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Vegetation Stress Study in Chon-Alai Area Using NDVI, Kyrgyzstan

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Abstract:
Agriculture and livestock are the main sectors of Kyrgyzstan's economy. This makes sustainable pasture and land management critical for human well-being, economic stability, social welfare and ecosystem resilience. Both human-induced and natural factors play a key role in the sustainability issues of rural mountainous communities in Kyrgyzstan that rely heavily on land resources. This study focuses predominantly on finding a linear relationship between NDVI and climatic variables such as air temperature, land surface temperature and precipitation. This helps to understand the seasonal and inter-annual behavior and dynamics of the vegetative characteristics. The secondary goal of this research is to prepare land cover classification for the Doorot-Korgon area in Chon-Alai District. Overall, the implications of this study are directed towards the general understanding of interaction between terrestrial ecosystems and climate change. The study encompassed two time periods (1993-1996 and 2000-2003). A linear relation and positive correlation coefficient was found only in two years (1994 and 2003) which is not sufficient for establishing a significant annual trend between NDVI and climatic variables. However, a seasonal trend was found. As a rule, the lowest NDVI values are observed in May, reaching its peak at the end of July and/or the beginning of August and decreasing in the middle or end of September. In addition, a trend was found in NDVI values over the last five years in the Daroot Korgon area, there is an inter-annual even distribution of values without any sharp fluctuations and variations.

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1. INTRODUCTION

Land cover information plays a significant role in climate change studies as well as in understanding complex interconnectivities between human activities and global change. Accurate and up-to-date land cover information also plays a critical role in sustainable resource management, planning and monitoring activities. (Arora, 2010). Conventional ways of land cover classification, generally constrained by field surveys, are insufficient and time-consuming. In addition, despite the fact remote sensing has long served as a generator of accurate land cover information, there are still problems that occur while working with extraction of land cover information (Arora and Foody, 1996). Improper and mishandled satellite image treatment may result in

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inappropriate output in classifying land cover. Much has been recently researched on climate change vegetation response to identify spatio-temporal variations in Central Asia. Earth soil has always been subject to change and alteration due to both natural and anthropogenic factors.

Over the last couple of decades Central Asia has suffered from severe land cover and land use alterations caused partly by socio-economic and institutional changes after the collapse of the Soviet Union. This is significant on a global scale as Central Asia owns the biggest adjoined area of rangeland worldwide (Mirzabaev et al. 2016), though has low capacity to properly manage it (Kerven et al. 2011).

The complexity of changing land resource cover and use is affected by both natural and human factors: unsustainable pasture management that leads to land degradation due to overgrazing and natural phenomena such as salinization of soils, desertification and erosion. Soil erosion and decrease in land productivity has already reached a critical point in Kyrgyzstan. It is worth mentioning that in the mountainous ecosystems of Kyrgyzstan, which are highly vulnerable to natural and anthropogenic impacts, biological resources are still increasingly depleting.

Based on one climate change scenario estimation, Kyrgyzstan will face drastic annual and seasonal variations of temperature and precipitation (Kulikov and Schickhoff, 2017). Some valuable ecosystems are threatened and are subject to loss due to both unsustainable natural resource use and climate change (Kerven et al. 2011; Crewett, 2012). Therefore, a study of how the influence of temperature and precipitation can change vegetation dynamics is necessary for better land use economy and climate change adaptation planning.

Livestock husbandry and agriculture are essential activities in the Chon-Alay region and play critical roles in the local economy. Animal husbandry is highly dependent on climate conditions which have a great impact on pastureland and fodder. Periodically, natural disasters such as landslides and earthquakes as well as heavy precipitation and long winters severely damage local economies.

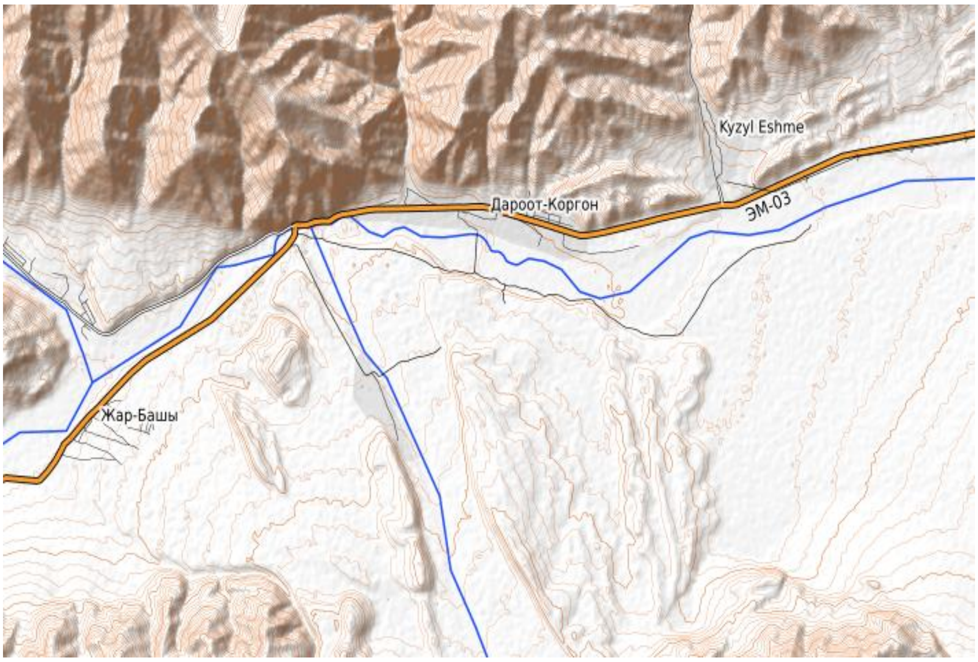

Figure 1. Topographic map of Daroot-Korgon [https://kac.centralasia.kg/maps/#topographical-maps]

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1.1. Research questions and objectives

This study aims to identify seasonal and inter-annual variations in NDVI, precipitation and temperature in the Chon-Alay valley. In addition, the research focuses on finding an interrelationship between the abovementioned variables. Initially, it was planned to encompass a 20-year time period from 1993 to 2013, but due to poor weather data quality and unavailability of some satellite images from the USGS database, this study considers two time intervals: 1993-1996 and 2000-2003.

The following questions are answered by this research paper:

1) Is there any seasonal and inter-annual interrelationship between NDVI, temperature and precipitation in the Chon-Alay valley?
2) If there is some interrelationship between these parameters, is it possible to predict the dynamics of one through knowledge of the others?
3) How did NDVI values change over time from 1993 to 2003?

Subsidiary question:

Is there any significant NDVI change over that last five years?

2. BACKGROUND INFORMATION

2.1. GIS Application

GIS (Geographical Informational Systems) are systems created to capture, store, analyze and visualize geographic and spatial data. GIS contain tools that let users search, analyze, edit and manipulate digital maps.

As a management system, GIS are designed to provide solutions for the optimal management of land and resources, urban management, transport and retail management, and the use of oceans or other spatial objects. GIS involves many new technologies for spatial data analysis. Because of this, GIS serves as a powerful tool for transforming and synthesizing various data for management tasks. As automated information systems, GIS unites a number of technologies or technological processes of known information systems such as automated research systems (ARS), computer-aided design (CAD) systems and automated reference and information systems (ARIS). As geosystems, GIS technologies include systems such as geographic information systems (GIS), cartographic information systems (CIS), automated mapping systems (AMS), automated photogrammetric systems (APS) and land information systems (LIS).

2.2. GIS software

GIS software embraces a wide range of applications including data visualization, geocoding, spatial querying and so on. GIS software is either open source and free or commercial, and can be classified into several categories:

There are a variety of software applications and tools used for LCLU (land cover and land use classification). Users can choose any program for classifying specific areas depending on project goals and available resources. Plenty of open source, free-to-download software are being used globally for LCLU. However, sometimes commonly used free source software is limited functionally; for example, some commercial GIS software such as ArcGIS, ESRI and ENVI have numerous high-level geospatial and geostatistical tools that are missing in open source software.

2.3. Remote sensing

Over the last decades, with the rapid development of geospatial technologies such as high-resolution satellite imagery and remote sensing, it has become much easier to study the Earth's surface. Remote sensing has become an irreplaceable tool for monitoring, mapping and

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managing land cover. This is partly due to its ability to quickly collect geo data on a large regional scale. Numerous land cover maps have been produced globally through remote sensing. Remote sensing refers the ability to obtain information about objects on Earth without entering into physical contact with them. Images obtained by remote sensing satellites are used in many sectors - agriculture, geological and hydrological research, forestry, environmental protection, territorial planning, educational and other purposes. Remote sensing technologies from space are an indispensable tool for studying and constantly monitoring our planet, helping to effectively use and manage its resources. The modern development of remote sensing (RS) technologies expands the scope of their application, covering all aspects of our life. The main advantages of RS are the high speed of obtaining data on large volumes of the atmosphere (or large areas of the Earth's surface), as well as the possibility of obtaining information about objects that are practically inaccessible to research in other ways. The information received by means of remote sensing is necessary for many branches of science, technology and economics. The number of potential consumers of this information is constantly growing.

In the context of land cover and land use classification, remote sensing is very useful in terms of land use inventory planning, land cover change detection, land resource assessment and traffic monitoring. The introduction of monitoring methods through remote sensing into the sphere of land and property relations can help to identify and predict adverse environmental phenomena associated with agricultural production (wind and water erosion, salinization, trampling of soil), identify unused and inefficiently used agricultural land, and provide reliable information about the condition of the land to the bodies of state power and local self-government.

2.4. Correlation

As a rule, correlation coefficients are used in statistics to measure interdependence between two variables. These can be either quantitative variables or categorical variables.[1] They indicate probabilistic or statistical dependence, which, generally speaking, does not have a strictly functional character. Unlike functional dependence, correlational dependence arises when one of the characteristics depends not only on the other, but also on a number of random factors, or common conditions impact both factors. When calculating correlations, one tries to determine whether there is a statistically reliable relationship between two or more variables in one or more samples. For example, the relationship between height and weight of children, the relationship between performance and the results of the IQ test, or between work experience and labor productivity. It is important to understand that correlation dependence reflects only the relationship between the variables and does not speak of cause-effect relationships. For example, if there was correlation dependence between the growth and weight of a person, then this would not mean that weight is the cause of a person's growth, otherwise dropping excess pounds would also reduce the person's height. The correlation relationship only indicates the interconnectedness of these parameters, in the particular sample under study. In another sample, the correlations obtained might not be observed. The correlation coefficient (r) characterizes the value reflecting the degree of interrelation of two variables among themselves. It can vary from -1 (negative

[1] Stephanie. "What Is Correlation in Statistics? Correlation Analysis Explained." *Statistics How To,* Statistics How To, 10 Aug. 2013, www.statisticshowto.com/what-is-correlation/.

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correlation) to +1 (positive correlation). If the correlation coefficient is 0 then this indicates that there are no correlations between the variables. The closer the correlation coefficient to 1 (or -1), the stronger the correlation. With positive correlation, an increase (or decrease) in the values of one variable leads to a regular increase (or decrease) in the other variable, i.e. interrelationships such as increase-increase (decrease-decrease). The inverse is true with regards to the negative correlation.

2.5. NDVI calculations

Over the last 40 years, the Normal Difference Vegetation Index (NDVI) has served as a valuable tool for agronomists and natural scientists for healthy crop assessment. Knowledge of the relationship between the structure and the state of vegetation with its spectrally reflective capabilities makes it possible to use remote sensing imagery for mapping and identifying vegetation types and their stress state (Figure 2).

Vegetation indices are built on the theory that different land surfaces reflect different types of light differently; this is possible because characteristic feature of vegetation and its state is its spectral reflectivity, characterized by large differences in the reflection of radiation of different wavelengths. NDVI is the most widely used indicator to determine the level of vegetation "greenness" and photosynthetic activity in order to judge the development of plant biomass during vegetation. Green leaves of plants absorb electromagnetic waves in the red range and reflect waves in the near infrared. The larger the leaf surface of plants and the more chlorophyll in the leaves, the stronger the plants absorb the red light that falls on them (and the less it is reflected). NDVI is a coefficient that measures the level vegetation that is derived from the difference between near-infrared and red light. In other words, NDVI is the ratio of the difference and the sum of the values of spectral brightness in the near infrared and red regions of the spectrum. Healthy vegetation is characterized by a large difference in this brightness, and therefore, this index can be used to detect health status. Normalization allows us to obtain standard values, and NDVI values typically range from -1 to +1. Values close to 0 can be classified as scarce vegetation, while rich and dense vegetation is somewhat equal to 1. For example, sandy, snowy or exposed rocky areas have NDVI values equal to 0.1 or less. Grassland, shrub land and steppe biomes have NDVI values ranging from approximately 0.2 to 0.5. Densely vegetated areas such as tropical rainforests or healthy crops at their peak stage have very high NDVI levels, ranging from 0.6 to 0.9.

In agriculture, NDVI values change throughout the season during the growth, flowering and maturation of the plants. At the beginning of the growing season ranking on the index increases, this stops at the time of flowering, and then, as the plant matures, NDVI decreases. Depending on soil fertility, meteorological conditions and crop cultivation technology, the rate of biomass development can be different. The most accurate forecast of crop yields on the NDVI index can be given at the peak value of NDVI. For example, for the sowing of winter wheat cultivated using intensive technologies, the NDVI value during the peak reaches 0.80-0.88. The NDVI peak usually occurs at the beginning of the earing phase. Knowing the potential crop yield, it can be predicted that, with this value of NDVI, the yield will be the maximum for this variety. If, in the earing phase, NDVI reaches a value of only 0.60-0.65, the yield will be below the maximum by 25-30%. After all, NDVI is associated with green plant biomass, and yield is also a measure of a kind of percentage of biomass. NDVI allows us to identify the problem areas of stressed vegetation, enabling

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us to make better decisions in the long term aimed at increasing yields. Plots with different vegetation states or the volume of green biomass can be depicted in different colors. With the help of statistical processing of NDVI maps, in addition to determining the amount of biomass, it is also possible to isolate the areas of sowing of various agricultural crops

As a rule, healthy plants absorb blue and red visible light and reflect green visible light, thus people see them green. As well as green visible light, plants also reflect Near-Infrared (NIR), which is not as strongly reflected if a plant is weak.

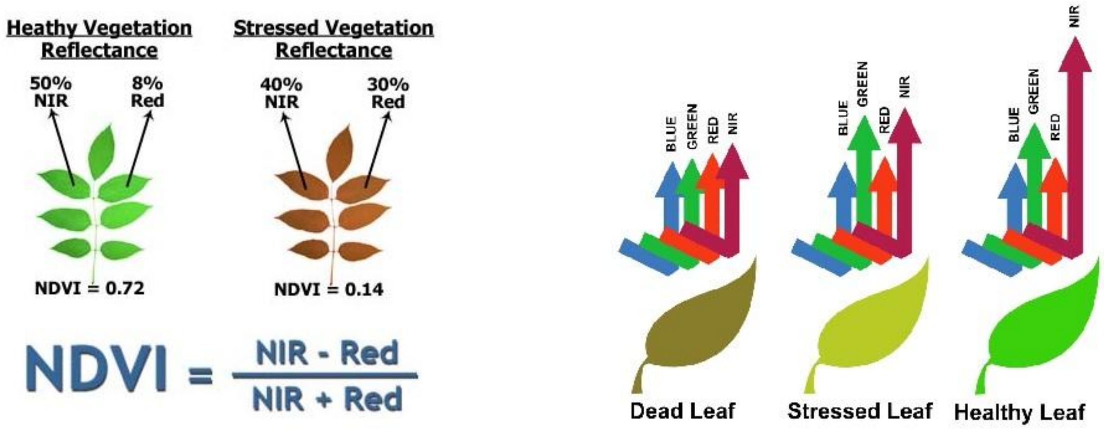

Figure 2. Representation of NDVI

There are numerous factors that influence NDVI values such as level of precipitation and temperature, landscape characteristics, biomass, evenness of plant distribution, plant and soil moisture, photosynthetic activity and so forth. Such multi-dependency opens room for researchers and scientists to investigate correlation coefficients within some ecosystem parameters.

NDVI can be generally applied to monitor and assess vegetation dynamics, plant phonological changes over time, biomass production, soil moisture, carbon sequestration, pasture management and land cover classification.

2.6. Disadvantages of NDVI

A key disadvantage of the NDVI is the inability to use data that has not passed the radiometric correction (calibration) stage. Inaccuracies are most often caused by weather conditions such as strong clouds and haze – the effects of which can partly corrected for using improved coefficients and composite images with NDVI series for several days, weeks or months (MVC - Maximum Value Composite). The averaging of values helps avoid the influence of both random and some systematic error. Thus this approach is often used to prepare data for the creation NDVI maps.

Furthermore, the NDVI necessitates comparison of the results with pre-collected data for test sites (or in situ assessment), and should take into account seasonal environmental and climatic indices, both in checking the image itself and in the test areas at the time of data collection. These materials and variations become especially significant in the calculation of productivity, biomass reserves and other quantitative indicators.

2.7. Different band combinations

Landsat 8 is the most up-to-date satellite in the Landsat program, having new features such as the Operational Land Manager (OLI) and Thermal Infrared Sensor (TIRS). OLI operates eight spectral bands collecting information within the visible electromagnetic spectrum, while TIRS has two bands capturing the thermal infrared part of the electromagnetic spectrum. Every band combination provides information about objects on the Earth’s surface – vegetation, buildings, rocks and water.

3.2.1 is the standard “natural color” band combination composed of three visible bands, allowing the human eye to see objects on the land surface as they really are. Healthy vegetation is presented as green, unhealthy vegetation is brown and yellow and roads are displayed as grey. Without atmospheric and radiometric correction, images become subject to effect of haziness.

The 4.3.2 band arrangement is commonly referred as “false color”, where vegetation is displayed in red gradation; built-up structures appear in greenish-blue; soils range from dark to light brown; and clouds, snow and ice are white. This band combination is widely used for vegetation analysis, crop growth and soil monitoring.

The 5.4.1 band combination can be applied to agricultural crop monitoring. Healthy vegetation is represented by light green, whereas shrubs and trees are dark green. Poorly vegetated areas and exposed soils are brown and violet.

In general, the relevant wavelengths of the electromagnetic spectrum are as follows:

- Blue (0.45 – 0.53 μm)
- Green (0.52 – 0.61 μm)
- Red (0.64 – 0.72 μm)
- NIR (0.77 – 0.88 μm)

2.8. Classification of satellite sensor technologies

Remote sensing is a process for obtaining data from the Earth’s surface from space, particularly in the form of electromagnetic radiation using sensors installed in satellites or space aircrafts. Generally, remote sensors are subdivided into two categories: active and passive. Active sensors release energy towards object on Earth and then receive radiation back from the target, measuring the time it takes to reflect back to the sensor. On the other hand, passive sensors collect radiation that is reflected or emitted from the Earth’s surface – thus the most common source of radiation detected by passive sensors is reflected sunlight. Remote sensing has a significantly broad range of applications such as natural resource management, land cover change detection, desertification identification, ocean and coast-related studies, climatology, urban development and so one. The quality of the data obtained from remote sensing depends on four parameters: spectral resolution, radiometric resolution, spatial resolution and temporal resolution. Spectral resolution plays a huge role in remote sensing and is specified by the number and width of the spectral bands (red, green, blue, NIR, SWIR, thermal, etc.) that satellite sensor can receive in form of radiance reflected from the Earth. The ability to distinguish different ground objects depends on the number of spectral bands and their width – the higher the spectral resolution is, the better the identification of different targets. It is also determined by the characteristic intervals of wavelengths of the electromagnetic spectrum to which the sensor is sensitive. The lowest spectral resolution of hundreds of nanometers is panchromatic, and the highest, up to 10 nanometers, is hyperspectral. Radiometric resolution is determined by the number of gradations of color values corresponding to the transition from the brightness of absolutely "black" to absolutely "white", and is expressed in the number of bits per pixel of the image. The radiometric resolution is determined by the sensitivity of the detectors to the differences in the spectral density of the energy brightness of the signal reflected from the surface and fixed by a set of clearly differentiated quantization levels of the bit dynamic range. Spatial resolution is a measure of the size of the smallest objects that can be seen in the image. Spatial resolution is also specified by the minimum angular or linear values of the represented terrain object and fixed by a pixel. Spatial resolution characterizes the size of the smallest objects that can be seen in the image. Depending on the tasks to be completed, data of low (more than 100 m), medium (10 - 100 m) and high (less than 10 m) resolution can be used. The images of low spatial resolution are surveyed and allow one to cover large areas simultaneously - right up to a whole hemisphere. Temporal resolution is determined by the frequency of that pictures are taken of a particular area. Temporal resolution is the time during which a satellite can re-survey the same section of the earth's surface. The parameter is very important for monitoring emergency situations and other rapidly developing phenomena but less important for long-term studies.

2.9. Methods for land cover and land use classification

In remote sensing satellite images can be classified using three commonly used methods: unsupervised image classification, supervised image classification and object-based image analysis. Unsupervised classification is used when no prior knowledge and training about the area are available and uses K-mean and the ISODATA clustering algorithm for grouping together pixels according their multispectral composition. After assigning each pixel to the relevant class, clusters can be combined to generate categories for final map.

Supervised image classification is three-phase process that uses ‘maximum-likelihood’, ‘minimum distance’ and ‘artificial neural network (ANN)' algorithms to create different classes. The first stage is called training, where the data is a-priori known and derived from topographic maps, ground truth, and aerial images. This process involves sampling of pixels related to one predetermined and known class. The training input provides necessary statistics such as mean and standard deviation which are consequently used as an input for the next stage. In the next phase, pixels are assigned to the matching classes according to the statistics derived from the training sample. The third stage defines the accuracy of classification. A group of selected pixels and related classes are compared to the reference data. The spectral signature of each class is assigned for training input which is then processed and automatically generated to the whole image.

Unlike both supervised and unsupervised classifications which are completely pixel-based, OBIA (object-based image classification) uses geographic objects as the basis for classification (Phiri and Morgenroth, 2017).

2.10. Landsat land cover classification methods

Land cover classification and land surface monitoring through the Landsat satellite program has a rich history. Landsat 1 was launched in July 1972 and, since then, several methods for land classification have been incorporated. Land cover classification using Landsat satellite images has become an increasingly important matter of discussion in the context of climate change over the last couple of decades (Phiri and Morgenroth, 2017). Landsat satellite imagery has been

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continuously advancing with the development of new upgraded sensors. This was mainly achieved by upgrading the level of spatial, spectral, radiometric and temporal resolution (Zhu et al, 2016).

It is worth mentioning that relatively recently Landsat images have become integrable with other satellite images through the use of image fusion techniques (Phiri and Morgenroth, 2017). The invention of new remote sensing technologies such as advanced very high-resolution radiometer (AVHRR) and moderate-resolution imaging spectroradiometer (MODIS) as well as advancement in image fusion methods have dramatically increased the quality of land cover classification (Phiri and Morgenroth, 2017).

2.11. Literature review

Numerous studies have been conducted to analyze how climatic factors, including precipitation and surface temperature, affect NDVI and vegetation dynamics using remote sensing, and vegetation dynamic patterns can be characterized quantitatively using satellite imagery (Justice and Hiernaux, 1986; Menenti et al., 1993). Inter-annual climate variations have a huge impact on the growing season length, total amount of biomass and ecosystem components (Roerink et al., 2003). Many scholars recognize that vegetation is subject to climatic factors, particularly temperature and precipitation which both greatly affect vegetation dynamics (Fant et al 2004; Ji and Peters 2004). Studies related to finding the relationship between NDVI and climatic variables thus involve a wide range of data types, including satellite imagery and temperature and precipitation information taken either from meteorological stations or from internet databases. Ding et al (2007) have reported that continuing studies in the field of climatic variables, vegetation interconnection, and spatial variation have the potential to foster research on vegetation dynamics forecasting. Information about precipitation, temperature and NDVI and how they correlate with each other has been intensively used by researchers to investigate effects of climatic conditions on vegetation growth. While Schultz and Harpert (1995) carried out large-scale investigation to find relationship between LST (land surface temperature) and NDVI, and did not find any correlation between them, there are cases when studies resulted in finding substantial interrelation between these three parameters. For example Rasmussen (1998) and Guo et al (2008) found substantial correlation between NDVI, temperature and precipitation. Yet, in many of these studies, due to a wide range of factors, including complexity of vegetation characteristics, climate conditions and geographical location, results differed significantly (Bonan et al., 2003; Crucifix et al., 2005; Ni et al., 2006; Meng et al., 2011a). In most cases scholars did not differentiate between plants, examining various kinds of vegetation as a one body, not keeping in mind that each type of vegetation responds to climate change in a different manner (Chuai et al., 2012).

Li Leilei et al (2014) examined the interrelation of LST (land surface temperature), rainfall and spatio-temporal distribution of vegetation cover in Tibet. They used MODIS NDVI from MOD13A2 products, using the 16-Day L3 Global 1-km SIN Grid VI datasets[2], and generate land surface temperature (LST) data through MOD11A2 products available at a spatial resolution of 1x1 km and a temporal resolution of 8 days. Their research shows that, depending on specific location, mean vegetation coverage varied from 0% to 99%, In terms of precipitation, significant variations also took place depending on location: the southeastern

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part of Tibet ranges from 600 to 800mm, while the western part, mostly affected by drought, had values somewhat below 200mm. The mean annual land surface temperature varied between -8.9°C and 16.3°C. Correlation coefficient analysis revealed July to be least correlating month in the year. September was found the highest-correlating month in terms of vegetation and rainfall. Leilei also found that vegetation was more affected by rainfall than by land surface temperature from April to October.

A quite similar study was conducted by Chuai (et al 2012) on the relationship between NDVI, temperature and precipitation changes and their effects on different vegetation types in Inner Mongolia from 1998-2007. The Chuai et al study used slightly different in methods, taking SPOT-VEGETATION NDVI data for Inner Mongolia from 1998 to 2007, and Meteorological data, i.e. monthly mean temperature and precipitation, from all 118 meteorological stations installed and maintained across study area. A 1:1 000 000-scaled vegetation map of Inner Mongolia was used to gather information on vegetation features.

As for methods used, Chuai exploited a non-traditional, “true” NDVI formula: NDVI= DN*0.004-0.1 which was previously proposed by Cui and Shi (2010). As for statistical analysis, Pearson’s method was employed to identify the correlation coefficient between seasonal NDVI- temperature and NDVI-precipitation using SPSS.

Likewise, Chu et al. (2007) studied the interrelation between changes in NDVI and climatic conditions in the Lhasa area of the Tibetan Plateau with the timespan from 1985 to 1999. For that, the NOAA third-generation Global Vegetation Index (GVI) dataset was processed temporarily and spatially in order to produce weekly maximum-value images. Weekly NDVI values from 1985 to 1999 were averaged into month NDVI values. This was done in order to reduce the effects of cloudiness and off-nadir view angle that can generate low and incorrect NDVI values (Holben and Frazer, 1984; Holben, 1986). The default Gauss-Kruüger projection was converted into a Plate Carrée (latitude/ longitude) projection in order to fit the criteria of weekly NDVI applicable for the GVI dataset.

IDRISI 3.2 remote-sensing software application was used to process all the NDVI-related data. Course of action was as follows: extraction of NDVI data from the GVI dataset, calculation of monthly-average NDVI values from weekly-maximum NDVI for each pixel and domain-averaged monthly-mean NDVI values acquired through the spatial averaging of all the pixels. The meteorological data from local meteorological stations was obtained from Tibet Climate Data Center. Daily data of temperature and precipitation were then averaged to find a monthly mean value.

In terms of the principal finding of this study, a positive trend in NDVI from 1985 to 1999 in the Lhasa area can be outlined. It was found that “maximum precipitation is not always accompanied by maximum vegetation growth” as well as “total accumulated annual precipitation seems to relate more to the magnitude of NDVI than any specific monthly maximum. Temperature also plays an important role; “elevated temperature, if combined with increased rainfall can lead to prolonged and maximized vegetation growth”. [2] Overall, researchers reported strong seasonal and inter-annual variations in NDVI values as well as positive correlation coefficient between monthly precipitation, temperature and NDVI.

3. STUDY AREA

3.1. Geographical extent

The study area covers the Chon-Alay district located in the south-western part of Kyrgyzstan. The area of interest is the Daroot-Korgon, the

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administrative center of Chon-Alay rayon, which lies between the latitudes 39° 32' 27 " N and 39° 33' 24" N, and longitudes 72° 10' 24" E and 72° 15' 46" E and covers a total area of 6.41 km². Chon-Alay is situated in the western part of the Alay Valley, lying between the Alay and Trans-Alay Mountain Ranges. The study area embraces various ecological zones and biomes including steppes, hills, mountains, rocks, valleys and grasslands, as well as managed agricultural lands and pasture rangelands.

3.2. Climate

The climate is sharply continental and is subject to annual variations in temperature – severely cold and long winters and moderately warm summers. The hottest months are July and August, with mean temperatures of 15.5 °C and 16.3 °C respectively.

4. DATA AND METHODS

4.1. Methods

Despite the fact that the study area is located in the southern part of Kyrgyzstan, the vegetation period starts far later than it normally occurs due to the climatic conditions and altitude. For that reason, NDVI values were calculated from May to August to trace the dynamics of vegetation growth. Landsat 7 ETM + satellite imagery was employed for calculation of NDVI from 2000 to 2005, and Landsat 8 OLI satellite images were used for the period from 2015 to 2017. For the raster image processing, i.e. NDVI calculation, QGIS 2.18.17 software was used. The same application was exploited for land cover classification using the Semi-Automatic Classification Plugin. As for data visualization, Minitab 18 statistical software was used to plot scatterplots, pie charts, graphs and other visual representations of the results. Satellite images from Landsat 7 ETM+ and Landsat 8 OLI were atmospherically and radiometrically corrected.

4.2. NDVI

Landsat satellite images were downloaded from the United States Geological Survey website, particularly for Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper + (ETM+). Landsat products were imported into QGIS Desktop 2.18.18 and, after some image preprocessing procedures such as radiometric calibration, atmospheric correction and conversion from DN to Surface Reflectance, NDVI values were calculated. The time period covered is from 1993 to 1996 and from 2000 to 2003. NDVI values for the last five years were calculated using Landsat 8 OLI (Operation Land Manager). For the last five years, images of the same area (Daroot-Korgon) and of the same time (middle of August) were calculated using QGIS 2.18.18 with all the radiometric calibrations and atmospheric corrections done beforehand. For different Landsat satellite products, different band combinations were used: for Landsat 5 TM as well as for Landsat 7 ETM +, Band 3 (Red) and Band 4 (Near Infrared) were used, whereas for Landsat 8 OLI Band 4 (Red) and Band 5 (Near Infrared) were imported. Calculations were made in the Raster Calculator using previously mentioned NDVI formula and maximum, mean and minimum values were found.

4.3. Land cover classification

The procedure of land cover classification was similar to that for NDVI at the early stages – image preprocessing steps include radiometric calibration, atmospheric correction and conversion from Digital Number to surface reflectance. Following this, a Semi-Automatic Classification plugin – an open source plugin for QGIS for both supervised and unsupervised classification analysis – was used. To make a classification all 11 bands available for Landsat 8 OLI were required. The supervised classification method was selected based on familiarity with the site and prior knowledge of

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the different vegetative classes in the region. For supervised classification, it was first necessary to create a Training Input File to identify ROI's (regions of interest). ROI creation involves adding "Classes and Macroclasses" – for example, a class of river and macroclass of water resources as a whole. ROI's were identified by highlighting polygons over the areas of interest. Classification quality was checked to ensure that ROIs corresponded to reality before the process was finished. The 'Maximum Likelihood' algorithm was chosen for application of the ROIs to the images as it best fit the supervised method of classification in QGIS. The results of the land cover classification can be seen in Figure 26. Four different classes were generated for Daroot-Korgon: Cropland, Water, Bare Soil and Vegetation.

4.4. Temporal characteristics

Due to the long winters and short vegetation period, it was logical to calculate NDVI only during the period of vegetation – from May to September. In Daroot-Korgon, as in the whole Chon-Alay region, snow melts only at the end of April or beginning of May, making May the logical starting point. At the beginning of September practically all the vegetation there stops growing – this is why NDVI calculation ends at the end of September.

4.5. Meteorological data

Meteorological data was obtained from the local weather station. As was previously mentioned, due to the poor quality and improper state of the data, it was decided to omit inapplicable documented files. Thus, instead of twenty years of meteorological observation (1993-2013) only 8 years (1993-1996; 2000-2003) were studied. Initially, it was planned to find monthly averaged values of temperature and precipitation, but this would have decreased the scope of the work.

4.6. Statistical analysis

One of the main goals of the study was to identify whether there was a correlation between NDVI and climatic variables (Figure 3). For that, the Minitab 18 statistical software application was used. All the data from the weather station was imported into the program and the average of every ten days from May to September was calculated. NDVI values calculated in QGIS were than imported into Minitab as well. Once mean meteorological data values were found, Pearson correlation coefficient was determined and NDVI was calculated using the formula in Figure 4.

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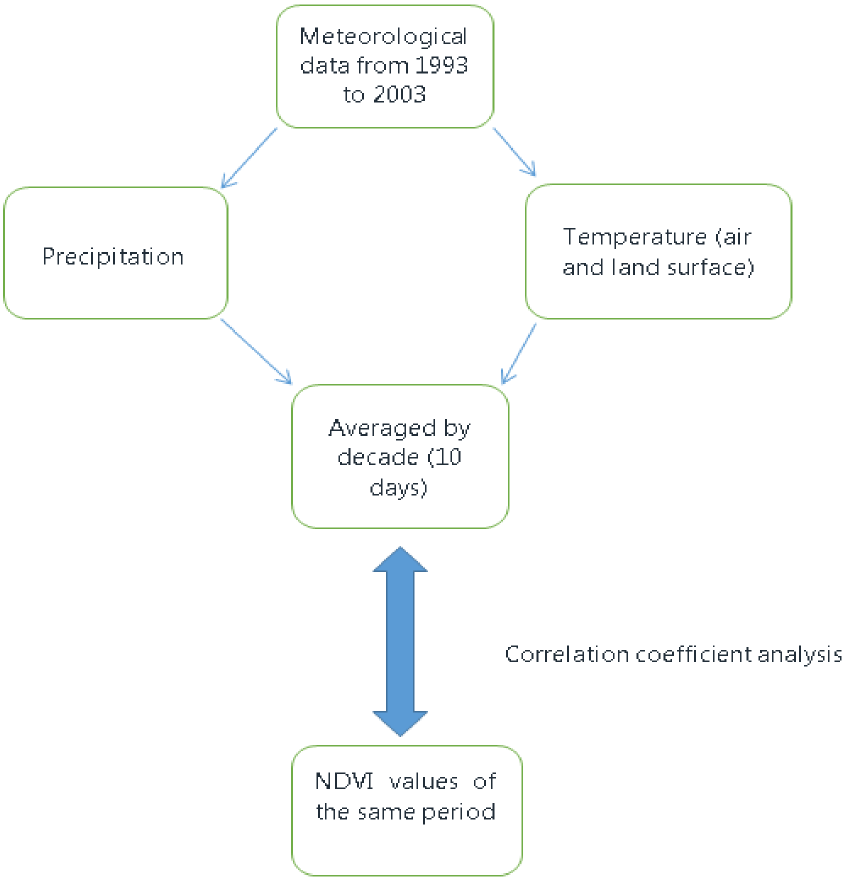

Figure 3. Algorithm for finding the correlation coefficient between NDVI and climatic variables

$$r = \frac{N\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{[N\Sigma x^2 - (\Sigma x)^2][N\Sigma y^2 - (\Sigma y)^2]}}$$

Where:

N	=	number of pairs of scores
Σxy	=	sum of the products of paired scores
Σx	=	sum of x scores
Σy	=	sum of y scores
Σx^2	=	sum of squared x scores
Σy^2	=	sum of squared y scores

Figure 4. Formula of Pearson correlation coefficient

5. RESULTS AND DISCUSSION

The duration and the coverage of territory for the study were limited by the availability of data from only one weather station. As seen from the Figures 5-10, there are only two years (1994, 2003) found to have a positive correlation coefficient between NDVI and climatic variables. In 1994, the Pearson correlation coefficient between temperature and NDVI is 0.753 and P value is 0.00; the Pearson correlation coefficient between NDVI and LST is 0.862 and P-value is 0.000 and the Pearson

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correlation coefficient between NDVI and precipitation is -0.140 and P-value is 0.619. In 2003, the Pearson correlation coefficient for precipitation and NDVI is 0.714 and P-value is 0.176, and the Pearson correlation coefficient between temperature and NDVI is 0.672 and P-value is 0.214.

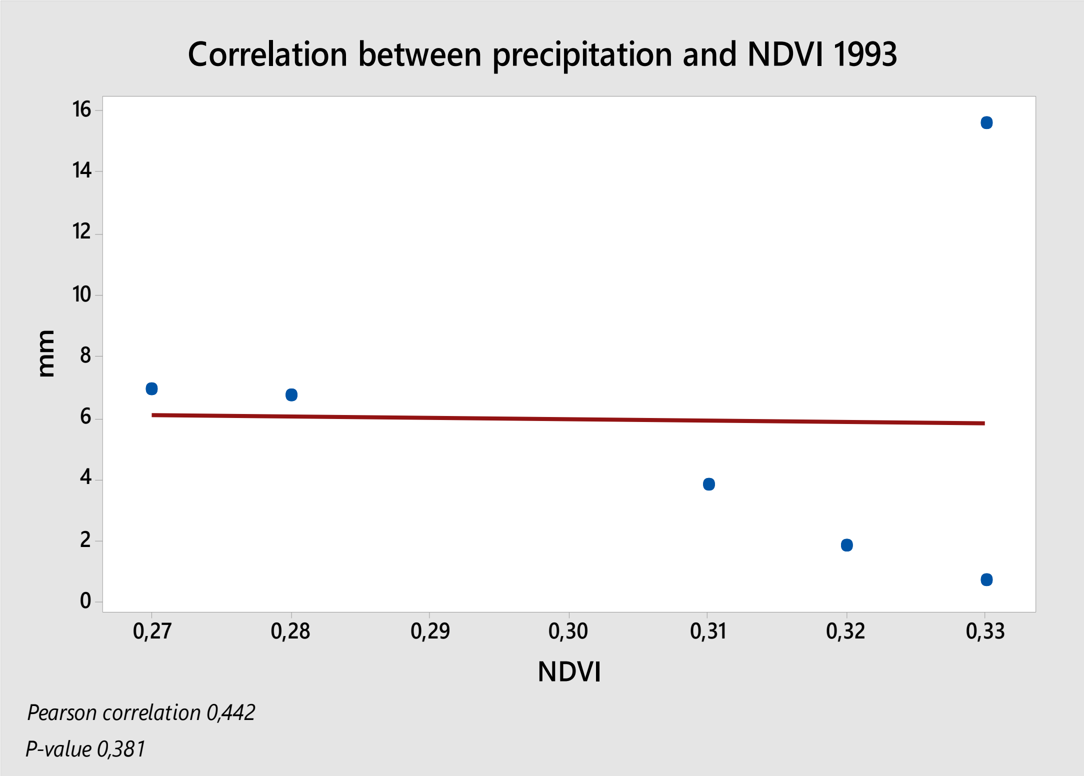

Figure 5. Correlation coefficient between NDVI and precipitation for 1993

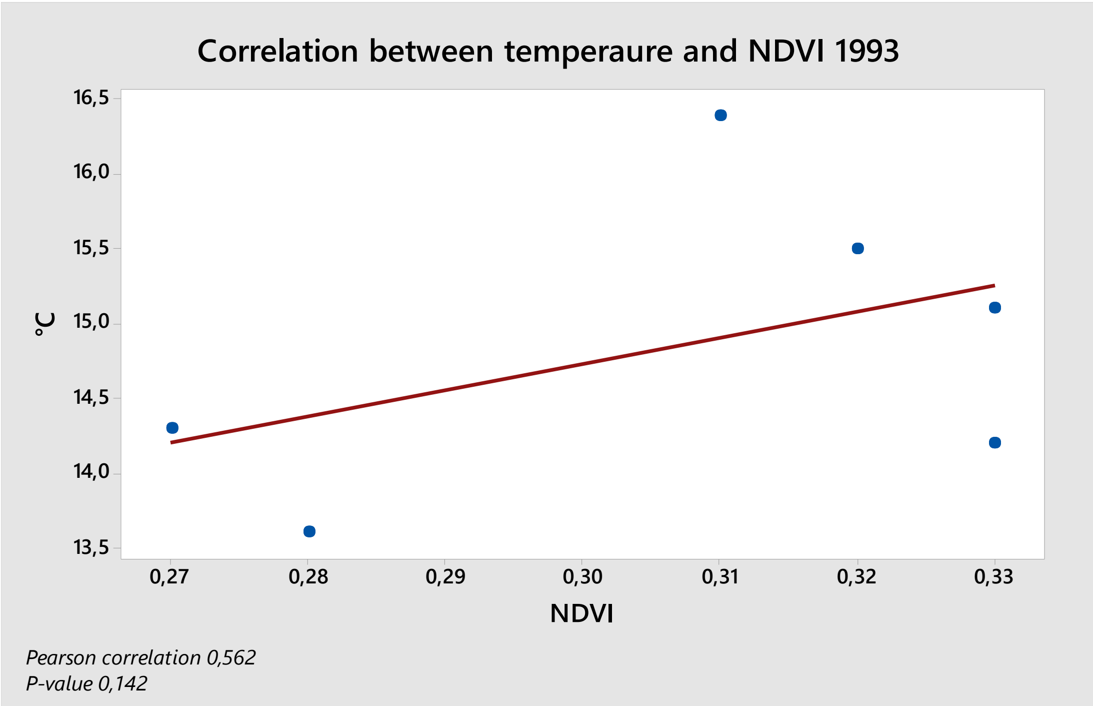

Figure 6. Correlation coefficient between NDVI and temperature for 1993

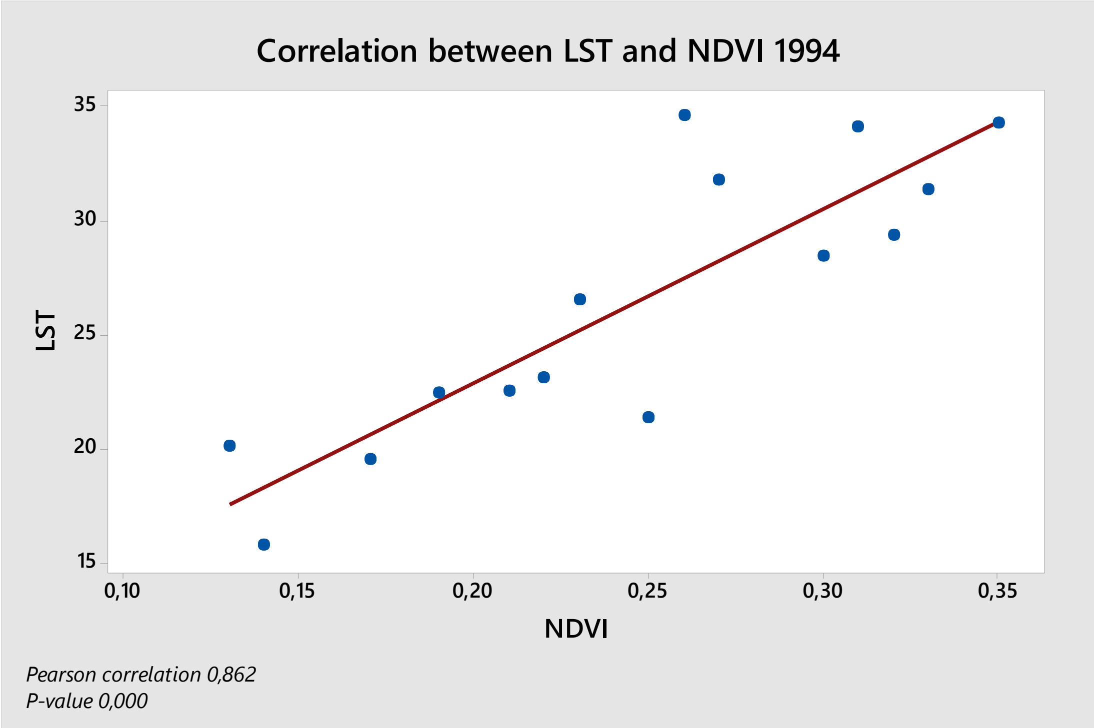

Figure 7. Correlation coefficient between NDVI and LST for 1994

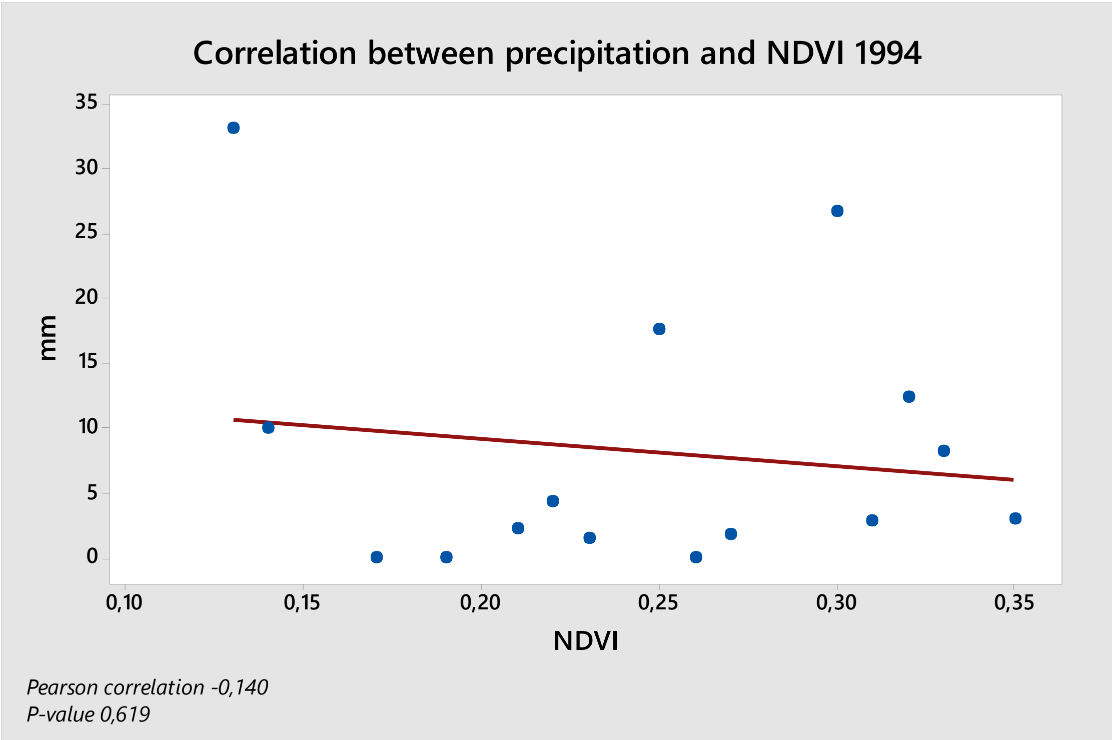

Figure 8. Correlation coefficient between NDVI and precipitation for 1994

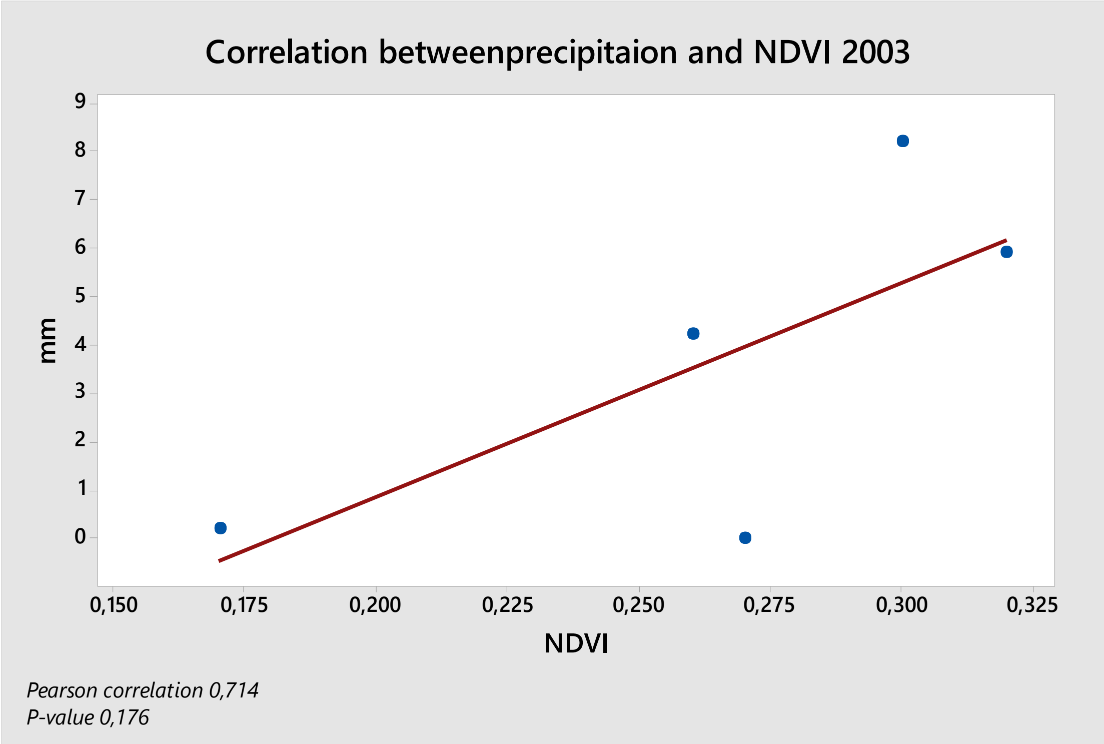

Figure 9. Correlation coefficient between NDVI and precipitation for 2003

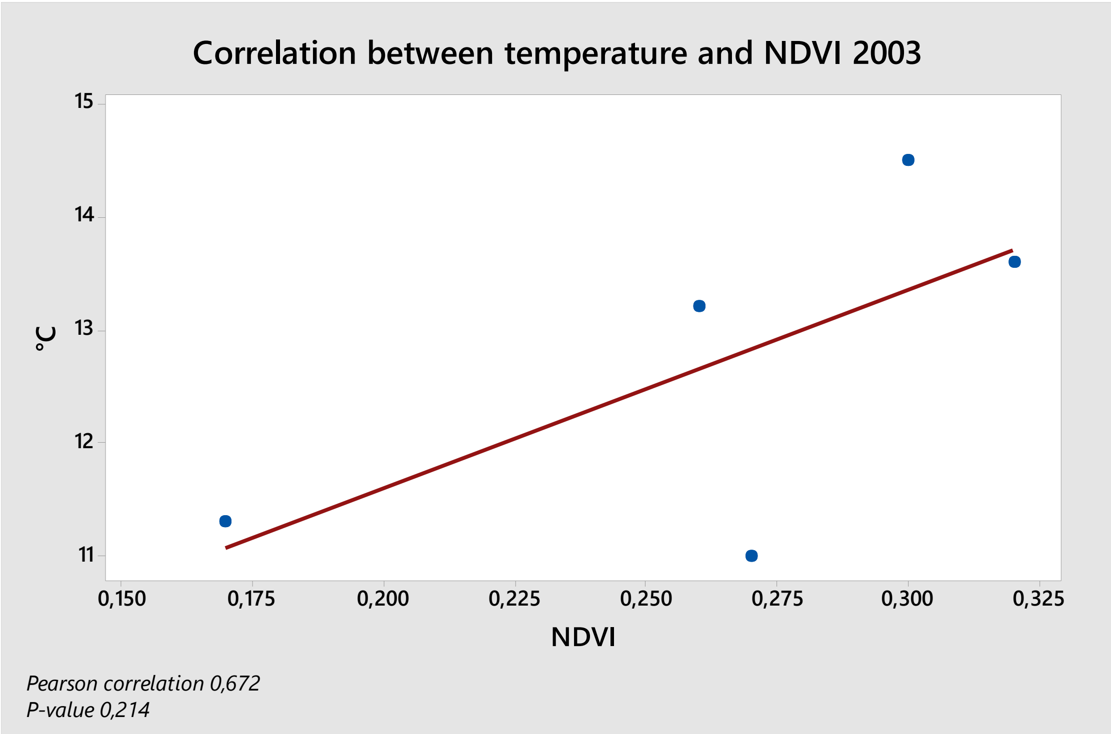

Figure 10. Correlation coefficient between NDVI and temperature for 2003

5.1. Temporal distribution of NDVI

In Figure 11-12, a time series plot of NDVI can be observed and how it changed over time. The plot illustrates NDVI fluctuations from 1993-1996 and 2000-2003. A seasonal trend can be vividly observed: as a rule, the lowest NDVI values are observed in May, reaching their peak at the end of July or beginning of August, and decreasing in the middle or end of September.

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As seen from Table 1, seasonal NDVI variations are different annually: in 1993 the minimum value was 0.27 and maximum value reached 0.33; in 1994 minimum value was 0.14 and maximum value reached 0.35 – this demonstrates a significant variation. In May of 1995 there was significant variation of NDVI: 0.10 and 0.22 within one month. In 1996 the lowest and the highest NDVI was recorded in September – 0.10 in first decades and 0.25 in third decades. So, the years 1995 and 1996 clearly demonstrate that NDVI can change drastically even within one month. In 2000, remarkable NDVI fluctuations were observed: in May the lowest and highest values reached 0.9 and 0.23 respectively; in June, 0.17 and 0.29; in July, 0.18 and 0.33; in August, 0.27 and 0.30; and, in September, 0.20 and 0.25. In 2001, the lowest and the highest values were equal to 0.15 and 0.33 in September and in July respectively – this is the only year when the September NDVI value is lower than that of May. In 2002, the lowest and the highest values reached 0.19 and 0.35 in May and July and August respectively. Finally, in 2003, the lowest and the highest results were equal to 0.17 and 0.32 in May and August respectively. In figure 12, time-series plot of precipitation from 1993 to 1996 and from 2000 to 2003. Figure 13 shows land cover classification made in QGIS 2.18. In Table 2 an inter-annual sequence of maximum NDVI values for August in Daroot-Korgon can be seen. It is clear that August 2016 was the highest in terms of NDVI. In Figures 14a and 15b, the darker green shades indicate higher NDVI values. However, neither graphically nor numerically can be identified very strong variations of NDVI in August of each year, except for 2016. Thus, based on a five year analysis, August is the month with the highest NDVI value with positive trend: values do not decrease sharply, they increase and decrease evenly.

Figures 15a and15b illustrate band combinations of Landsat 7 ETM+ (Band 4 – Near Infrared, Band 5 – Shortwave Infrared and Band 1 - Blue) and Landsat 8 OLI (Band 5 – Near Infrared, Band 6 – Shortwave Infrared and Band 2 - Blue). This band combination displays healthy vegetation: dense and healthy plants are yellow, orange, brown and red colors. Bare soil and rocks are represented in green, water bodies are dark (either violet or blue), and clouds are white. Visually, it is possible to judge how productive and healthy croplands are – for example, 2016 as the highest in terms of productivity and density can be pointed out. Thus, a clear correlation between NDVI and plant health and productivity can be observed as well.

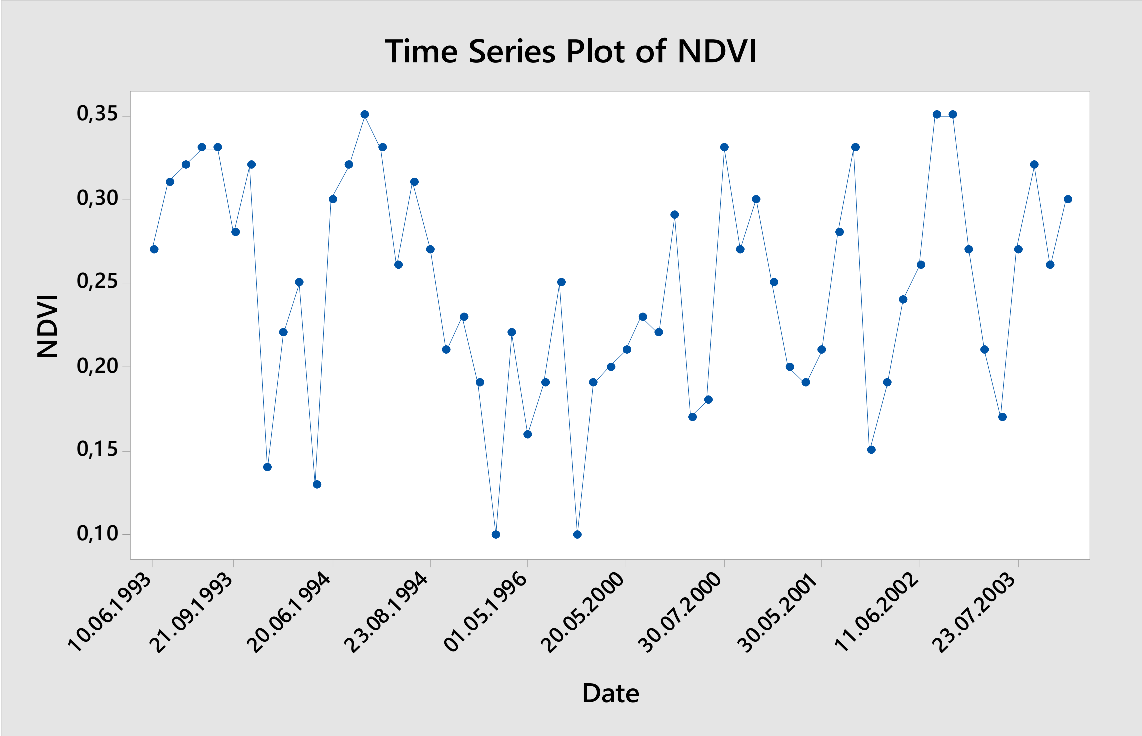

Figure 11. Time – series plot of NDVI from 1993 to 1996 and from 2000 to 2003

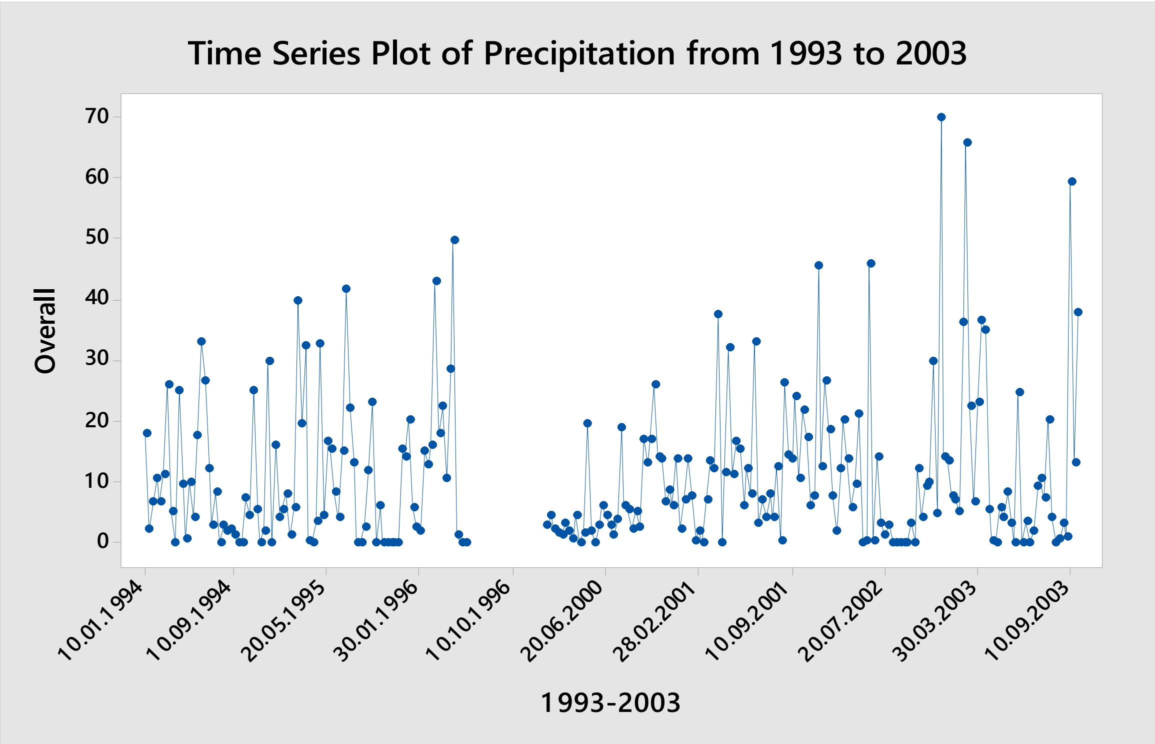

Figure 12. Time – series plot of precipitation from 1993 to 1996 and from 2000 to 2003

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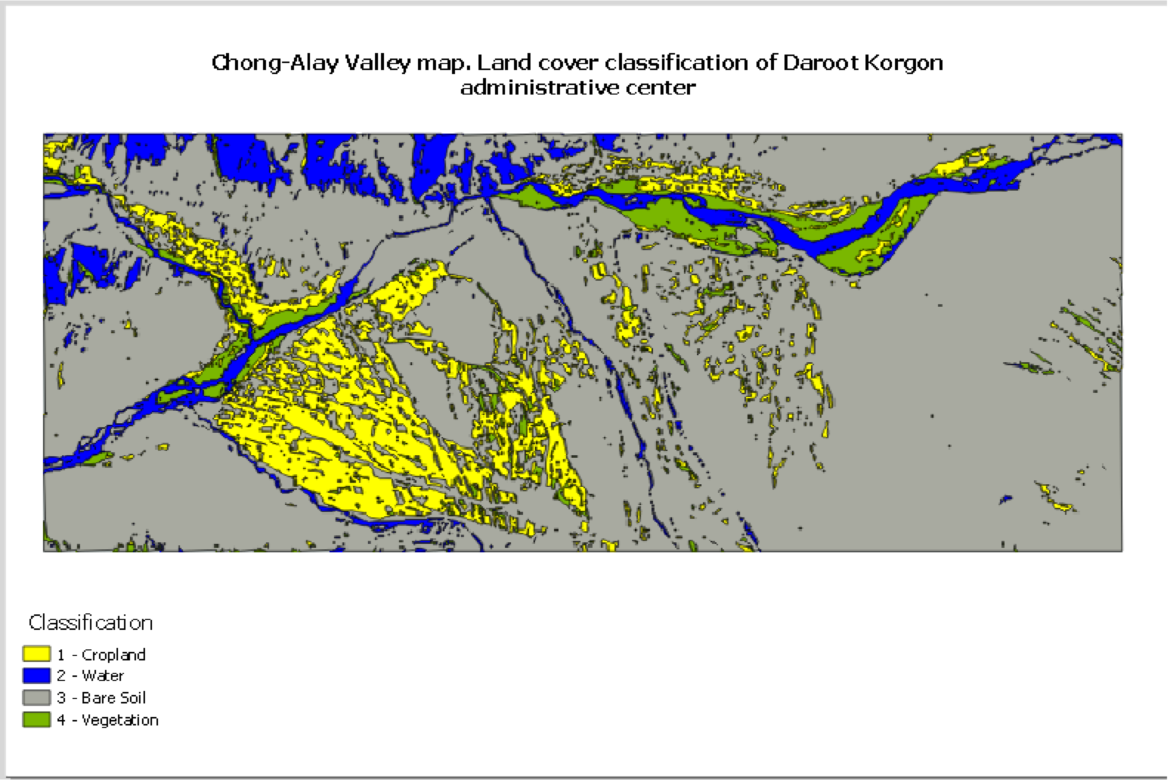

Figure 13. Land cover classification made in QGIS 2.18.

Table 1. Average NDVI values from 1993 to 1996 and from 2000 to 2003

Date	NDVI	Date	NDVI	Date	NDVI	Date	NDVI	Date	NDVI	Date	NDVI	Date	NDVI	Date	NDVI
10.06.1993	0,27	12.05.1994	0,14	06.05.1995	0,10	01.05.1996	0,16	12.05.2000	0,9	23.05.2001	0,19	01.05.2002	0,19	20.05.2003	0,17
03.07.1993	0,31	28.05.1994	0,22	15.05.1995	0,22	18.06.1996	0,19	19.05.2000	0,20	30.05.2001	0,21	02.06.2002	0,24	23.07.2003	0,27
12.7.1993	0,32	04.06.1994	0,25			06.09.1996	0,25	20.05.2000	0,21	08.06.2001	0,28	11.06.2002	0,26	24.08.2003	0,32
13.08.1993	0,33	13.06.1994	0,13			22.09.1996	0,10	27.05.2000	0,23	26.07.2001	0,33	20.07.2002	0,35	18.09.2003	0,26
20.08.1993	0,33	20.06.1994	0,30					04.06.2000	0,22	28.09.2001	0,15	05.08.2002	0,35	20.09.2003	0,30
21.09.1993	0,28	29.06.1994	0,32					21.06.2000	0,29			30.08.2002	0,27		
30.09.1993	0,32	06.07.1994	0,35					28.06.2000	0,17			22.09.2002	0,21		
		22.07.1994	0,33					07.07.2000	0,18			20.05.2003	0,17		
		31.07.1994	0,26					30.07.2000	0,33			23.07.2003	0,27		
		07.08.1994	0,31					23.08.2000	0,27			24.08.2003	0,32		
		23.08.1994	0,27					24.08.2000	0,30			18.09.2003	0,26		
		01.09.1994	0,21					16.09.2000	0,25			20.09.2003	0,30		
		08.09.1994	0,23					24.09.2000	0,20						
		24.09.1994	0,19												

Table 2. August averaged NDVI values over the last five years (2013-2017) for Daroot-Korgon

August 2013	August 2014	August 2015	August 2016	August 2017
0.37	0.35	0.38	0.43	0.40

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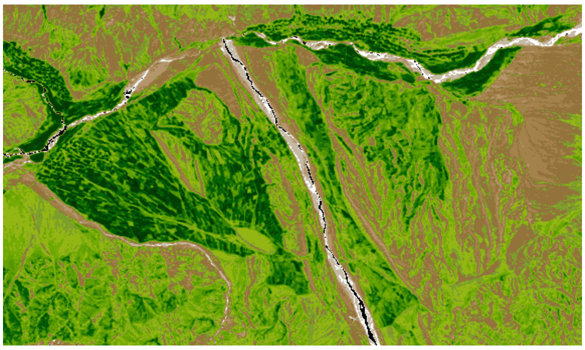
a)  b) 

Figure 14a. NDVI mid-August 2013

Figure 14b. NDVI mid-August 2017

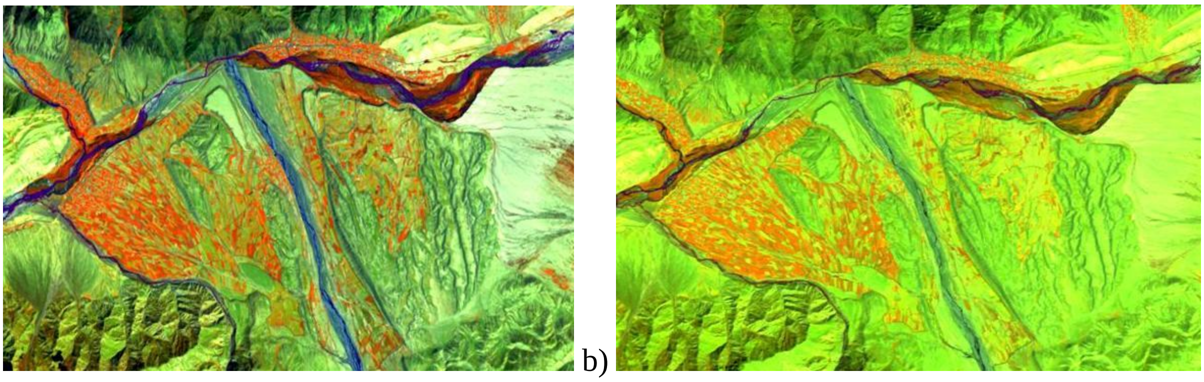
a) b) 

Figure 15a,b. Band combination for healthy vegetation for 2013 and 2017 accordingly

5.3 Limitations of the study

While this study did achieve its stated goals, there were certain inevitable methodological limitations and constraints. First, due to a partial lack of necessary data from the only weather station, particularly in terms of air and land surface temperature and precipitation, the scope of analysis was limited. This forced the reformation of the initial analysis model designed for 20 years of observations from 1993 to 2013 to fragmented periods of time from 1993 to 1996 and from 2000 to 2003. As a consequence, it was impossible to find a systematic and comprehensive trend or significant relationship between variables for the whole 20 year-period. The reason for the limitation was quite simple- most of the data needed was from the Soviet and post-Soviet era and was simply physically unavailable due to vagueness and erasure. A further limitation came from the technologies that were available. While QGIS 2.18.18, a software program which is free to download, can be used for land cover and land use classification, it is limited in terms of tools and functions. Use of more costly programs such as ENVI and ERDAS Imagine would have allowed for the generation of more accurate and reliable results.

6. Conclusions

This study included two main goals: finding an interrelationship between NDVI and climatic variables such as precipitation and air and land surface temperature in Daroot-Korgon village, and developing land cover classification for the region. Due to missing meteorological data, the study was fragmented into two timeframes: 1993-1996 and 2000-2003. Based on the data available, the first research question was answered, and two years (1994 and 2003) were found to show positive correlation between vegetation dynamics and climatic parameters. In other years, again due to partial data availability, no significant interrelationship between variables was found. Unfortunately, the study was not able to determine whether it is possible to predict one variable knowing the others or whether there is a liner relationship between NDVI and any climatic parameters. Given that there were only two years with positive linear interdependence in the 8 years of observation, it is difficult to claim that there is a significant trend. However, the fact that two years do show such a trend gives us reason to believe that, had more data been available, the analysis would have been much more fruitful and reliable. A clear correlation between NDVI and plant health and productivity can be observed as well.

Analysis of NDVI trends over the last five years in Daroot-Korgon, however clearly do illustrate a trend: little inter-annual variation, with regular seasonal variation.

7. Recommendations

This study was undertaken partly to bridge a gap in the knowledge as the region of Chon-Alay, and more specifically Daroot-Korgon village, have not been sufficiently studied. Using the research questions posed in this paper, future researches can conduct similar studies using other methods and approaches.

In order to avoid the issues encountered in this study in terms of data availability, it is recommended that such a study be conducted where such data is available. In addition, despite the multi-functionality of QGIS software, it is recommended that image analysis by conducted using other GIS programs such as ENVI, ArcGIS or ERDAS Imagine. Owing to the high-level performance of these software programs, results are likely to be better and more accurate. ENVI is much more advanced in terms of geospatial analysis and image processing which make it probably the best application to for land use and land cover classification and change detection analysis.

8. References

1. Arora, V.K., and Boer, G.J., (2010): Uncertainties in the 20th century carbon budget associated with land use change. Global Change Biol., 16, 3327–3348.
2. Allen, Kym. "Systems and Sensors for NDVI Mapping | Agricultural Drone Specialists." Integral Drones, Publisher Name Integral Promotions, 23 Feb. 2018, www.integraldrones.com.au/comparing-ndvi-mapping-systems/.
3. Bonan G.B., Levis S., Sitch S., Vertenstein M., Oleson K.W. (2003). A dynamic global vegetation model for use with climate models: concepts and description of simulated vegetation dynamics. Global Change Biology 9: 1543– 1566, DOI: 10.1046/j.1365–2486.2003.00681.x.
4. Guo, X., P. Dixon, Y. He, and Z. Li. (2007). Satellite monitor-ing of northern ecosystems 2004–2006. Report for contract#5P401–06-5042. Gatineau, QC: Parks Canada.
5. Chuai X. W., Huang X. J., Wang W. J., Bao Gang, (2013) International Journal of Climatology NDVI, Temperature and Precipitation Changes and Their Relationships with Different Vegetation Types during 1998–2007 in Inner Mongolia, China. 33(7):1696-1706. DOI: 10.1002/joc.3543
6. Crucifix M, Betts RA, Cox PM. (2005). Vegetation and climate variability: a GCM modelling study. Climate Dynamics 24: 457–467, DOI: 10.1007/s00382-004-0504-z.
7. Crewett, W. (2012): Improving the sustainability of pasture use in Kyrgyzstan. In: Mountain Research and Development 32, 267-274. https://doi.org/10.1659/ MRD-JOURNAL-D-1 1-00128.1
8. Foody, G. M. and Arora, M. K. (1996), Incorporating Mixed Pixels in the Training, Allocation and Testing Stages of Supervised

Classifications, Pattern Recognition letters , 17, 1389-1398.

9. Holben, B., and Frazer, R. S., (1984): Red and near-infrared sensor response to of –nadir viewing. International Journal of Remote Sensing, 5: 145–160.
10. Holben, B. N., 1986: Characteristics of maximum-value composite images from temporal AVHRR data. International Journal of Remote Sensing, 7: 1417–1434.
11. Jinru Xue and Baofeng Su, (2017) “Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications,” Journal of Sensors, vol. 2017, Article ID 1353691, 17 pages,. https://doi.org/10.1155/2017/1353691.
12. Justice, C. O., and Hiernaux, P. H. Y., 1986: Monitoring the grasslands of the Sahel using NOAA AVHRR data: Niger 1983. International Journal of Remote Sensing, 7: 1475–1497
13. Kerven, C.; Steimann, B.; Ashley; L., Dear, C. and ur Rahim, I. (2011): Pastoralism and farming in Central Asia’s mountains: a research review. MSRC Background Paper No. 1. Bishkek
14. Kulikov, Maksim & Schickhoff, Udo. (2017). Vegetation and climate interaction patterns in Kyrgyzstan: Spatial discretization based on time series analysis. Erdkunde. 71. 143-165. 10.3112/erdkunde.2017.02.04.
15. Li Leilei et al (2014). The relationship analysis of vegetation cover, rainfall and land surface temperature based on remote sensing in Tibet, China. IOP Conference Series Earth and Environmental Science 17(1):012034. DOI: 10.1088/1755-1315/17/1/012034
16. Meng QH, Fei M, Han S, Ying YH. (2011a). Study of normalized difference vegetation index variation and its correlation with climate factors in the three-river-source region. International Journal of Applied Earth Observation and Geoinformation 13: 24– 33, DOI: 10.1016/j.jag.2010.06.003.
17. Menenti, M., Azzali, S., de Vries, A., Fuller, D., and Prince, S., 1993: Vegetation monitoring in Southern Africa using temporal Fourier analysis of AVHRR/NDVI observations. In: Proceedings, International Symposium on Remote Sensing in Arid and Semi-Arid Regions., Lanzhou: LIGG, 287–294.
18. Ni J, Harrison S P, Prentice IC, Kutzbach JE, Sitch S. (2006). Impact of climate variability on present and Holocene vegetation: a model-based study. Ecological Modeling 191(3–4): 469– 486, DOI: 10.1016/j.ecolmodel.2005.05.019.
19. Phiri D. and Morgenroth J. (2017). Developments in Landsat Land Cover Classification Methods: A Review. [ebook] New Zealand School of Forestry, University of Canterbury. Available at: http://www.mdpi.com/2072-4292/9/9/967/pdf [Accessed 13 May 2018].
20. Rasmussen, M. S. (1998): Developing simple, operational, consistent NDVI-vegetation models by applying environmental and climatic information: Part I. Assessment of net primary production, Internat. J. Remote Sens., 19, 97–117.
21. Roerink, G. J., Menenti, M., Soepboer, W., and Su, Z., 2003: Assessment of climate impact on vegetation dynamics by using remote sensing. Physics and Chemistry of the Earth, 28: 103–109. Saugier, B., 1996: Vegetation et atmosphere. France: Dominos Flammarion.107
22. Rouse JW Jr, Haas RH, Schell JA, Deering DW. 1974. Monitoring vegetation systems in the great plains with ERTS. Presented at Third Earth Resources Technology Satellite-1 Symposium, NASA, Washington, DC, 309–317.
23. Schultz PA, Halpert MS. 1995Global analysis of the relationships among a vegetation index, precipitation, and land surface temperature.. International Journal of Remote Sensing 16: 2755–2777.
24. Stephanie. (2013) “What Is Correlation in Statistics? Correlation Analysis Explained.” Statistics How To, Statistics How To, 10 Aug., www.statisticshowto.com/what-is-correlation/.
25. Tingjun Zh., Duo C. D., Chu L. L., Lixin L. Sensitivity of Normalized Difference Vegetation Index (NDVI) to Seasonal and Interannual Climate Conditions in the Lhasa Area, Tibetan Plateau, China. Institute of Arctic

November-December 2019
ISSN: 0193-4120 Page No. 5062 - 5084

and Alpine Research (INSTAAR), University of Colorado, 2007. Electronic.

26. Zhu X.; Helmer E.; Gao F.; Liu D.; Chen, J.; Lefsky M. A. (2016) Flexible spatiotemporal method for fusing satellite images with different resolutions. Remote Sens. Environ., 172, 165–177.