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Araştırma / Research

Application of Landsat 8 Satellite Image – NDVI Time Series for Crop Phenology Mapping: Case Study Balkh and Jawzjan Regions of Afghanistan

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Abstract

In this article, it was targeted to reveal the variations of NDVI which may represent the phenological stages of agricultural crops derived from Landsat 8 imagery from the start to end of growing seasons which eventually influence the final yields. An effective method was developed to map seasonal phenological variations of crops over large geographic regions using 16-day Landsat 30 m resolution NDVI time series data obtained from USGS. The Google Earth Engine (GEE) platform was used for processing the Landsat 8 data. The areas with cloud cover and cloud shadows were masked out, filled by no data and smoothing double logistic filter was fitted on the time series of the reflectance values. Phenological metrics extracted from the NDVI time series were obtained by the TIMESAT software. Seasonal data were extracted for growing seasons of the years of 2015 and 2016. The phenology maps were created for study area.

Keywords: NDVI, crop phenology, remote sensing

Landsat 8 Uydu Görüntü Uygulaması – Ürün Fenolojisinin Haritalanması İçin NDVI Zaman Serisi: Afganistan'ın Balkh ve Jawzjan Bölgeleri Örneği

Özet

Bu makalede tarımsal ürünlerin yetiştirme sezonu boyunca nihai verimini etkileyen fenolojik dönemleri temsil edebilecek Landsat 8 görüntüsünden elde edilen normalize edilmiş vejetasyon indeksi (NDVI) değişiminin ortaya konulması hedeflenmiştir. Amerika Birleşik Devletleri Jeoloji Araştırmaları Kurumundan (USGS) elde edilen Landsat 16-gün 30 m çözünürlüklü NDVI zaman serileri verisi kullanılarak geniş coğrafi alanlar üzerindeki ürünlerin mevsimsel fenolojik değişimlerini haritalama amacıyla etkin bir metot geliştirilmiştir. Landsat 8 verilerinin işlenmesi için Google Earth Engine (GEE) platformu kullanılmıştır. Bulut örtüsüne ve bulut gölgelerine sahip alanlar maskelenmiş, verilerle doldurulmamış ve yansıma değerlerinin zaman serisine çift lojistik filtresi uyarlanmıştır. NDVI zaman serilerinden elde edilen fenolojik metrikler TIMESAT yazılımı ile elde edilmiştir. 2015 ve 2016 yılı yetiştirme sezonu için mevsimsel veriler sağlanmış ve çalışma alanı için fenoloji haritaları oluşturulmuştur.

Anahtar Kelimeler: NDVI, ürün fenolojisi, uzaktan algılama

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1. Introduction

Agricultural development plays a key role in the economic growth of many developing countries (Ustuner et al., 2014). Georeferenced land cover data sets are the basic data sources for natural resources management, environmental monitoring and policy development (Wardlow and Egbert, 2008). Automated, low-cost, accurate and timely information about crop performance are useful for farmers, policy maker and inventors (Osman et al., 2015; Xijie, 2013). Particularly, the application of remotely sensed information in agriculture field can grant essential information for the macro, and micro management (related on resolution) of agricultural production as well as for yield estimation, crop condition and timely vegetation variations (Xue and Su, 2017; Zhao et al., 2017). Recently, satellite imagery has been used for several purposes such as estimation of cultivated land, identification of crop types, yield forecast, developing of hydrological model (Jakubauskas and Legates, 2002; Sakamoto et al., 2005). Crop type identification maps are known the most important data source in crop management and yield assessment (Zhao et al., 2017; Ustuner et al., 2014). For crop mapping purpose seasonal parameters such as the starting, middling, ending of the season, seasonal length, seasonal amplitude etc., can be obtained from several time series vegetation indexes (Zhao et al., 2017).

The normalized difference vegetation index (NDVI) is mainly used for monitoring of vegetation which is computed from the red and near-infrared ratio of vegetation reflectance in the electromagnetic spectrum (NDVI = (NIR − RED)/ (NIR + RED) (Pan et al., 2015). The NDVI provides accurate and timely information on vegetation condition and different phonology steps of plant over large scale (Hamel et al., 2009). The capability of how the NDVI quantify the amount of green vegetation is based on the principle that green vegetation during photosynthesis- absorbs radiation in the visible band of the electromagnetic spectrum. While, in contrast to visible light, near infrared (NIR) light is not used for photosynthesis and it is strongly reflected by the plant. The NDVI are correlated with green biomass, green leaf area index (LAI), and percent vegetation cover (Zhang et al., 2003).

The NDVI can easily predicts the photosynthetic activity, because the NDVI contain both red and near infrared light (Govaerts and Verhulst, 2010). In recent decade, several different methods have been developed for the detection of the timing of vegetation green-up and agedness applying time series NDVI data. A variety of different approaches have been employed by these methods containing the use of particular NDVI thresholds (Zhang et al., 2003). It is difficult to define the NDVI threshold value for determining the start/end of season, since it depends on the preference of the researcher (Pan et al., 2015). The determination of crop production by NDVI is connected to complete plant vigor, photosynthetic activity throughout the growing season and stress caused by water (Qamer et al., 2014). The NDVI/ Satellite obtained periodical greenness data have the capability to indicate temporally the amount of growth, aging, periodicity of photosynthetic activity as well as the start, end, peak and duration of vegetation greenness (Van Leeuwen et al., 2006). The NDVI multi temporal analysis have verified to be a functional device enabling monitoring and detecting land used land cover (LULC) changes (Borini et al.,2015).

The general purpose of this research was to investigate the possibility of the application of vegetation index such as NDVI in operational crop pattern mapping. The specific objectives was to apply NDVI values for predicting and developing the crop pattern map and creating crop calendar based on remote sensing imagery monitoring for pilot study area in the north part of the country.

2. Material and Methods

2.1. The Study Area

The two Northern provinces of Afghanistan including Balkh and Jawzjan were selected as study area which is located between latitude of 36° 45' 22.86" N and longitude of 66° 53' 49.92" E. The study area totally covers 30335.12 km^2 areas with the population of more than 1672087 people. These provinces are categorized as highly agricultural productive provinces of country (Central Statistic Organisation, 2012). The land cover types in this area are very heterogeneous. Generally, due to lack of accessible water resources for irrigation purpose the agricultural activity taken place only for one growing season (there is rainfed agriculture) in the study area has only one growing season but vegetations growing for two or three seasons.

2.2. Remotely Sensed Data and Pre-processing

Google Earth Engine (GEE) platform (https://code.earthengine.google.com/) was used for processing the Landsat 8 data. GEE is a cloud-based platform that makes easy to access high-performance computing resources for processing very large geospatial datasets (Gorelick et al., 2017). This dataset is the atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS sensors. These images contain 5 visible and near-infrared (VNIR) bands and 2 short-wave infrared (SWIR) bands processed to orthorectified surface reflectance, and two thermal infrared (TIR) bands processed to orthorectified brightness temperature. The VNIR and SWIR bands have a resolution of 30 m/pixel. The TIR bands, while originally collected with a resolution of 100 m/pixel has been resampled using cubic-convolution to 30 m. These data have been atmospherically corrected using Landsat Surface Reflectance Code (LaSRC), and includes a cloud, shadow, water and snow mask produced using CFMASK, as well as a per-pixel saturation mask. Landsat data is collected on a nominal 16-day repeat cycle. It means we have processed 2 images in each single month (32 days). Strips of collected data are packaged into overlapping "scenes" covering approximately 170 km × 183 km, using a standardized reference grid. During this study all the available scenes about 44 images which represent the years of 2015 and 2016 were chosen. In Timesat, we have processed all data independently for each single year (about 22 images per year) to determine the parameters including start of season, middle of season and end of season; respectively. The Timesat reads the data for each single parameter.

2.3. Cloud Masking

In case of using optical images for analysis we have to deal with the possible cloud coverage and the presence of cloud shadows. Areas covered by clouds and shadows have to be identified and masked out before further processing. During the generation of the Surface Reflectance products (atmospheric correction) a Scene Classification Layer is generated which contains information on cloud and cloud shadow coverage of individual scenes. Using this layer as a mask layer of cloud cover and cloud shadows were masked out, and the values of cloudy pixels were replaced by no data value.

2.4. Calculation of Vegetation Index

To generate a variable whose temporal variability is used for phenology mapping Normalized Difference Vegetation Index (NDVI) was calculated according to the following formula:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)}$$

Where NIR is the reflectance on the Near Infrared (5th) band, and RED is the red (4th) band of the Landsat 8 scene.

2.5. TIMESAT 3.3 With Seasonal Trend Decomposition and Parallel Processing

Timesat software has been developed for the obtaining and analyzing seasonal parameters of satellite data (Eklundh and Jönsson, 2017). Timesat composed of several graphical and numerical routines coded in Matlab and Fortan. Recently, Timesat has been used in a wide range of application including mapping environmental and phenological changes, in savanna ecosystem for evaluate satellite and climate data-obtained indices of fire risk, monitor human footprints of fire seasons, improving data in ecosystem classification, characterizing phenology, and mapping high-latitude forest phenology (Eklundh and Jönsson, 2017). Menu system is the main driver for all Timesat processing, Matlab or Fortran (see Figure 2.1).

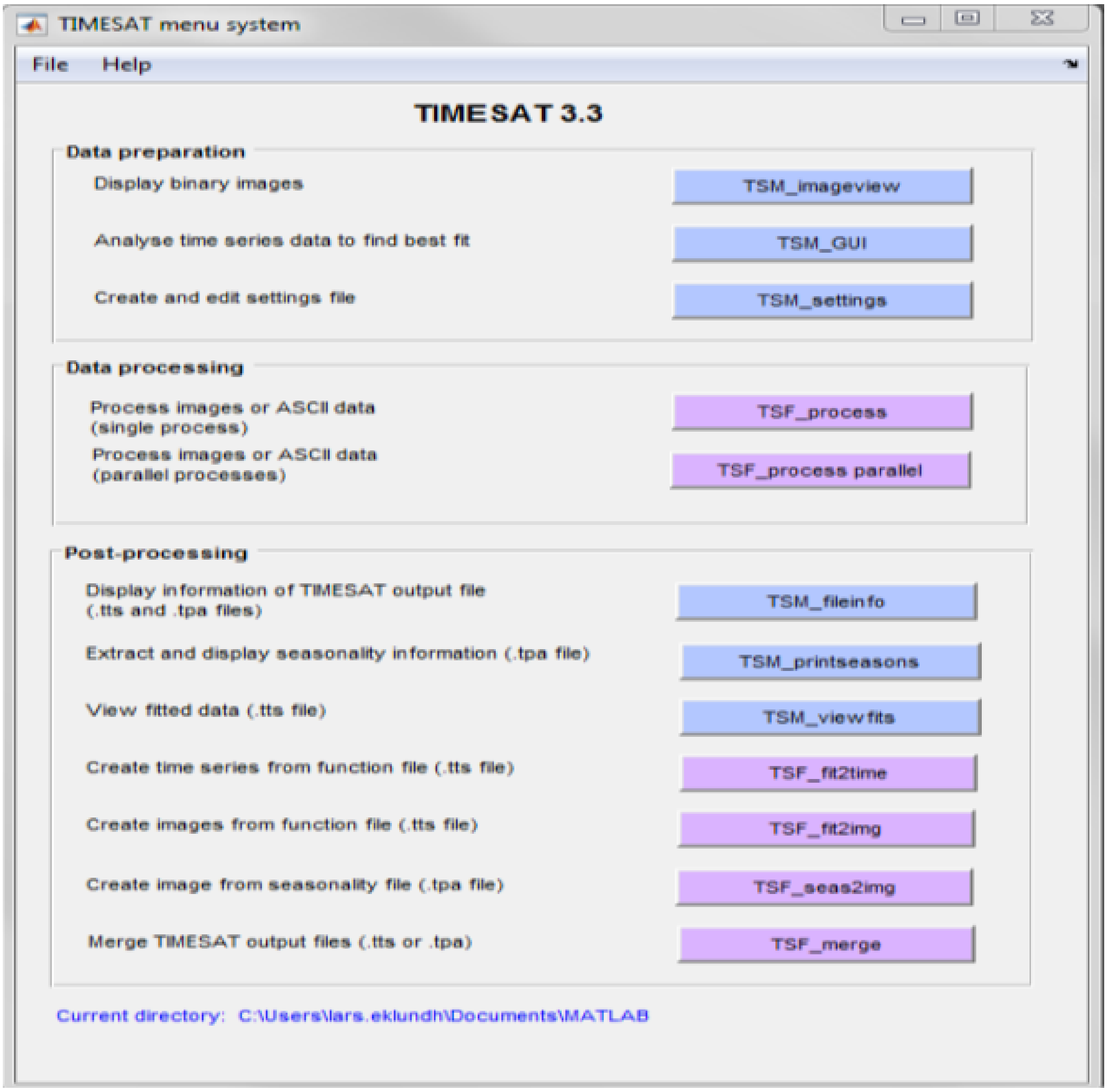

Figure 2.1. TIMESAT menu system.

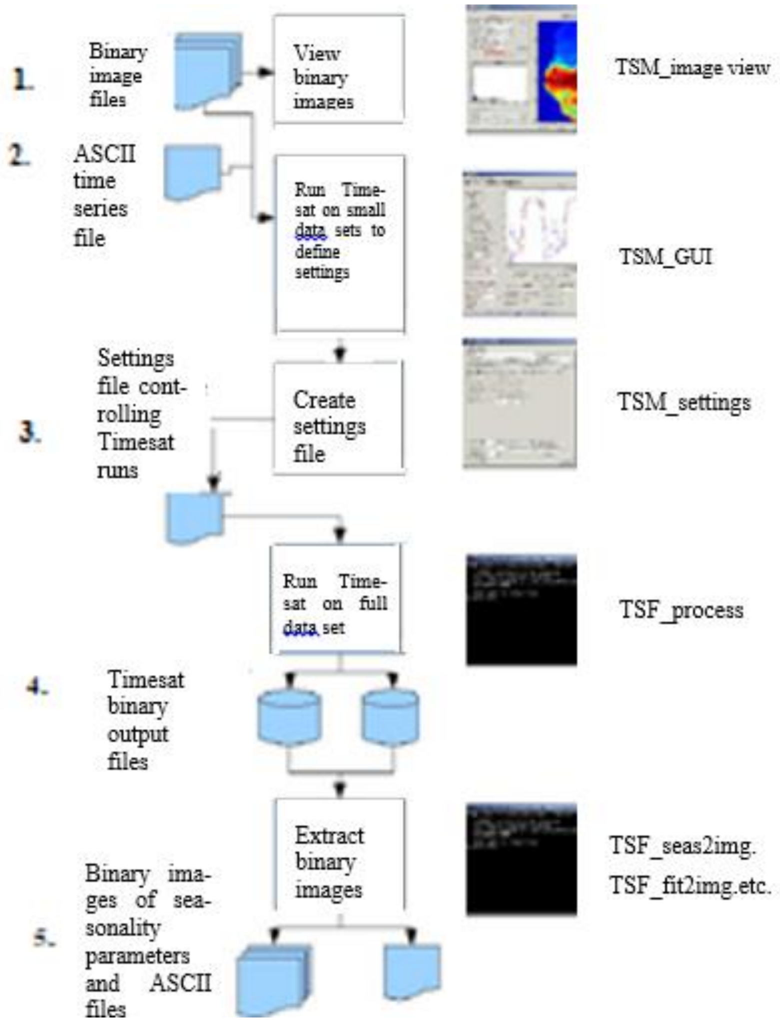

Figure 2.2. General TIMESAT processing logic.

Mainly, in our work we have dealt with (a) Data preparation including TSM_imageview, TSM_GUL, TSM_ settings, (b) Data processing including TSF_ process, and TFS_ process parallel, and (c) Post processing mainly TSF_ seas2 img.

Phenological metrics extracted from the NDVI time series were obtained by the TIMESAT software (version 3.3) (Jönson and Eklundh, 2004). Seasonal data were extracted for growing seasons of the years between 2015 and 2016. For smoothing double logistic filter was fitted on the time series of the reflectance values. The graphical representation of the derived phenological indicators is presented on Figure 2.3.

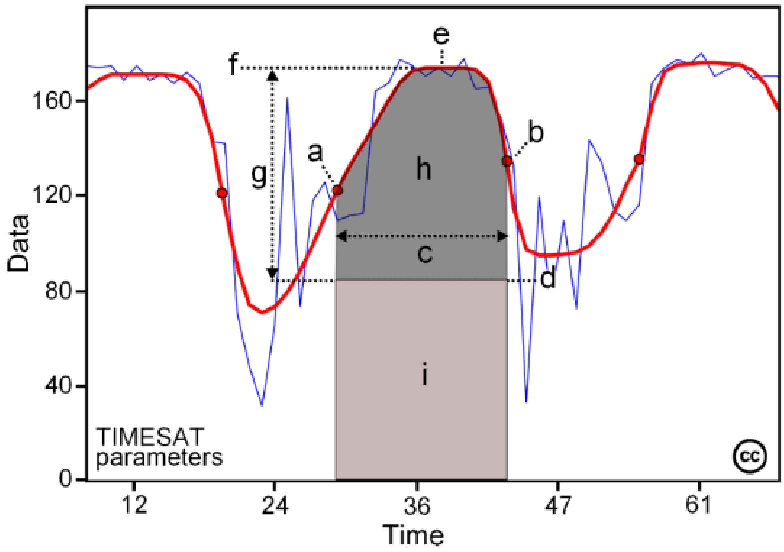

Figure 2.3. Examples of seasonality parameters generated by TIMESAT: (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value

2.6. Land Cover Classification Map

In the frame of this study irrigated agricultural areas were focused on. To limit the study area, a land cover classification map of Balkh and Jawzan provinces provided by the Ministry of Agriculture and Livestock (MAIL) was used. The land cover classification map of the study area was produced by MAIL in the year of 2014 and it is still valid for the years of 2015 and 2016. This shapefile classifies the landscape into 15 classes which can be seen on Figure 2.4.

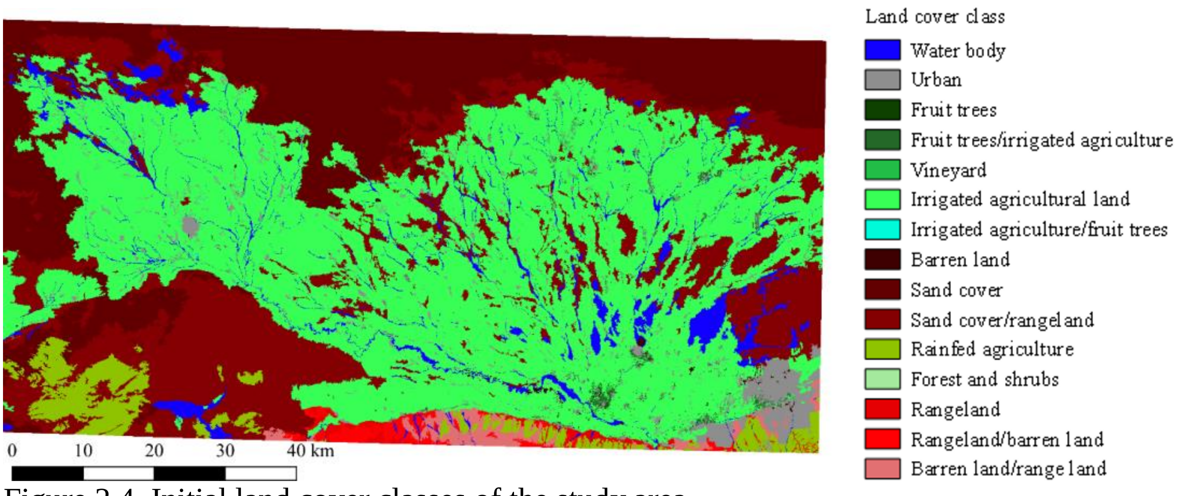

Figure 2.4. Initial land cover classes of the study area

Irrigated agricultural areas were determined by reclassifying the shapefile and combining into 6 broader classes using ArcGIS. The result of the combination procedure is presented on Figure 2.5. By using this classification map it was able to mask out the non-irrigated agricultural areas and focused on the relevant land covers when running the TIMESAT analysis.

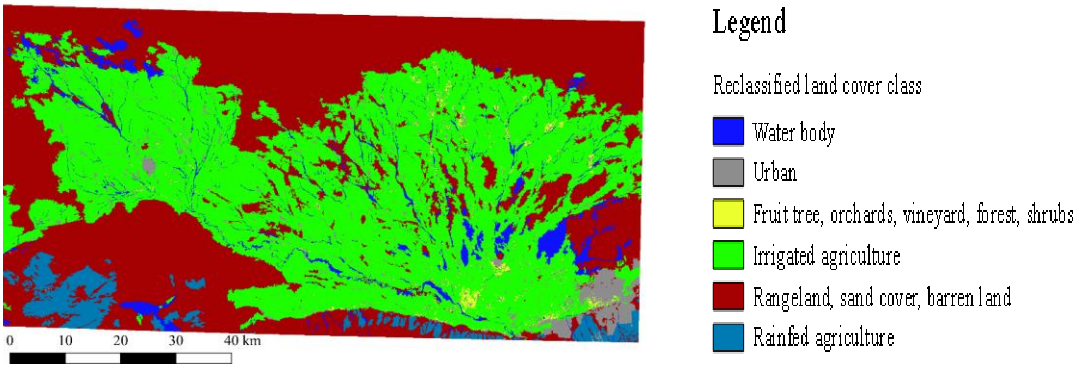

Figure 2.5. Reclassified land cover classes of the study area

3. Results and Discussion

3.1. Explanation of Seasonal Parameters

Phenological metrics extracted from the NDVI time series were obtained by the TIMESAT software. As time for the start of season (SOS) the time for which the left edge has increased to 20 % of the seasonal amplitude measured from the left minimum level was defined. As time for the end of season (EOS) the time for which the right edge has decreased 80 % of the seasonal amplitude measured from the right minimum level. The middle of season (MOS) represents the date of the mean of times between dates of 80 % of right and left edge, respectively. TIMESAT software can read data in ENVI format; therefore we convert our data from geotiff files (Geostationary Earth Orbit Tagged Image File Format) to ENVI (Environment for Visualizing Image) format using R commander software. The type of colors is our choice based on symbology provided by ArcGIS. However, the variation in colors for different season is based on Timesat given results for each single season. For the determination of crop type and land cover we used land cover classification map in raster format. Timesat has ability to generate an image from the seasonality parameters (Eklundh and Jönsson 2017). We deal with seasonality parameters via this software.

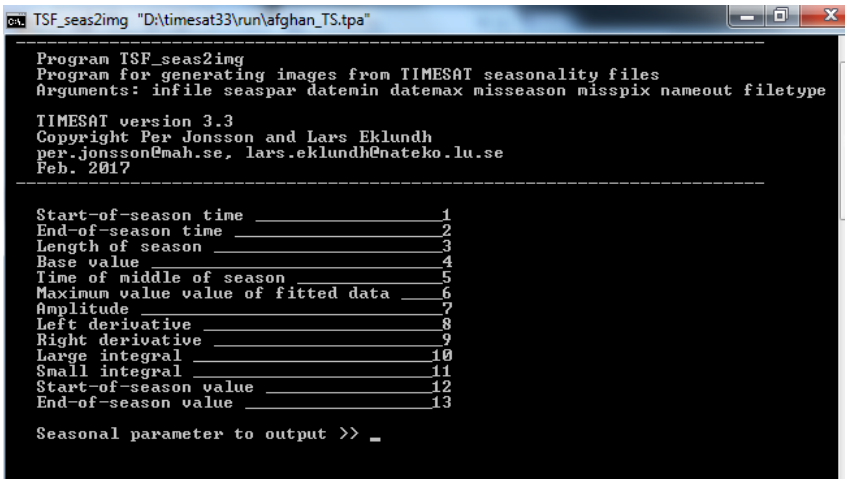

Figure 3.1. Command window for running TSF_seas2img started from the command prompt with seasonality parameters.

The most widely method which is used to extract seasonal data from NDVI time-series is based on value thresholds, supposing that a particular phenomenon has started and ended when NDVI values exceed a defined threshold (Pan et al. 2015). According to this approach, the TIMESAT program loops every pixel in every image and then extraction of phenology parameters is individually depending on NDVI`s variation behavior in day of year (Pan et al. 2015). In Timesat program, for the NDVI the start of season (SOS) is depending on the NDVImax and NDVImin values.The start/end of season values of NDVI for the agricultural activities and crop phenological steps in the small scale can be defined as follow:

$$\text{NDVI threshold } v\text{alue}=\frac{\mathrm{NDVImin}}{\mathrm{NDVImax}}$$

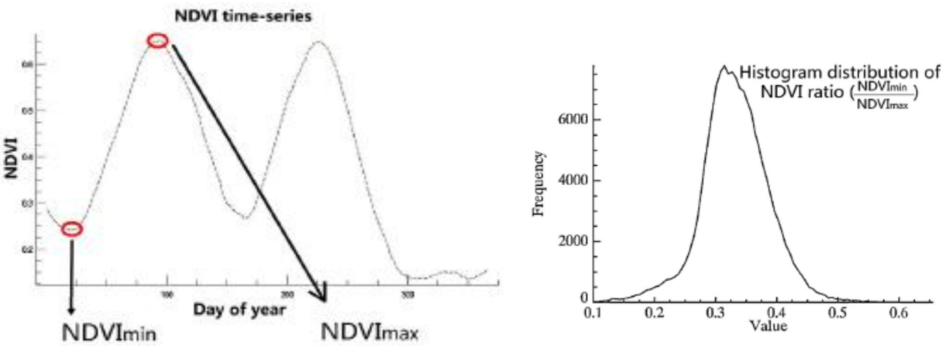

Figure 3.2. Pixel-based time-series was looped over to identify the max/min value within a specific range of NDVI time-series; definition of NDVI threshold value for season start/end was based on the NDVI ratio of min/max

3.1.1. Start of Season 2015 (SOS)

Remote sensing data analysis indicates that the start of season values begins earlier in north side of the study area than south side. According to the crop calendar of the study area the main crops which have early start of season are fruit trees such as apples, grapes, apricot, and almond. Season starts lately in southern side of study area which is mountainous, and lies higher above sea level. Therefore, growing season for horticultural crops starts early around February but the season for vegetable and cash crops which need of a little warm weather starts later from late February to early May.

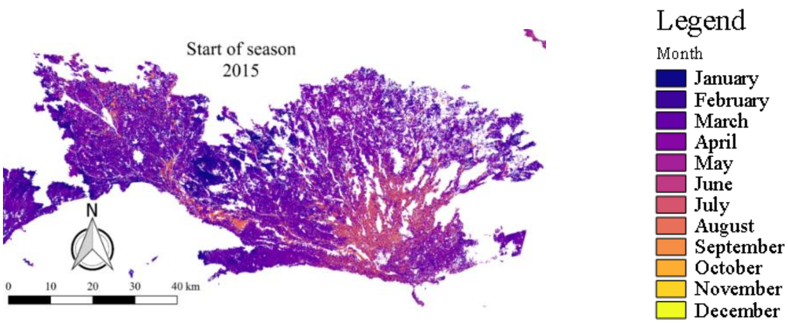

Figure 3.3. Map of start of season, 2015

3.1.2. Middle of Season 2015 (MOS)

Based on remote sensing data analysis and the crop calendar the fruits have middle of season from March to May. But mainly, the vegetable crops and cash crops have short middle of season from late April to May.

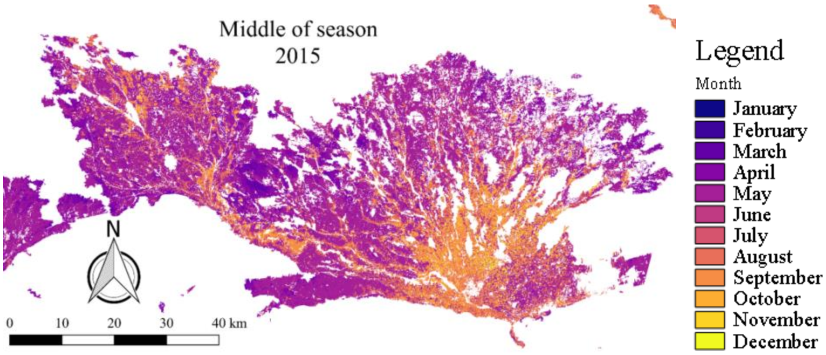

Figure 3.4., Map of middle of season, 2015

3.1.3. End of Season 2015 (EOS)

According to crop calendar, the map of end of season indicates that different crops have different time of harvesting. Harvesting time for apples and apricot is June; for tomato, watermelon, melon, okra, eggplant is from late May to July; for flax and cumin is April to May; for wheat spring/fall are (May-June); and for sesame is late July.

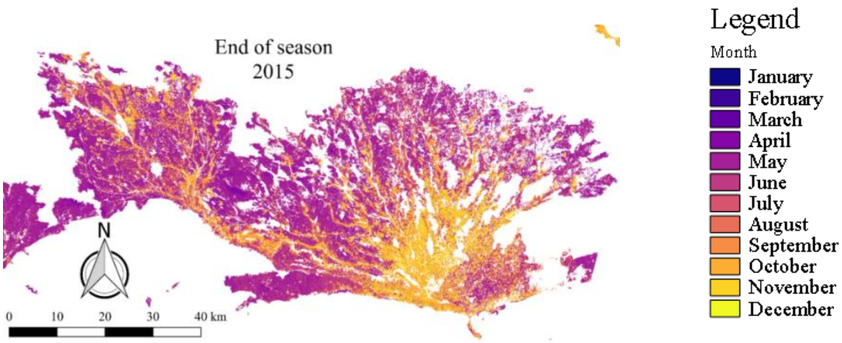

Figure 3.5. Map of end of season, 2015

3.1.4. Start of Season 2016 (SOS)

The map of start of season shows that the season starts early in the north of the study area. According to the crop calendar, the crops which have early start of season are mainly fruits trees. The start of season takes place in February. In the southern side the growing season starts later, based on crop calendar the vegetable and cash crops' growing season starts from February to early May.

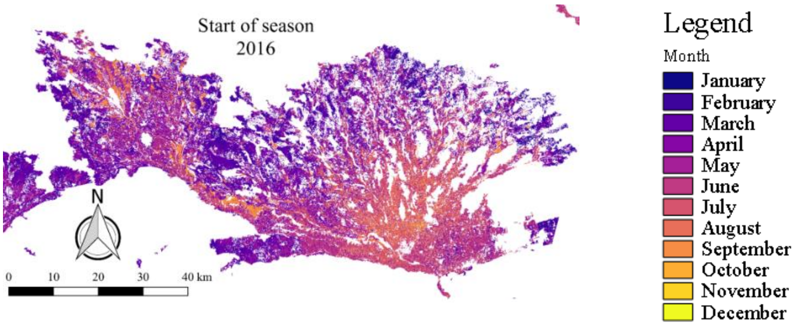

Figure 3.6. Map of start of season, 2016

3.1.5. Middle of Season 2016 (MOS)

The middle of season starts early in Qarchi Gak, Zadain, Eastern side of Acha. According to crop calendar, it might be fruits tress which take place from March to May. But, mainly, the vegetable crops and cash crops have short middle of season from late April to May.

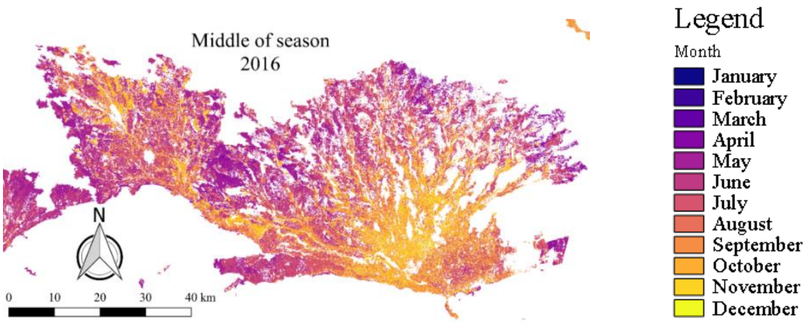

Figure 3.7. Map of middle of season, 2016

3.1.6. End of Season 2016 (EOS)

Due to different types of crops in study area, the end of season starts early in Qarchi Gak, Zadain, and Eastern side of Acha while the season end later in the area around Balkh.

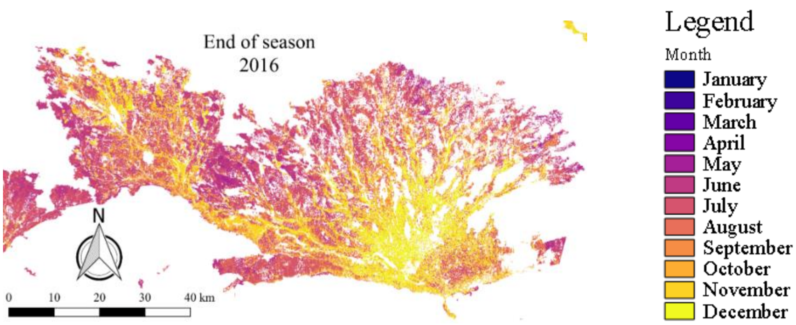

Figure 3.8.Map of end of season, 2016

Generally, the year of 2016 was warmer than the year of 2015. Due to high suitable tempra-ture, crops start growing season earlier in 2016 than 2015.

4. Conclusion

Monitoring of crop phenology is a common application of time series remote sensing data. For time series processing, TIMESAT software is able to obtain vegetation phenology (Pan et al., 2015). The data gaps due to cloud covers create difficulties in reorganization of crop phenology cycles (Li et al., 2014). The main objective of this work was to determine the crop seasonality phenological pathern using Landsat 8 Images NDVI time series. Based on the results this approach provides unique but at this stage of the research coarse information for farmers. In the frame of this research Landsat 8, remote sensing based seasonality maps were developed for Balkh and Jawzan provinces of Afghanistan. Although this study focuses on using Landsat 8 data, this approach is entirely compatible with Landsat TM and ETM as well. Based on the result of this research the applicability of this approach has limitations in the monitoring of field scale phenological variations due to the coarse spatial resolution of the remotely sensed dataset (30 m/pixel). However the methodology can be effectively used for the determination of seasonality pattern on a regional scale.

In order to use the optical dataset it was needed to deal with the cloud coverage and the presence of cloud shadows especially in months of December, January, and February. This kind of temporal and spatial noise might affect the reliability of the determination of start of season dates, due the frequent occurrence of this kind of noise. Based on the generated seasonality maps general patterns of crop production in the study area could be identified. Using the provided crop calendar it was attempted to relate different kind of crops to the pixel values of the maps. For the validation of our results we used average crop calendar as reference and there is no ground reference data. Our maps do not account for small scales or sub-pixel variation that means the output is most reliable for large scale area than small field size. The collection of ground truth dataset is essential not only in the determination of the reliability of the result but in the determination of the phenological thresholds at the beginning of the analysis (e.g. the exact date of start of, middle of, end of season of different crops).

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