
130. MODIS (1999). MODIS Vegetation Index (MOD 13): Algorithm theoretical basis document pp.26-29 (version 3). URL: http://modis.gsfc.nasa.gov/data/atbd/atbd_mod13.pdf. (Accessed on December 04, 2008).
131. Moran, M.S., Inoue, Y. and Barnes, E.M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sensing of Environment, Vol. 61(3), pp.319-346.
132. Moran, M.S., Jackson, R.D., Slater, P.N. and Teillet, P.M. (1992). Evaluation of simplified procedures for retrieval of land surface reflectance factors from satellite sensor output. Remote Sensing of Environment, Vol. 41(2-3), pp.169-184.
133. Moulin, S., Kergoat, L., Viovy, N. and Dedieu, G. (1997). Global scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements. Journal of Climate, Vol. 10, pp.1154-1170.
134. Mulianga, B., Bégué, A., Simoes, M. and Todoroff, P. (2013). Forecasting regional sugarcane yield based on time integral and spatial aggregation of MODIS NDVI. Remote Sensing, Vol. 5, pp.2184-2199.
135. Murthy, C.S., Raju, P.V., Jonna, S., Hakeem, K.A. and Thiruvengadachari, S. (1998). Satellite derived crop calendar for canal operation schedule in Bhadra project command area, India. International Journal of Remote Sensing, Vol. 19(15), pp.2865-2876.
136. Myneni, R.B. and Asrar, G. (1994). Atmospheric effects and spectral vegetation indices. Remote Sensing of Environment, Vol. 47, pp.390-402.
137. Myneni, R.B., Dong, J., Tucker, C.J., Kaufmann, R.K., Kauppi, P.E., Liski, J., Zhou, L., Alexeyev, V. and Hughes, M.K. (2001). A large carbon sink in the woody biomass of Northern forests. In: Proceedings of the National Academy of Sciences of the United States of America, Vol. 98, pp.14784-14789.
138. Myneni, R.B., Keeling, C.D., Tucker, C.J., Asrar, G. and Nemani, R.R. (1997). Increased plant growth in the northern high latitudes from 1981-1991. Nature, Vol. 386, pp.698-702.
139. Nasr, A.H. and Helmy, A.K. (2009). Integration of Misrsat-1 and SPOT-2 data for quantitative change detection applications. ICGST-GVIP Journal, Vol. 9(5), pp.53-59. URL: http://www.icgst.com/gvip/volume9/Issue5/GVIP_V9_I5.pdf. (Accessed on November 04, 2011).
140. Nicandrou, A. (2010). Hydrological assessment and modelling of the river Fani catchment, Albania. Faculty of Advanced Technology, University of Glamorgan. URL: http://dspace1.isd.glam.ac.uk/dspace/handle/10265/461 (Accessed on November 11, 2012).
141. Niel, T.G.V. and McVicar, T.R. (2001). Remote sensing of rice-based irrigated agriculture: A review. URL: http://prijipati.library.usyd.edu.au/bitstream/2123/175/1/P1105TR01-01.pdf. (Accessed on January 23, 2014).
142. Nightingale, J.M., Esaias, W.E., Wolfe, R.E., Nickeson, J.E. and Pedelty, J.A. (2008). Assessing the effect of climate change on honey bees using scale hive records and satellite derived vegetation phenology products. URL: http://www.igarss08.org/Abstracts/pdfs/2282.pdf. (Accessed on November 10, 2011).
143. NRC (2007). Earth Science and Applications from Space: National Imperatives for the Next Decade and Beyond. National Research Council of the National Academies, The National Academies Press, Washington, D.C., p.428. URL: http://www.nap.edu/openbook.php?record_id=11820&page=428. (Accessed on September 17, 2011).

© 2014 Global Journals Inc. (US)

144. Nuarsa, I.W., Nishio, F. and Hongo, C. (2011). Spectral characteristics and mapping of rice plants using multi-temporal Landsat data. Journal of Agricultural Science, Vol. 3(1), pp.54-67.
145. Nuarsa, I.W., Kanno, S., Sugimori, Y. and Nishio, F. (2005). Spectral characterization of rice field using multi-temporal Landsat ETM+ data. International Journal of Remote Sensing and Earth Sciences, Vol. 2, pp.65-71.
146. Nuarsa, I.W., Nishio, F., Hongo, C. and Mahardika, I.G. (2012). Using variance analysis of multitemporal MODIS images for rice field mapping in Bali Province, Indonesia. International Journal of Remote Sensing, Vol. 33(17), pp.5402-5417.
147. Ouyang, W., Hao, F.H., Skidmore, A.K., Groen, T.A., Toxopeus, A.G. and Wang, T. (2012). Integration of multi-sensor data to assess grassland dynamics in a Yellow River sub-watershed. Ecological Indicators, Vol. 18, pp.163-170.
148. Ozdogan, M. and Gutman, G. (2008). A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US. Remote Sensing of Environment, Vol. 112, pp.3520-3537.
149. Ozdogan, M., Woodcock, C.E., Salvucci, G.D. and Demir, H. (2006). Changes in summer irrigated crop area and water use in southeastern Turkey from 1993 to 2002: Implications for current and future water resources. Water Resources Management, Vol. 20, pp.467-488.
150. Ozdogan, M., Yang, Y., Allez, G. and Cervantes, C. (2010). Remote sensing of irrigated agriculture: Opportunities and challenges. Remote Sensing, Vol. 2, pp.2274-2304.
151. Paruelo, J.M., Epstein, H.E., Lauenroth, W.K. and Burke, I.C. (1997). ANPP estimates from NDVI for the Central Grassland Region of the United States. Ecology, Vol. 78(3), pp.953-958.
152. Pauchard, A., Aguayo, M., Peña, E. and Urrutia, R. (2006). Multiple effects of urbanization on the biodiversity of developing countries: The case of a fast-growing metropolitan area (Concepción, Chile). Biological Conservation, Vol. 127, pp.272-281.
153. Pax-Lenney, M., Woodcock, C.E., Collins, J.B. and Hamdi, H. (1996). The status of agricultural lands in Egypt: The use of multitemporal NDVI features derived from Landsat TM. Remote Sensing of Environment, Vol. 56, pp.8-20.
154. Piao, S.L, Mohammat, A., Fang, J.Y., Cai, Q. and Feng, J. (2006). NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. Global Environmental Change, Vol. 16(4), pp.340-348.
155. Piao, S.L., Fang, J.Y., Zhou, L.M., Guo, Q.H., Henderson, M., Ji, W., Li, Y. and Tao, S. (2003). Interannual variations of monthly and seasonal NDVI in China from 1982 to 1999. Journal of Geophysical Research, Vol. 108(D14), pp.4401-4413.
156. Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.M., Tucker, C.J. and Stenseth, N.C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology & Evolution, Vol. 20(9), pp.503-510.
157. Potter, C.S., Randerson, J.T., Field, C.B., Matson, P.A., Vitousek, P.M., Mooney, H.A. and Klooster, S.A. (1993). Terrestrial ecosystem production, a process model based on global satellite and surface data. Global Biogeochemical Cycles, Vol. 7, pp.811-841.
158. Prasad, A.K., Sudipta, S., Singh, R.P. and Kafatos, M. (2007). Inter-annual variability of vegetation cover and rainfall over India. Advances in Space Research, Vol. 39(1), pp.79-87.
159. Prenzel, B. and Treitz, P. (2004). Remote sensing change detection for a watershed in north Sulawesi, Indonesia. Progress in Planning, Vol. 61, pp.349-363.
160. Propastin, P. and Kappas, M. (2009). Modeling net ecosystem exchange for grassland in central Kazakhstan by combining remote sensing and field data. Remote Sensing, Vol. 1, pp.159-183.
161. Quarmby, N.A., Milnes, M., Hindle, T.L. and Silleos, N. (1993). The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction. International Journal of Remote Sensing, Vol. 14, pp.199-210.
162. Rahman, Md.R., Islam, A.H.M.H. and Hassan, Md.S. (2004). Change detection of winter crop coverage and the use of Landsat data with GIS. The Journal of Geo-Environment, Vol. 4, pp.1-13.
163. Ramachandra, T.V. and Kumar, U. (2004). Geographic resources decision support system for land use, land cover dynamics analysis. In: Proceedings of the FOSS/GRASS Users Conference, 12-14 September 2004, Bangkok, Thailand. URL: http://www.ces.iisc.ernet.in/energy/paper/grdss/viewpaper.pdf. (Accessed on September 29, 2013).
164. Reed, B.C., Brown, J.F., VanderZee, D., Loveland, T.R., Merchant, J.W. and Ohlen, D.O. (1994). Measuring phenological variability from satellite imagery. Journal of Vegetation Science, Vol. 5(5), pp.703-714.
165. Richardson, A.D., Hollinger, D.Y., Dail, D.B., Lee, J.T., Munger, J.W. and O'keefe, J. (2009). Influence of spring phenology on seasonal and annual carbon balance in two contrasting New

© 2014 Global Journals Inc. (US)

England forests. Tree Physiology, Vol. 29(3), pp.321-331.
166. Romero, H. and Ordenes, F. (2004). Emerging urbanization in the Southern Andes: Environmental impacts of urban sprawl in Santiago de Chile on the Andean piedmont. Mountain Research and Development, Vol. 24, pp.197-201.
167. Rondeaux, G., Steven, M. and Baret, F. (1996). Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment, Vol. 55, pp.95-107.
168. Rouse, J.W., Haas, R.H., Schell, J.A. and Deering, D.W. (1973). Monitoring vegetation systems in the Great Plains with ERTS. 3rd ERTS Symposium, NASA SP-351 I, pp.309-317. URL: http://geol.hu/data/online_help/Vegetation_Indices.html. (Accessed on January 10, 2012).
169. Ruecker, G.R., Shi, Z., Mueller, M., Conrad, C., Ibragimov, N., Lamers, J.P.A., Martius, C., Strunz, G. and Dech, S.W. (2007). Cotton yield estimation in Uzbekistan integrating MODIS, Landsat ETM+ and field data. URL: http://www.isprs.org/proceedings/XXXVI/8-W48/123_XXXVI-8-W48.pdf. pp.123-128. (Accessed on January 20, 2013).
170. Running, S.W. and Nemani, R.R. (1991). Regional hydrologic and carbon balance responses of forests resulting from potential climate change. Climatic Change, Vol. 19, pp.349-368.
171. Sader, S.A., Hayes, D.J., Hepinstall, J.A., Coan, M. and Soza, C. (2001). Forest change monitoring of a remote biosphere reserve. International Journal of Remote Sensing, Vol. 22(10), pp.1937-1950.
172. Schowengerdt, R.A. (1983). Techniques for image processing and classifications in remote sensing. 1st Edition, Academic Press, USA, pp.48-71.
173. Schowengerdt, R.A. (2006). Remote Sensing: Models and methods for image processing. 3rd Edition, Academic Press, USA, pp.98-124.
174. Schwartz, M.D. (1999). Advancing to full bloom: Planning phenological research for the 21st century. International Journal of Biometeorology, Vol. 42(3), pp.113-118.
175. Schwartz, M.D. and Reed, B.C. (1999). Surface phenology and satellite sensor-derived onset of greenness: An initial comparison. International Journal of Remote Sensing, Vol. 20(17), pp.3451-3457.
176. Sellers, P.J., Tucker, C.J., Collatz, G.J., Los, S., Justice, C.O., Dazlich, D.A. and Randall, D.A. (1994). A global 1° by 1° NDVI data set for climate studies, Part 2: The adjustment of the NDVI and generation of global fields of terrestrial biophysical parameters. International Journal of Remote Sensing, Vol. 15, pp.3519-3545.
177. Senseman, G.M., Bagley, C.F. and Tweddale, S.A. (1996). Correlation of rangeland cover measures to satellite-imagery-derived vegetation indices. Geocarto International, Vol. 11(3), pp.29-38.
178. Sesnie, S.E., Gessler, P.E., Finegan, B. and Thessler, S. (2008). Integrating Landsat TM and SRTM-DEM derived variables with decision trees for habitat classification and change detection in complex neotropical environments. Remote Sensing of Environment, Vol. 112, pp.2145-2159.
179. Shah, A.H. (2007). Land resource inventory and agricultural land use plan of Narowal district. National Agricultural Land use Plan (Project), Soil Survey of Pakistan, Lahore, Pakistan.
180. Shao, Y., Fan, X., Liu, H., Xiao, J., Ross, S., Brisco, B., Brown, R. and Staples, G. (2001). Rice monitoring and production estimation using multitemporal RADARSAT. Remote Sensing of Environment, Vol. 76(3), pp.310-325.
181. Shinners, K.J. and Binversie, B.N. (2007). Fractional yield and moisture of corn stover biomass produced in the Northern US Corn Belt. Biomass and Bioenergy, Vol. 31, pp.576-584.
182. Shippert, P. (2004). Why use hyperspectral imagery? Photogrammetric Engineering & Remote Sensing, pp.377-380. URL: http://www.iro.umontreal.ca/~mignotte/IFT6150/ComplementCours/HyperspectralImagery.pdf. (Accessed on November 20, 2011).
183. Singh, A., Singh, S., Garg, P.K. and Khanduri, K. (2013). Land use and land cover change detection: a comparative approach using post classification change matrix and discriminate function change detection methodology of Allahabad city. International Journal of Current Engineering and Technology, Vol. 3(1), pp.142-148.
184. Singh, R.P., Roy, S. and Kogan, F. (2003). Vegetation and temperature condition indices from NOAA AVHRR data for drought monitoring over India. International Journal of Remote Sensing, Vol. 24(22), pp.4393-4402.
185. Singh, A. (1989). Digital change detection techniques using remotely sensed data. International Journal of Remote Sensing, Vol. 10(6), pp.989-1003.
186. Singh, A. (1986). Change detection in the tropical forest environment of northeastern India using Landsat remote sensing and tropical land management: Remote Sensing and Tropical Land Management. Eden, M.J. and Perry, J.T. (Eds.), John Wiley & Sons, Inc., New York, pp.237-254.
187. Solano, R., Didan, K., Jacobson, A. and Huete, A.R. (2010). MODIS vegetation index User's Guide. Collection 5, Vegetation Index and

© 2014 Global Journals Inc. (US)

Phenology Lab, The University of Arizona, Tucson, AZ, USA.
188. Starbuck, M.J. and Tamayo, J. (2007). Monitoring vegetation change in Abu Dhabi Emirate from 1996 to 2000 and 2004 using Landsat satellite imagery. Arab Gulf Journal of Scientific Research, Vol. 25(1-2), pp.71-80.
189. Stow, D. (1995). Monitoring ecosystem response to global change: Multitemporal remote sensing analyses. In: Moreno, J. and Oechel, W. (Eds.), Anticipated Effects of a Changing Global Environment in Mediterranean Type Ecosystems. Springer-Verlag, New York, pp.254-286.
190. Stroppiana, D., Boschetti, M., Brivio, P.A. and Bocchi, S. (2006). Remotely sensed estimation of rice nitrogen concentration for forcing crop growth models. Italian Journal of Agrometeorology, Vol. 3, pp.50-57.
191. Tan, B., Morisette, J.T., Wolfe, R.E., Gao, F., Ederer, G.A., Nightingale, J.M. and Pedelty, J.A. (2008). Vegetation phenology metrics derived from temporally smoothed and gap-filled MODIS data. URL: www.igarss08.org/Abstracts/pdfs/2347.pdf. (Accessed on November 10, 2011).
192. Tarpley, J.D., Schnieder, S.R. and Money, R.L. (1984). Global vegetation indices from NOAA-7 meteorological satellite. Journal of Climate and Applied Meteorology, Vol. 23, pp.4491-4503.
193. Taylor, H.M. and Gardner, H.R. (1963). Penetration of cotton seedlings tap roots as influenced by bulk density, moisture content and strength of soil. Soil Science, Vol. 96, pp.153-156.
194. Thelin, G.P. and Heimes, F.J. (1987). Mapping irrigated cropland from Landsat data for determination of water use from the high plains aquifer in parts of Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming. US Geological Survey Professional Paper, Washington, DC, USA.
195. Thenkabail, P.S., Dheeravath, V., Biradar, C.M., Gangalakunta, O.R.P., Noojipady, P., Gurappa, C., Velpuri, M., Gumma, M. and Li, Y. (2009). Irrigated area maps and statistics of India using remote sensing and national statistics. Remote Sensing, Vol. 1, pp.50-67.
196. Thenkabail, P.S., Schull, M. and Turral, H. (2005). Ganges and Indus river basin land use/land cover (LULC) and irrigated area mapping using continuous streams of MODIS data. Remote Sensing of Environment, Vol. 95, pp.317-341.
197. Thenkabail, P.S., Smith, R.B. and Pauw, E. De. (2000). Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment, Vol. 71(2), pp.158-182.
198. Thiam, A. (2003). The causes and spatial pattern of land degradation risk in southern Mauritania using multitemporal AVHRR-NDVI imagery and field data. Land Degradation & Development, Vol. 14, pp.133-142.
199. Thiruvengadachari, S. (1981). Satellite sensing of irrigation patterns in semiarid areas: An Indian study. Photogrammetric Engineering & Remote Sensing, Vol. 47, pp.1493-1499.
200. Thomas, D.S.G. and Leason, H.C. (2005). Dunefield activity response to climate variability in the southwest Kalahari. Geomorphology, Vol. 64(1-2), pp.117-132.
201. Townshend, J.R.G. (1992). Improved global data for land applications: A proposal for a new high resolution data set. Report No. 20. International Geosphere–Biosphere Program, Stockholm, Sweden. URL: http://library.wur.nl/WebQuery/clc/916308. (Accessed on June 04, 2012).
202. Townshend, J.R.G. and Justice, C.O. (1988). Selecting the spatial-resolution of satellite sensors required for global monitoring of land transformations. International Journal of Remote Sensing, Vol. 9(2), pp.187-236.
203. Townshend, J.R.G., Justice, C.O., Li, W., Gurney, C. and McManus, J. (1991). Global land cover classification by remote sensing: present capabilities and future possibilities. Remote Sensing of Environment, Vol. 35(2-3), pp.243-255.
204. Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, Vol. 8(2), pp.127-150.
205. Tucker, C.J., Gatlin, J., Schnieder, S.R. and Kuchinos, M.A. (1982). Monitoring large scale vegetation dynamics in the Nile delta and river valley from NOAA AVHRR data. Proceedings of the Conference on Remote Sensing of Arid and Semi-Arid Lands, Cairo, Egypt, pp.973-977.
206. Tucker, C.J., Slayback, D.A., Pinzon, J.E., Los, S.O., Myneni, R.B. and Taylor, M.G. (2001). Higher northern latitude normalized difference vegetation index and growing season trends from 1982 to 1999. International Journal of Biometeorology, Vol. 45(4), pp.184-190.
207. Tucker, C.J. and Sellers, P.J. (1986). Satellite remote sensing of primary production. International Journal of Remote Sensing, Vol. 7(11), pp.1395-1416.
208. Tucker, C.J., Dregne, H.E. and Newcomb, W.W. (1991). Expansion and contraction of the Sahara Desert from 1980 to 1990. Science, Vol. 253, pp.299-301.
209. Unger, P.W. and Kasper, T.C. (1994). Soil compaction and root growth: A review. Agronomy Journal, Vol. 86(5), pp.759-766.
210. USGS (2008). Earth Resources Observation and Science Center. URL: http://glovis.usgs.gov/ (Accessed on September 09, 2013).

© 2014 Global Journals Inc. (US)

211. USGS (2010). What is NDVI? United States Geological Survey: Science for Changing World. URL: http://ivm.cr.usgs.gov/ (Accessed on September 10, 2011).
212. Vazifedoust, M., Van Dam, J.C., Bastiaanssen, W.G.M. and Feddes, R.A. (2009). Assimilation of satellite data into agrohydrological models to improve crop yield forecasts. International Journal of Remote Sensing, Vol. 30(10), pp.2523-2545.
213. Villalba, R., Grau, H.R., Boninsegna, J.A., Jacoby, G.C. and Ripalta, A. (1998). Tree-ring evidence for long-term precipitation changes in subtropical South America. International Journal of Climatology, Vol. 18, pp.1463-1478.
214. Villalba, R., Lara, A., Boninsegna, J.A., Masiokas, M., Delgado, S., Aravena, J.C., Roig, F.A., Schmelter, A., Wolodarsky, A. and Ripalta, A. (2003). Large-scale temperature changes across the southern Andes: 20th century variations in the context of the past 400 years. Climatic Change, Vol. 59, pp.177-232.
215. Verbesselt, J., Hyndman, R., Zeileis, A. and Culvenor, D. (2010). Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment, Vol. 114(12), pp.2970-2980.
216. Verhoef, W., Meneti, M. and Azzali, S. (1996). A colour composite of NOAA-AVHRR NDVI based on time series analysis (1981–1992). International Journal of Remote Sensing, Vol. 17(2), pp.231-235.
217. Vermote, E.F., Kotchenova, S.Y. and Ray, J.P. (2011). MODIS surface reflectance User's Guide. MODIS Land Surface Reflectance Science Computing Facility, NASA, College Park, MD, USA, pp.1-40.
218. Wang, J., Rich, P.M. and Price, K.P. (2003). Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. International Journal of Remote Sensing, Vol. 24, pp.2345-2364.
219. Wessels, K.J., Steenkamp, K., Maltitz, von G. and Archibald, S. (2011). Remotely sensed vegetation phenology for describing and predicting the biomes of South Africa. Applied Vegetation Science, Vol. 14(1), pp.49-66.
220. Wolfe, R.E., Nishihama, M., Fleig, A.J., Kuyper, J.A., Roy, D.P., Storey, J.C. and Patt, F.S. (2002). Achieving sub-pixel geolocation accuracy in support of MODIS land science. Remote Sensing of Environment, Vol. 83(1-2), pp.31-49.
221. Woomer, P.L., Touré, A. and Sall, M. (2004). Carbon stocks in Senegal's Sahel transition zone. Journal of Arid Environments, Vol. 59(3), pp.499-510.
222. Xie, Y. (2008). Remote sensing imagery in vegetation mapping: A review. Journal of Plant Ecology, Vol. 1(1), pp.9-23.
223. Yang, Y., Yang, L. and Merchant, J.W. (1997). An assessment of AVHRR/NDVI-ecoclimatological relations in Nebraska, USA. International Journal of Remote Sensing, Vol. 18(10), pp.2161-2180.
224. Zhang, X., Friedl, M.A., Schaaf, C.B. and Strahler, A.H. (2004). Climate controls on vegetation phenological patterns in northern mid- and high latitudes inferred from MODIS data. Global Change Biology, Vol. 10, pp.1133-1145.
225. Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C. and Huete, A.R. (2003). Short communication: Monitoring vegetation phenology using MODIS. Remote Sensing of Environment, Vol. 84(3), pp.471-475.
226. Zhao, M., Heinsch, F.A., Nemani, R.R. and Running, S. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sensing of Environment, Vol. 95, pp.164-176.
227. Zhou, L.M., Kaufmann, R.K., Tian, Y., Myneni, R.B. and Tucker, C.J. (2003). Relation between interannual variations in satellite measures of northern forest greenness and climate between 1982 and 1999. Journal of Geophysical Research, Vol. 108(D1), 16 p.
228. Zhou, L.M., Tucker, C.J., Kaufmann, R.K., Slayback, D., Shabanov, N.V. and Myneni, R.B. (2001). Variations in northern vegetation activity inferred from satellite data of vegetation index during 1981 to 1999. Journal of Geophysical Research, Vol. 106(D17), pp.20069-20083.
229. Zoran, M. and Stefan, S. (2006). Climatic changes effects on spectral vegetation indices for forested areas analysis from satellite data. In: Proceedings of the 2nd Environmental Physics Conference, 18-22 February 2006, Alexandria, Egypt, pp.73-83.

© 2014 Global Journals Inc. (US)