Spatiotemporal and multi-sensor analysis of surface temperature, NDVI, and precipitation using google earth engine cloud computing platform

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Vegetation, precipitation, and surface temperature are three important elements of the environment. By increasing the concerns about climate change and global warming, monitoring vegetation dynamics are considered to be crucial. In this study, the cross-relationship between vegetation, surface temperature, and precipitation, and their fluctuations over the past 21 years are evaluated. Day time LST from Terra sensor of MODIS, nir and red bands of Landsat 7 ETM+ and Landsat 8 OLI, and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) are used in this research. Data were evaluated and processed using the google earth engine cloud processing platform. According to the results, it was concluded that the correlations between the annual average of normalized difference vegetation index and precipitation are not significant. Evaluation of the cross-seasonal correlations exhibited the availability of the strong and significant correlation with a value of $r^2 = 0.82$ between vegetation thickness and precipitation, during the spring and summer, especially from April to August. Moreover, surface temperature exposed an inverse correlation with precipitation and NDVI with the values of $r^2 = 0.776$ and $r^2 = 0.68$ respectively, these relationships are highly significant. According to the results of this study, vegetation declined sharply in particular years, and this decrease occurred due to insufficient rainfalls. *KEYWORDS:* Land surface temperature; Landsat; NDVI; Balkh Province.

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1. Introduction

Satellite remote sensing is an efficient tool for studying, monitoring, and observation of land cover changes, deforestation, and impacts of global climate change [*Pettorelli et al.,* 2011]. Through the evolution of remote sensing technology, various algorithms and techniques are designed to facilitate driving information from satellite imageries [*Zhang et al.,* 2017].

Spectral indices are the simplest, essential, and widely used techniques amongst the vast variety of methods to drive and extract significant information from remotely sensed data [*Roerink et al.,* 2000]. The normalized difference vegetation index (NDVI) is a satellite-derived global vegetation index calculated from the ratio of vegetation reflectance bed red and near-infrared (NIR) of the electromagnetic spectrum [*Hamel et al.,* 2009]. NDVI is an effective tool to monitor the Spatiotemporal variation of the vegetation in any geographical location. [*Weiss et al.,* 2004], assessed the long-term variability of growing vegetation and its peak, and demonstrated bimodal seasonal growth with the peak in spring.

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[*Wang and Tenhunen,* 2004], classified NDVI derived images using supervised and unsupervised classification methods to create the temporal map of vegetation, and created an up-to-date vegetation map in China. [*Piao et al.,* 2006] applied NDVI to specify the growth of vegetation in temperate rangelands, they also assessed the response vegetation growth to climate change and indicated the variation of vegetation based on the changes of climate. [*Pettorelli et al.,* 2011], conducted a review on the utilization of NDVI in ecology prior based on research, and reported capability of this index in defining animal ecology according to a massive number intended of researches. [*Yue et al.,* 2007], used Landsat 7 ETM+ NDVI to assess the relationship between NDVI and land surface temperature and reported a negative correlation. [*Wang et al.,* 2003], investigated NDVI temporal response to temperature and rainfall, and a strong correlation was concluded. [*Fuller,* 1998], used the AVHRR derived images to inveterate spatiotemporal variation of vegetation in Senegal, and provided feasible outputs. [*Potter and Brooks,* 1998], investigated seasonal NDVI and its relationship with annual climate change, and reported a strong reliance of vegetation on climate conditions. [*Richard and Poccard,* 1998], intended interannual precipitating and sensitivity of NDVI in North Africa, the results exposed a positive correlation between these two phenomena. [*Karnieli et al.,* 2010], used satellite images derived from NDVI and LST to assess the drought occurrence, they reported a positive relationship between LST and drought and a negative relationship between drought and NDVI.

Google earth engine is a platform that contains massive data repositories and is ready to be analyzed. It is accessed and controlled through an Internet-accessible application programming interface (API) and an associated web-based interactive development environment (IDE) that enables rapid prototyping and visualization of results [*Gorelick et al.,* 2017]. Google earth engine (GEE) facilitates Time series analysis of NDVI and any other spectral indices thousands of satellite images within a wide range of years can be imported and analyzed through this platform [*Campos-Taberner et al.,* 2018a]. The relationship between land surface temperature and environmental factors such as NDVI is calculated using GEE and data derived from Giovanni repositories by [*Jamali et al.,* 2022] and exposed feasible performance and acceptable results.

[*Kumari et al.,* 2021] investigated a long-term analysis of spatiotemporal greenness and its relationship with the hydroclimatic factors, in the himation region and concluded the temporal increase of the vegetation in this area. [*Tamiminia et al.,* 2020] conducted a review investigation and the result of this study exposed, which hundreds of the papers were published within every using GEE Among ready-to-use products, the normalized difference vegetation index (NDVI) was used in 27% of studies for land cover mapping, vegetation monitoring, crop, and drought analysis. [*Johansen et al.,* 2015] researched the deforestation and vegetation clearing in the Queensland state of Australia and utilized various methods including NDVI and suing google earth engine and NDVI and reported high performance of the NDVI in specifying vegetation-cleared areas. [*Huang et al.,* 2017] used google earth engine platform to map major land covers in Beijing China, they extracted the intended classes of the land cover utilizing calculated NDVI from Landsat images specified a positive change of vegetation and quantified the area of obtained classes. [*Ding et al.,* 2007] utilized GEE to map and investigate the quantitative spatiotemporal analysis of vegetation dynamic and its influencing factors, in the alpine region of Tibetan, they used MODIS NDVI, the results of this study determined the feasibility of the NDVI performance in time series analysis of vegetation variation. Used normalized difference vegetation index (NDVI) algorithm and google earth engine (GEE) to investigate the spatiotemporal variation of vegetation in Indonesia utilizing Sentinel 2A images, they proved temporal reduction of the vegetation mean between 2016 to 2020.

[*Campos-Taberner et al.,* 2018b] studied the biophysical variables and their impacts on climate change, they used to google earth engine (GEE) for this purpose, the exhibited results exposed enough feasibility. Reviewed the application of GEE since its inception, the mainly focused on potential, usage, and trends, the result of this review proved that GEE is utilized mostly by the institutes in developed countries and the rate usage in less developed countries was significantly low compared to the developed nations. [*Mutanga and Kumar,* 2019] investigated the application of the GEE in various fields and research such as vegetation mapping and monitoring, land cover mapping, agricultural applications, disaster management, and earth science, the summary of this research implies the significance importance of the GEE in different fields of investigations specifically in environmental and geoscience.

[*Martín-Ortega et al.,* 2020] used Landsat NDVI and google earth engine to assess the effects of the illumination condition (IC) on vegetation indices and found a strong correlation between enhanced vegetation index (EVI), NDVI, and IC throughout the enhancement of Landsat position. [*Shen et al.,* 2015], researched the influences of seasonal rainfall on the growing of vegetation in Tibetan Plateau, the used NDVI, EVI, and vegetation greenness index to evaluate vegetation sensitivity to precipitation, the strong relationship between vegetation growth and precipitation was determined in semi-arid areas.

[*Song et al.,* 2020], evaluated impacts of artifact density on surface temperature, this research included 21 cities in China, they revealed a positive correlation between constructed objects and land surface temperature. [*Sharma et al.,* 2021], assessed the sensitivity between NDVI, LST, and Soil moisture in India, and reported stronger sensitivity of NDVI to LST rather than Soil moisture. [*Hilker et al.,* 2014], investigated impacts of precipitation on vegetation dynamic in the Amazon rainforest, and revealed that vegetation greenness strongly relies on the amount of precipitation. [*Tayyebi et al.,* 2018], researched to evaluate the impacts of urban growth on land surface temperature in Tehran, Iran, and concluded that LST has increased 6.77°C between 1986 and 2011.

[*Masoudi and Tan,* 2019], studied the influences of the spatial distribution of green spaces on the land surface temperature of the urban area in Singapore, and exhibited a significant relationship between well distributed green spaces and reduction of land surface temperature. [*Maimaitiyiming et al.,* 2014], also researched impacts of spatial patterns of green space on LST and the result was like the [*Masoudi and Tan,* 2019]. [*Mohd Jaafar et al.,* 2020], evaluated the effects of deforestation on the increase of the land surface temperature, and concluded that deforestation can cause the increase of land surface temperature. *Luyssaert et al.* [2014], evaluated land-use changes impacts on land surface temperature and pointed out that LST can increase rapidly in terms of changing landscapes without considering the importance of vegetation. [*Wu et al.,* 2011], evaluated the association between ecosystem, LST, and volume of rainfall and highlighted a significant correlation.

Satellite data and google earth engine play crucial roles in any geographical location, while they are more important in less developed countries, like Afghanistan. where the ground data is not available due to the destruction of the infrastructures and systems as the consequences of the log-term wars and internal conflicts. Utilizing satellite data in time series change detection of the landcover is the only available and easily applicable approach in Afghanistan. In this research, we are intended to examine the spatiotemporal changes of vegetation in the Balkh province of Afghanistan between 2000 to 2021 and its reliance on precipitation. The Landsat 7 ETM, Landsat 8 OLI images, MODIS products and google earth engine are used to map and quantify vegetation spatiotemporal dynamics in this province. Vegetation is one of the most important environmental factors and has a significant role in controlling air and land surface temperature, carbon emission, and air quality control. Therefore, Monitoring and preserving vegetation-covered areas is considered to be crucial, particularly in areas with poor vegetation.

Balkh province in the north of Afghanistan has a semi-arid climate, several rivers flow through this province, although this area has poor vegetation due to its climate. Serious monitoring of the vegetation trends in this province is extremely significant for future life in this area. Dense vegetations are available only on the sides of rivers, and the remaining areas have seasonal vegetation and usually dries up by the end of the spring season in July. The northern parts of this province, are covered by bare lands and deserts. Therefore, this region does not have adequate vegetation density even during the spring season. In this study, spatiotemporal variation of vegetation and its response to precipitation during the last two decades are evaluated in Balkh Province, Afghanistan.

2. Study Area

Balkh province located in the north of Afghanistan and lies between the latitudes of 35°35′24″ and 37°23′27″ N and between the longitude of 66°24′30″ and 68°12′17″, with an area of 16,731 km^2. This province is situated in a semi-arid climate region and three main rivers of Afghanistan cross through this province, Amu River in the north, Balkhab, and Sholgara rivers flow in the south and southwestern parts of this province [*Alan et al.,* 2012]. Although due to its climate most of the area in this province does not have enough vegetation and air temperature varies from −10°C in the winter to 50°C during the summer. The geographical location and elevation map of the study area is presented in Figure 1.

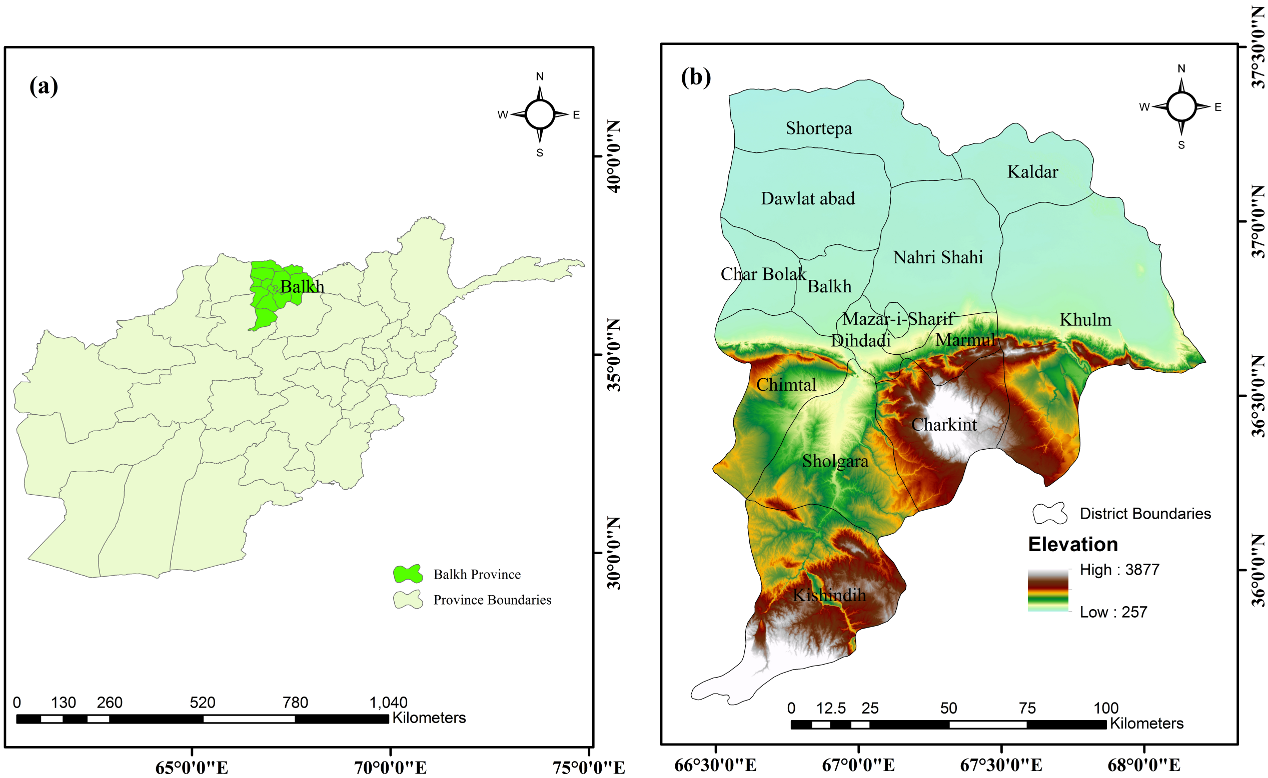

Figure 1. Indicates the location of the study area, (a) presents the political boundaries of Afghanistan, and (b) the location and elevation map of Balk province.

3. Data and Methodology

3.1. Data

Specific bands of all available images of Landsat 7 EMT+ between 2000 and 2014 were used to calculate Normalized Difference Vegetation Index (NDVI) and Land surface temperature was obtained from MODIS daytime 1 km LST between 2000 to 2022. Landsat 7 ETM+ sensor uses radiometers to measure the amount reflected and emitted electromagnetic radiations. Landsat 8 OLI are utilized from 2014 to 2021 to obtain the last five-year NDVI. Landsat 8 has two sensors, OLI and TIR, to measure the reflected radiation of the earth's surface. All multi-spectral bands in Landsat 7 and Landsat 8 have 30 m resolution with a panchromatic band which has a spatial resolution of 15 m. Atmospherically corrected visible, infrared, and thermal bands of Landsat 7 and Landsat 8 are accessible through the google earth engine platform [*Kuhn et al.,* 2019] and utilized in this research. A scale value assigned for each of these corrected bands and are essential to be applied during the process. The quality of the all-available images for Landsat 7 and Landsat 8 was evaluated within the specified range of dates and the images with the cloud cover percentage of greater than 2% were excluded from detailed information of the user data provided in Table 1. To evaluate the relationship between vegetation, land surface temperature, and precipitation, the daily rainfall data of Climate Hazards Group Infra-Red Precipitation with data Station (CHIRPS) data was utilized. The acquired rainfall data has a resolution of 0.05 degrees and provides long-term data for time series analysis. The quality and accuracy of the data were evaluated and proved by earlier researchers [*Dinku et al.,* 2018]. The NIR and RED bands of Landsat 8 OLI and Landsat 7 ETM Plus images between 2000 and 2021 are used to calculate NDVI in this research. Landsat 8 images are finer compared to the Landsat 7 EMT+, but available only since late 2013, thus the Landsat 7 images were utilized to obtain the normalized difference vegetation index between 2000 to 2014. Band saturation is increased in Landsat OLI, available bits of bands in Landsat 7 ETM+ is 8 and can easily be saturated and this was increased to 12 in Landsat 8 OLI, however, this sensor has a higher capability of extracting vegetation-

Table 1. Bands of Landsat 8 and 7 Were Utilized in This Research

Band no	Band Name	Spectral resolution	Sensor	Spatial resolution
Band 4	RED	0.64–0.67 μm	Landsat 8 OLI	30 m
Band 5	NIR	0.85–0.88 μm	Landsat 8 OLI	30 m
Band 3	RED	0.63–0.69 μm	Landsat 7 ETM+	30 m
Band 4	NIR	0.77–0.90 μm	Landsat 7 ETM+	30 m

Table 2. Related Information About Land Surface Temperature and Rainfall Data

Band name	Spatial resolution	Unit	Date of availability	Scale	Source
LST_Day_1 km	1000 m	Kalvin	2000–2022	0.02	terra Modis
Precipitation	5566 m	mm/day	1981–2022		CHIRPS

covered area. The spatial resolution of the pixels in Landsat 8 and 7 are 30 meters, but the spectral resolutions in Landsat 8 are narrower and capable to separate surface features based on their reflectance in different spectral bands [*Roy et al.,* 2016].

3.2. Methodology

All stages of this research were conducted in google earth engine cloud processing platform using Java programing language. Google earth engine is an open-source cloud and web-based platform and works based on Java and Python programming languages. This cloud-based environment helped researchers to remove obstacles, to the processing of time-series satellite images by its establishment. Time-series satellite images with the size of hundreds of Terabits (TBs) can be processed Simultaneously [*Gorelick et al.,* 2017]. To evaluate this research, atmospherically corrected Landsat images imported, the quality of the data, and the percentage of the cloud cover were determined. Specific bands of Landsat 7 and Landsat 8 with acceptable quality were selected for the particular range of dates, and the scale values applied for each of the included bands, Table 1.

Vegetations have the lowest reflectance of electromagnetic radiation in the range of visible wavelength (0.22 μm–0.68 μm) and the maximum reflectance in the NIR band. Therefore, the NDVI can be calculated using the ratio of the difference between the bands of NIR and RED bands (1).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \tag{1}$$

NDVI was calculated using NIR and RED bands for all the selected images of Landsat 7 ETM+ and Landsat 8 OLI for 21 years. Maps of NDVI were created for every five-year, using the average of the calculated NDVI values for every single image. However, to evaluate the variation trends in a possible minimum range of times, 8 days dynamic charts were created. To specify the NDVI variation impacts on land surface temperature, the CHIRPS daily rainfall data was included and the correlation of these two variables was assessed. Furthermore, the Land surface temperature captured by the Terra sensor of MODIS was imported to evaluate the relationship between NDVI, Precipitation, and LST, the maps of each of the variables (LST and NDVI) were created using five years average of all available selected qualified bands. The workflow of the research methodology is presented in Figure 2 and the detailed information about the land surface temperature and rainfall data is provided in the Table 2.

4. Result and Discussion

4.1 Time Series Evaluation of NDVI Variation

Time series change detections are essential to monitor the variation of environmental phenomena like veg-

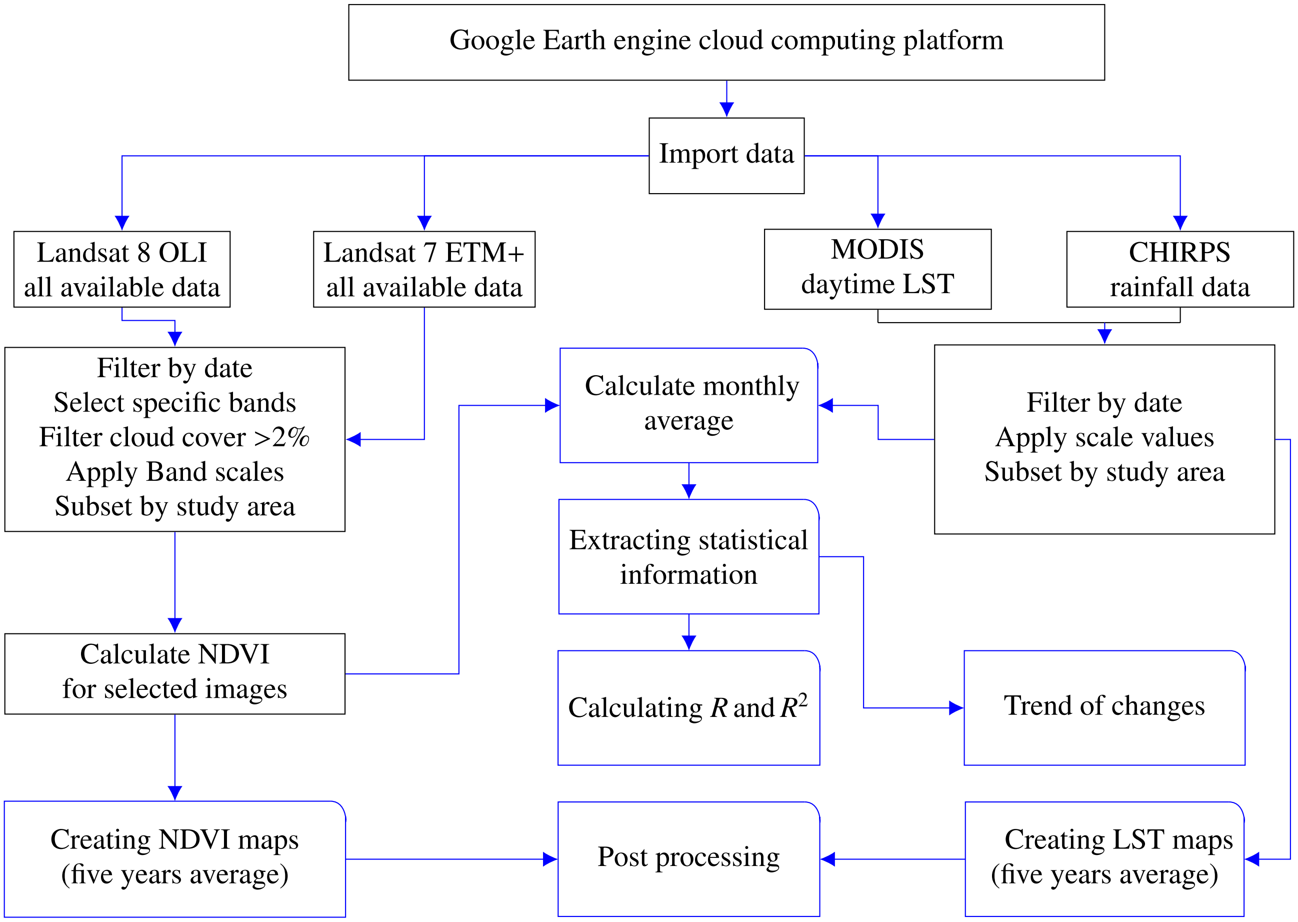

Figure 2. Workflow of the methodology.

etation density, land surface temperature, and precipitation. this monitoring will help organizations and planners to control and plan for natural disasters, environmental conservation, and protection of natural resources. The specified study area has a semi-arid climate and vegetation growths in this province generally depend on the amount of available rainfall, even small spatiotemporal variations vegetations are considered to be important. Spars or seasonal l vegetation play crucial roles in controlling seasonal floods and sandstorms. Statistical evaluation of all available Landsat OLI and ETM+ images for the last 21 years, using the google earth engine platform, demonstrated that the highest vegetation density in this province was recorded in 2003, between 2000 and 2005. vegetation thickness was declined sharply in 2001 compared to 2000. However, it was increased during the years of 2002, and 2003 and it indicates a downward trend in 2004 again. To evaluate the relationship between detected changes of vegetation with the rate of precipitation, monthly trends of rainfall were examined and indicated a strong reliance between vegetation thickness and amount of precipitation seasonal trends of vegetation between 2000 to 2005 within the selected study are presented in Figure 3. Flowing a sharp decrease of NDVI in 2004, vegetation thickness in this area increased in 2005, the trends of variation was normal during the years of 2006 and 2007 but it was decreased extensively in 2008 over again, and in 2009 this decline was recovered. In order to determine the effects of rainfall on vegetation fluctuations, we examined the condition of the rate of precipitation between 2005 and 2010 and found that the sharp decline in vegetation in 2008 was the result of a significant decrease in the amount of rainfall in this area. Investigating temporal variants of vegetation and precipitation during the first ten years (2000–2010) of study determines a strong reliance of vegetation growth on the amount of available rainfall in this region.

Vegetation condition in Balkh province in 2010 was similar to 2009, however, a massive change in NDVI values is detected in 2011 and indicated as the lowest

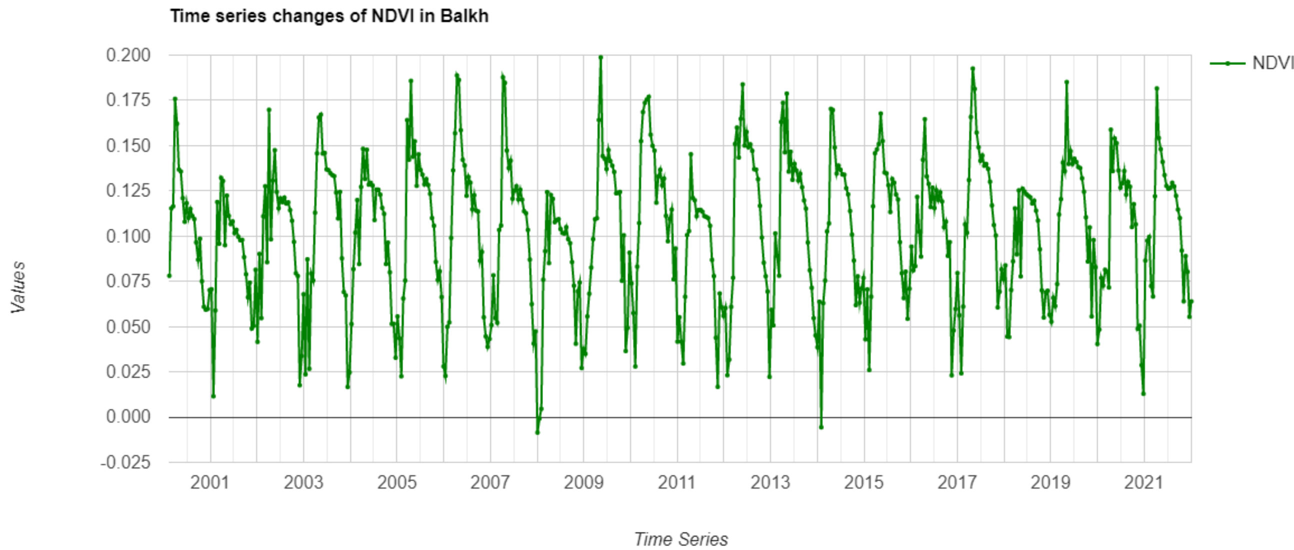

Figure 3. Vegetation trends from 2000 to 2022 in Balkh province Afghanistan.

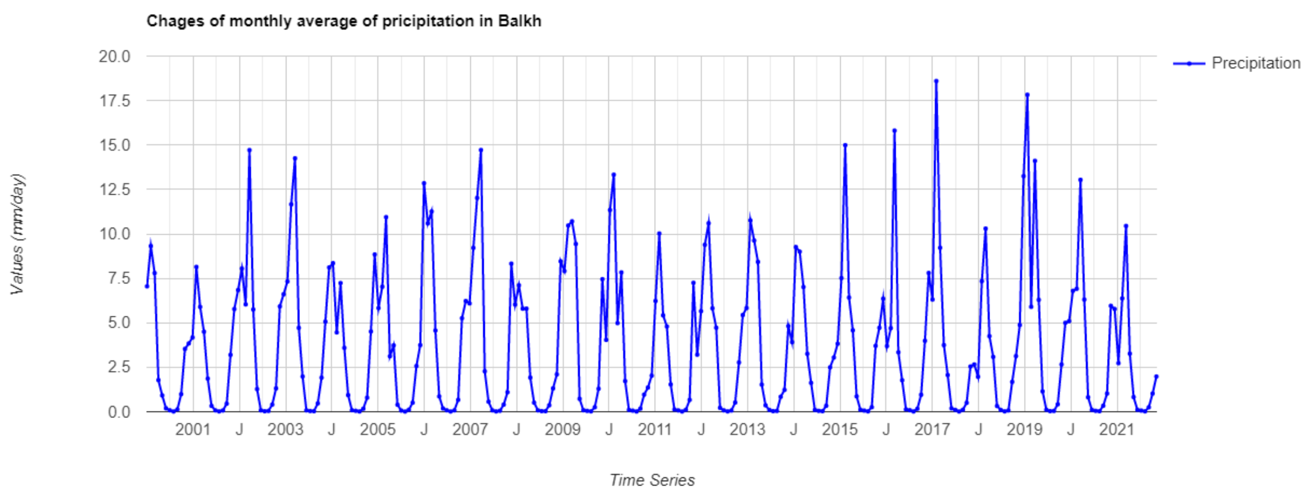

Figure 4. Monthly average of precipitation from 2000 to 2022 in Balkh province.

vegetation density during the last 21 years. This decline was also the result extensive decrease in the amount of precipitation in this area. In 2012 vegetation density also improved due to increases in the amount of precipitation and its variation was not significant in 2013 and 2014. From 2015 to 2016, temporal variation of vegetation was normal, however, in 2017 a significant increase in NDVI values is detected. In 2018 a sharp decline of vegetation was determined, while in 2019–2022 vegetation condition in the area was normal. To specify the influences of the precipitation on the fluctuation of the vegetation thickness, the amount of available rainfall was evaluated and revealed that fluctuation in vegetation density is affected by extensive changes in amount and time of precipitation, the daily average of precipitation presented in Figure 4. Five-year averaged maps of LST and NDVI are presented in Figure 5.

4.2. Impacts of Precipitation Fluctuations on Vegetation Thickness

Evaluation of the correlation between NDVI values and precipitation from April to August revealed the strong reliance of vegetation on the amount of precipitation. While the correlation between the annual average of NDVI and precipitation is not meaningful. This area has only seasonal and deciduous plants, and pre-

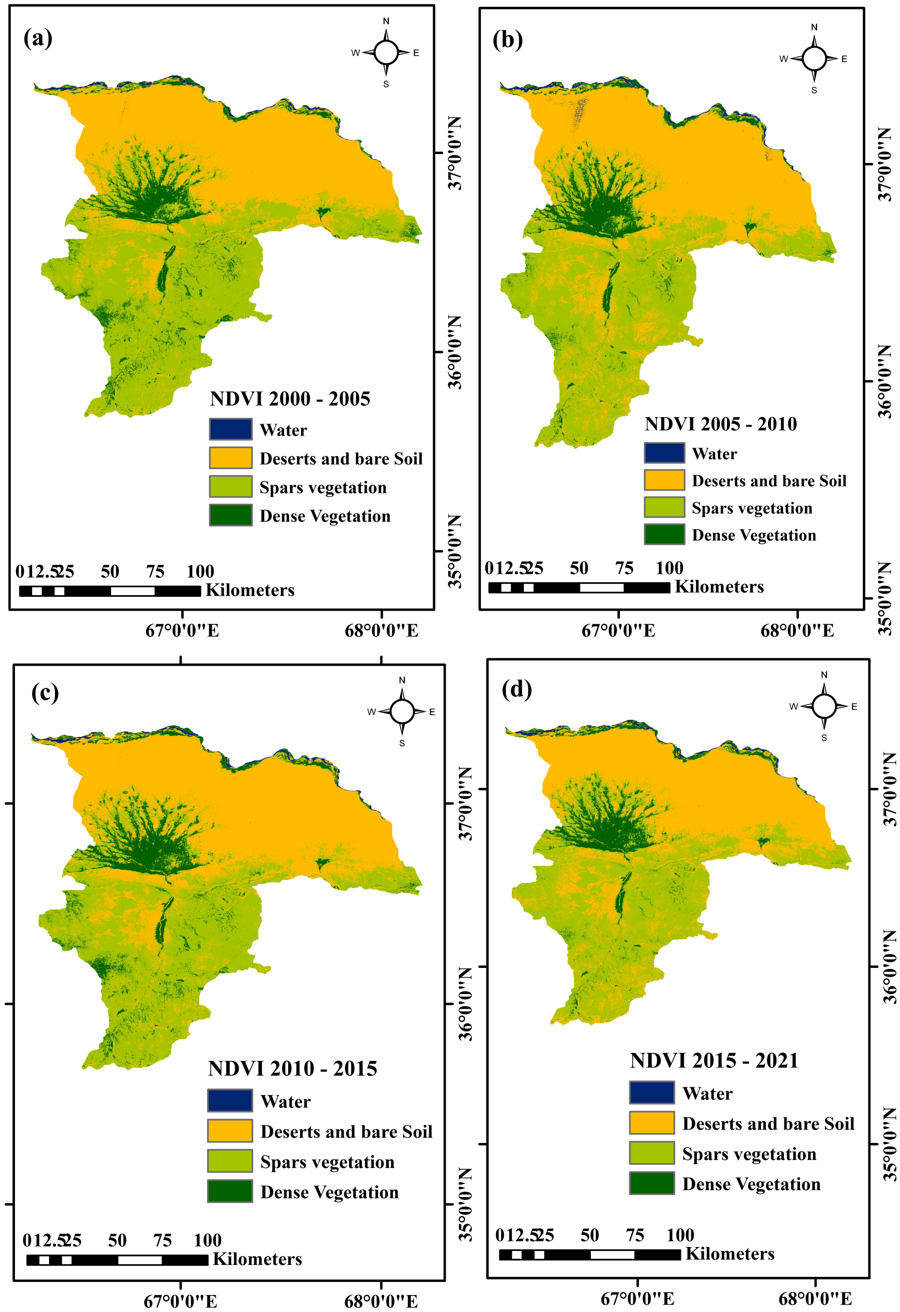

Figure 5. Presents averaged maps of NDVI within each five years.

cipitation occurs mostly during the winter, due to this reason the annual relationship between vegetation and precipitation can not be calculated. However, the correlation coefficient between vegetation thickness and amount of rainfall from April to August was detected 0.91 and with a high significance. the relationship between NDVI and Land surface temperature has a similar condition, where the annual correlation between these two phenomena is not significant, while it has a high and negative correlation during the season of vegetation growth. Balk province has a semi-arid climate and during the winter land surface temperature in this area drops sharply and reaches -10°C most of the time, furthermore, vegetation touches its lowest possible thickness. In contrast, LST rises sharply in the season of vegetation growth particularly from April and August. To distinguish the relationship between vegetation fluctuation and LST the correlation between

Table 3. Cross-Correlation Coefficient Between Monthly Average of NDVI, LST, and Precipitation From April to August

Parameters	significance	R	R^2
NDVI vs precipitation	4.94^{-07}	0.90526	0.8195
NDVI vs LST	1.1507^{-100}	−0.8241	0.67917
Precipitation vs LST	7.31407^{-81}	−0.8814	0.7768

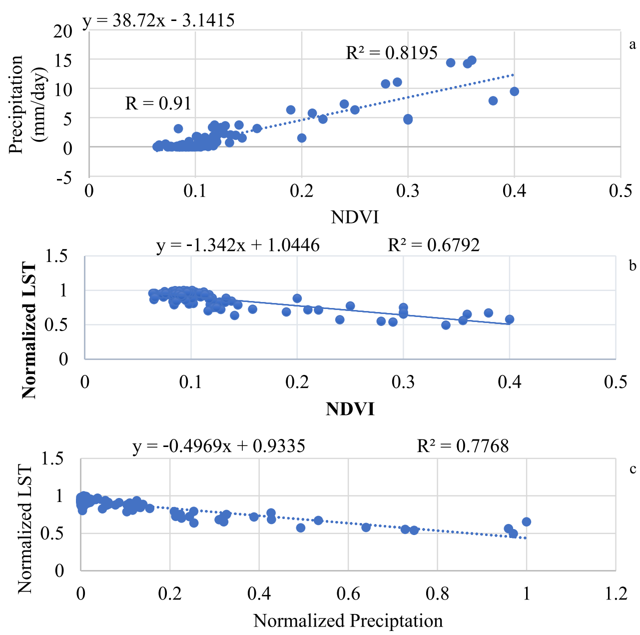

Figure 6. Indicates cross-correlation coefficient of the NDVI, LST and precipitation (a, b, c).

these two phenomena was calculated and revealed a strong and negative correlation with a value of 0.68 and this correlation was highly significant. The correlation between NDVI, LST, and precipitation is presented in Figure 6. Furthermore, the monthly average of the vegetation was calculated, and the cross-seasonal correlation coefficient was evaluated between precipitation and NDVI. Cross-seasonal analysis assists us to specify the associated correlation between NDVI and precipitation in a particular season. considering specific months, the correlation coefficient of rainfall and vegetation was evaluated during the periods of study, and the months with the highest correlation were detected. The correlation between the annual average of the precipitation and vegetation was not significant and the strong and negative relationship between vegetation thickness and precipitation was exposed from April to August. In addition to the amount of annual precipitation, the temporal distribution is also important for vegetation growth.

4.3. Impacts of Vegetation Thickness on Surface Temperature

Visual interpretation of the maps of land surface temperature and NDVI demonstrates strong impacts of vegetation on surface temperature. The interannual correlation coefficient was calculated and revealed that the relationship between vegetation and surface temperature from November to April is not significant. While the cross-seasonal correlation exposed a strong inverse relationship with the value of 0.6792 and high significance from April to August during the period of study. In order to evaluate Spatial influences of land use/cover and vegetation density on surface temperature, the linear regression between five-year averaged maps of LST and NDVI was created. Many studies reported massive effects of vegetation on the reduction of surface temperature. this research revealed a strong spatial inverse correlation between NDVI and LST. Bare lands, urban areas with low vegetation thickness exhibited the highest surface temperature. The correlation coefficient values of these three parameters are presented in Table 3. And maps of Land surface temperature are presented in Figure 7.

5. Conclusion

Vegetation, temperature, and precipitation are important factors of the ecosystem, and the balance between these three factors is considered to be important for the sustainability of the environmental ecosystem. Satellite remote sensing as essential tools provide facilities to evaluate and monitor time-series changes

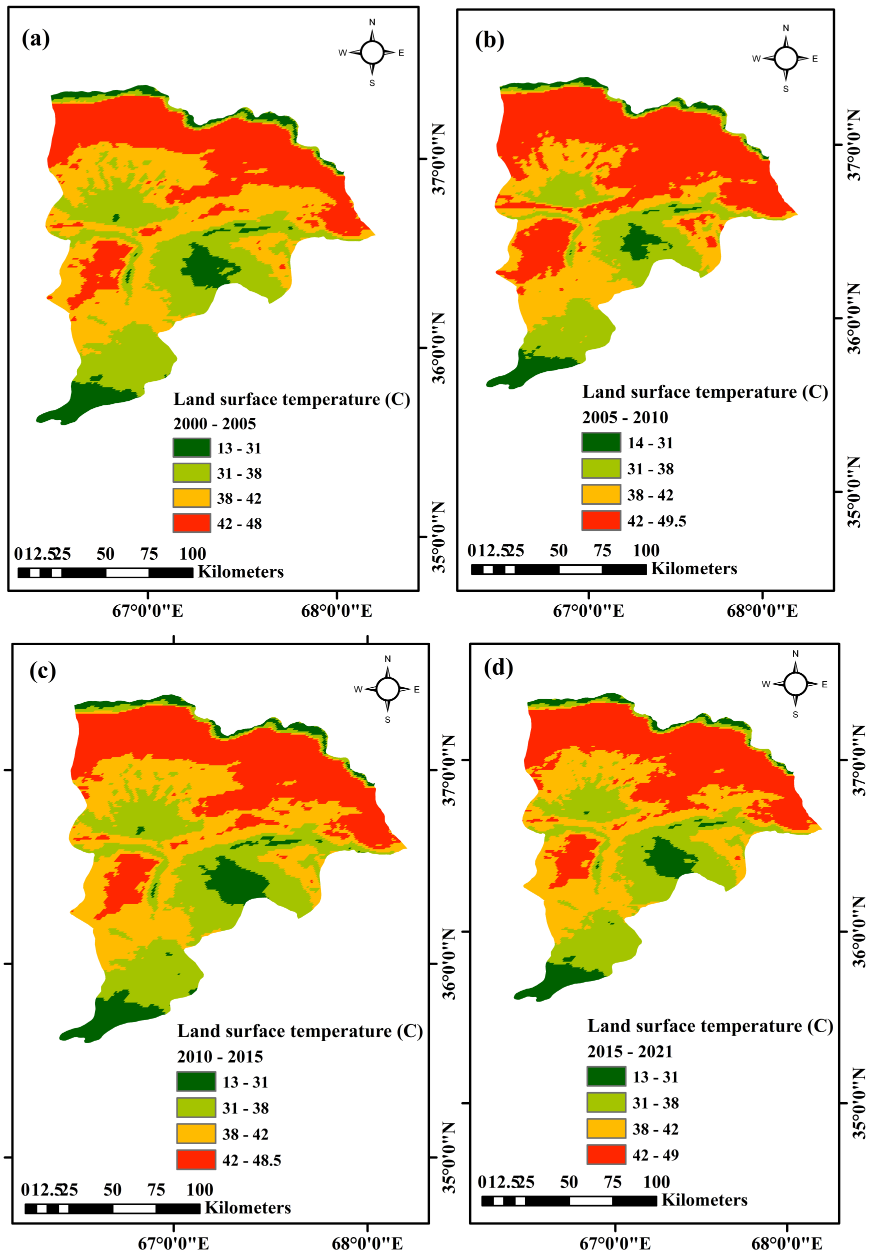

Figure 7. Presents averaged maps of Land surface temperature for Balkh Province within each five years.

of the earth's surface and is more vital for the countries like Afghanistan where access to terrestrial data is not possible. In this study, satellite data from various sources are used to evaluate the extent of changes and interrelationship between vegetation, amount of rainfall, and land surface temperature in Balkh province Afghanistan. The results of this study revealed a strong cross-correlation between precipitation, vegetation, and land surface temperature. Evaluation of the vegetation fluctuation in the last 21 years exposed, sharp declines of vegetation thickness in 2009, 2011, and 2018 to discover the reason, variation of the precipitation of these years were investigated. It was proved that decreases in vegetation density occurred due to considerable diminution of the precipitation. Examination of cross-seasonal and annual average correlation coefficients between NDVI values and rainfall demonstrated the different rates of vegetation response to precipitation in different seasons of the year. Calculation of the correlation between the annual average of the precipitation and NDVI exhibited less significance, however, a strong correlation with a value of 0.8195 was detected with a high significance from April to August during all the years of study. The outputs of this study indicated a strong inverse correlation between vegetation thickness and surface temperature with the value of 0.6792, however, this correlation is significant only during spring and summer. Furthermore, outcomes of evaluating the relationship between the monthly average of precipitation and LST exposed a negative correlation ($r^2 = 0.7768$) with high significance. The visual analysis of the five-averaged maps of NDVI and surface temperature demonstrates a strong and inverse spatial correlation between surface temperature and vegetation thickness. According to the results of this study, bare lands and built-up areas exhibits the highest surface temperature within specified research area and indicate the significance of vegetation on reduction of temperature.

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