Vegetation Drought Dynamics Analysis in European Russia

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Abstract. This research work deals with the spatial-temporal characteristics of the relationship between drought events (Standardized Precipitation Index [SPI]), land surface temperature (LSI) and vegetation indexes (VIs) in the spring-summer (May-August) over the European Russia (ER) from 2000 to 2018. We use Terra- MODIS - NDVI and LST product and TRMM for rainfall data. Statistical results indicate that year 2004, 2009 and 2015 were the most significant changing-point in mean annual rainfall values and VIs. Results indicate that vegetation area and VIs variate according to SPI values. Analysis results also indicate that low NDVI values (0.2-0.4) shift in high NDVI values (0.5-0.8) with high SPI values and vice-versa, also high LST values associate with low VIs values and vice-versa, with correlation coefficients 0.90, means high temperature show low vegetation. A correlation analysis of VIs, SPI and LST deficit shows that vegetation is closely related to rainfall and temperature, especially under the dry and wet conditions, and indicates that the use of this correlation can be a suitable near-real time monitoring of vegetation drought dynamics. All predictions and monitoring using satellite-derived VIs is a low cost and effective means of identifying longer-term changes as opposed to natural inter-annual variability in vegetation growth.

1. Introduction

Human society and the global economy are inextricably linked to forests. More than 1 billion people depend on forests for their livelihoods. And forest ecosystems play a critical role in stabilizing the climate; providing food, water, wood products, and vital medicines; and supporting much of the world’s biodiversity [1]. European Russian forest spread almost continuously over the Russian plain for 2000km from 66N to 53N. Besides, there is large forest areas located in the Caucasus within Russian federation: black sea cost and on the northern slope of the greater Caucasus. The timber industry is a significant contributor to the economy of Russia, worth around 20 billion dollars per year. Russian Forest Industry - a set of Russian industries related to wood harvesting and processing is one of the oldest sectors of the economy in Russia. On the territory of Russia are 1/4 of the world's reserves of wood. According to data for 2017 the total forest area has exceeded 885 million hectares, representing 45% of the total area of the country. At the same time the stock of wood was in the area of 82 billion cubic meters [2]. The main share of coniferous tree species comprises: pine, spruce, larch, cedar. Despite this Russian forest ecosystem is endangered by harvest, fuel, grazing, farming, industrial development, construction, mining, pollutions, forest fire, unmanaged tourism and non-native wildlife animals destroy seeds, trunks and branches and put further stress on the ecosystem [3].

The main cause of drought is shortage of rainfall in terms of low water availability from average annual condition and it's related with increasing temperature and evaporation, and both are effect on local vegetation condition. In European Russia long term drought occurrence and significant changes in rainfall pattern is the most imperative factor, which effect the vegetation. The effects of drought occurrence on vegetation in European Russia have not been computed yet. Currently various drought indicators have been use for drought events effect on vegetation including meteorological [4], remote sensed, hydrological and other indicators, to measure drought impacts. Other than these traditional methods of drought assessment and monitoring based on rainfall data are Palmer Drought Severity Index (PDSI) [5], Standardized Precipitation Index (SPI) [6] and Palmer Hydrological Drought Index (PHDI) [7]. The easy-to-use Standardized Precipitation Index (SPI) has been widely employed to determine the occurrence of drought episodes and enables investigations of water deficiencies at different spatial and temporal scales [8]. The main objective of this research work is to identify relationship in between vegetation condition with rainfall (SPI) and temperature (LST), and for that spatial-temporal change in drought events is the most promising tool. In this research work we enumerate the relationship in between vegetation with droughts intensities and trends to protection and restoration of ER vegetation on timely and effectively. For that we used satellite and long term rainfall data from 2000 to 2018 for European Russia and figured out Standardized Precipitation Index (SPI) to identify changes in rainfall patterns, which show changing-point year, that indicate drought dynamics in last two decades. Than we correlate SPI and drought occurrence to identify changes in the vegetation area and condition in ER over the period of 2000 to 2018. We also quantify the changes in vegetation condition and area separately for the intervals before and after of the changing-point years.

2. Study area

The study area of this research work is the entire European Russia (figure 1). Russia is a world`s largest and transcontinental country. European Russia is the western part of Russia that is a part of Eastern Europe, with a population of 110 million people, European Russia has about 77% of Russia's population, but covers 23% of Russia's territory; and occupies almost 40% of Europe's total area.

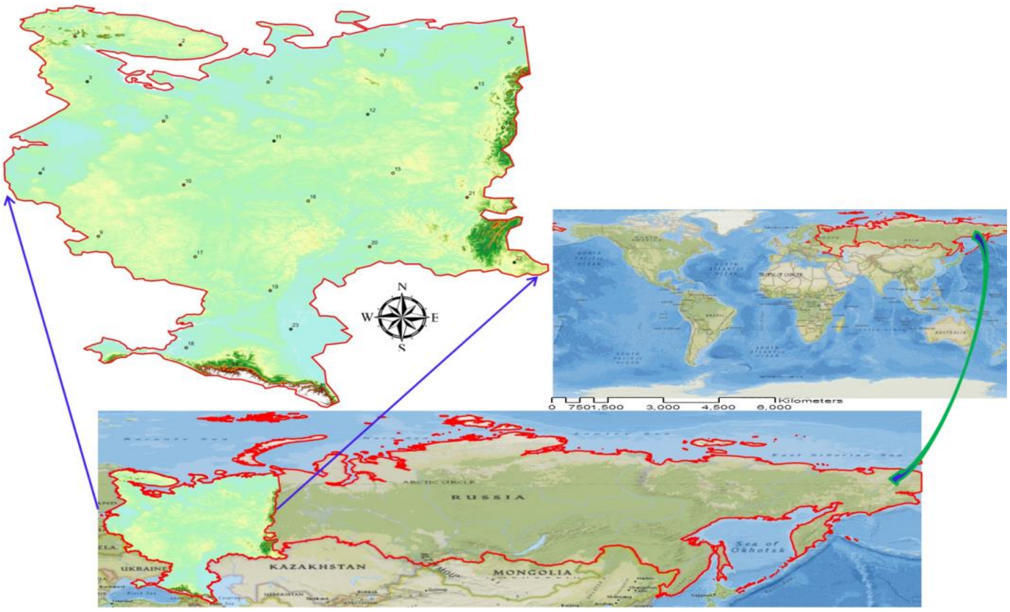


Figure 1. Geographic location of European Russia with DEM.

3. Materials and methods

3.1. Datasets

To obtain a sufficient spatial and temporal coverage of the study area on a yearly basis, and at low data costs, multispectral and ground data were incorporated such as: ASTER, MODIS and GLDAS Noah

Land Surface Model [9]. We used MODIS product MOD11A2 for LST, MOD13Q1 for VIs and MOD09Q1 for surface reflectance information. For elevation and slope information, we used ASTER-GDEM with 30m spatial resolution and for rainfall measurements or Standardized Precipitation Index (SPI), NASA Global Land Data Assimilation System (GLDAS) and other meteorological data were used. During field work we used high quality hand held GPS for ground truth and georeferenced of the satellite imagery. In secondary data, we used other ancillary data and ground data from metrology, climatology, agriculture, forest and survey departments such as geology and geography (topographic sheets). For GIS analysis and image processing work, we used ArcGIS, ER-Mapper and ERDAS software's and prepare thematic maps with the help of satellite data, topographic maps, field and ancillary data: such as vegetation, digital elevation model (DEM), rainfall, normalized difference vegetation index (NDVI), land surface temperature (LST). So to take the dual advantage in this research work, we used both primary (satellite data) and secondary data (field and socio-economic data) for this research work.

3.2 NDVI & LST

Following the streamlines in methodology, after image processing, all satellite data was processed for the mapping of vegetation indices - VIs (NDVI & EVI) and land surface temperature (LST). For vegetation indices (NDVI & EVI) a 16 day time series L3 global 250m resolution MODIS product MOD13Q1 and an 8 day L3 Global 1km average value of the composite land surface temperature (LST) MODIS product MOD11A2 were used in the study area from 2000 to 2018. Both data were collect form the U.S. National Aeronautics and Space Administration (NASA) Land Processes Distributed Active Archive Centre (LPDAAC). Normalized difference vegetation index (NDVI) is a proxy for photosynthetic activity and primary production from vegetation biomass and is a common index for monitoring vegetation health. Enhanced vegetation index *(*EVI), similar to NDVI, is less sensitive to noise from background soil and atmospheric conditions and less saturated in high-biomass areas. Here VIs was calculated from visible and infrared bands combinations in ArcGIS software, whereas LST was calculated by thermal bands (ground emissivity) combinations. VIs was help to identify forest canopy cover mapping and vegetation condition index (VCI), while LST can measured temperature condition index (TCI). The important thing is that NDVI generated VCI and LST generated TCI were useful to make vegetation health index (VHI), which show the actual vegetation health condition. These continuous VIs and LST time series values were helpful to calculate the baseline and change metrics of forest health for tree vulnerability detection to drought. MODIS MOD11A2 product consist 16 bit unsigned integer values from 7500 to 65500 and to derive actually ground temperature in kelvin, we need to multiply it with scaling factor 0.02. In NDVI some values are zero or less than zero, which represent water body or cloud in the image so need filters and finally generate maps of the study area from 2000 to 2018.

3.3 Standardized precipitation index (SPI)

Generally rainfall directly effect on temperature and soil moisture and later on vegetation. Normally in high rainfall regions, vegetation is very healthy and dense. A short time period of SPI values (1 to 3 months) is related to soil moisture changes that have greatly effect on agriculture. A longer time period (6 to 12 months) SPI values show longer time period change on precipitation, available water, land use/cover and ecosystem. In this research work we use almost two decade summer rainfall data (May to Aug.) from 2000 to 2018 to access the change in drought and to determine changing-point in rainfall pattern in ER (figure 2). Figure 1 show the location of all 25 rainfall stations, from where we collect rainfall data and derive relationship between drought and vegetation indices.

3.4 Change point detection

To detect changes in vegetation with drought, change point or breakpoint identification in rainfall pattern is compulsory thing which help to understand whole ecosystem process. A changing point is defining a point where frequency and distribution of variables change their direction for a time (figure. 2). There are many methods to identify change point such as [10, 11, 12, 13] tests that enable detection of changes in a data series. In this research work, we define change point in a time series of rainfall by using Pettitt-Mann-Whitney-Test and cumulative sum method (CUSUM) in the Change Point Analyzer (CPA) software. The CUSUM method is a very simple and flexible method and originally developed for controlling industrial process and can use in trained data in place of natural data. Many times it used in environmental monitoring programs to identify change point in time series of environmental and climatic variables. After identify change point in rainfall data series, we confirm it with t-test by comparing mean value of rainfall data before and after the change years.

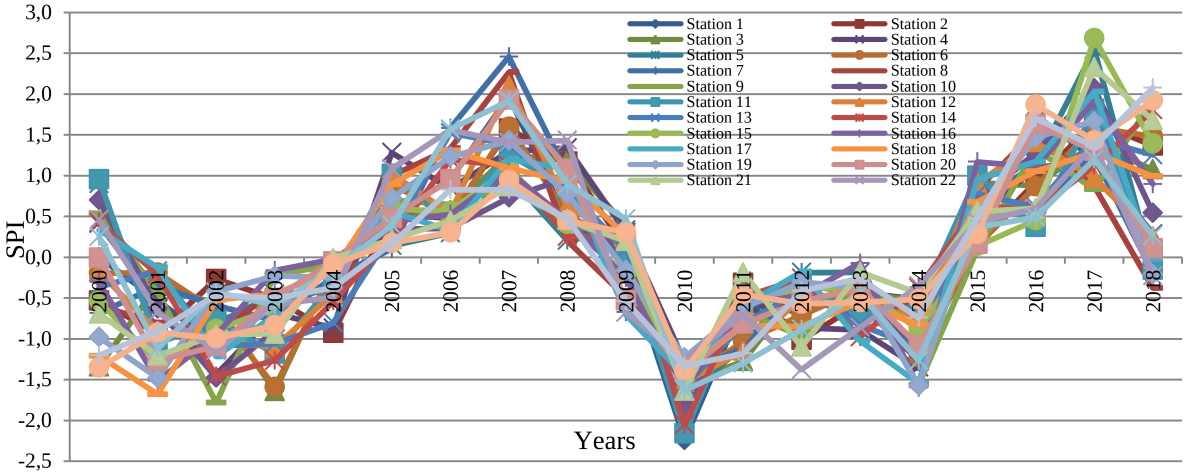


Figure 2. SPI based drought identification from 25 rainfall stations in ER from 2000 to 2018. SPI values above 2 indicate extreme wetness, between 2 and 1 severe to moderate wetness, between 1 and -1 normal conditions, between -1 and -2 moderate to severe droughts, and below -2 extreme droughts.

3.5 Mapping VIs area

Vegetation health or condition with total vegetation cover area is highly correlated with NDVI values. To identify changes in vegetation health over a period of time, we use [14] method that change in NDVI values are proxy of change in vegetation condition. According to this we classify NDVI values in terms of very healthy to no vegetation class as in table 1.

Table 1. Vegetation classes according to NDVI values.

Class name	NDVI range	Class level I	Class level II	Class level III	NDVI range	Subclass name
1	0.9 to 1	Vegetation	Dense vegetation	Very healthy vegetation	0.85 <	A
2	0.5 to 0.8		Open vegetation	Temperate and tropical rainforests	0.79 – 0.84	B
					0.66 – 0.78	C
					0.51 – 0.65	D
3	0.2 to 0.4		Degraded vegetation	Shrub and grassland	0.41 – 0.50	E
					0.31 – 0.40	F
					0.20 – 0.30	G
4	-0.1 to 0.1	No-Vegetation		Barren areas of rock, sand, or snow	0.00 – 0.19	H
5	-0.1 to -1			Water	0.00 – -0.50	I
					-0.51 >	J

Finally first we calculate total vegetation and non-vegetation area and then subclass level vegetation area according to NDVI values as table 1for over the last two decades from 2000 to 2018 for European Russia. As atmospheric condition were different for the different years during the image capturing so field work was an important task to increase accuracy in sub class level vegetation area calculations. For accuracy assessment of the all yearly NDVI maps from 2000 to 2018, 250 sampling plots with

30*30m were established in the entire study area. Other than this we also take help from Arial photos, high resolution satellite data and ancillary data related to vegetation for accuracy assessment and derive user accuracy, producer accuracy and overall accuracy. Finally calculate total area change in vegetation as well as area change in different NDVI values for the period before and after the change/break point year in the time series of rainfall data. Here we also did key interview with old peoples who living in the study area for a long time (more than 25 years).

4. Results

4.1. SPI patterns

We find that from 2001 to 2004 all SPI values falls 0 to -1.5, which show moderate to severe dry situation and from the year of 2004 all values move to positive direction so year 2004 is a changing point year (figure. 2). From 2005 to 2009 all SPI values are in positive direction, means its show wet weather condition. Year of 2007 have 2.5 SPI values represents the extreme wet condition. The year 2009 is again a changing point as all values goes in negative direction till 2014, with extreme dry year of 2010. From 2015 SPI values were move in above direction with extreme wet year 2017. In short we find 3 changing point years as 2004, 2009 and 2015. We also find year 2007 and 2017 have extreme wet condition and year 2010 had extreme dry condition (figure 2) so based on SPI values from 2000 to 2018, the wet and dry years patterns can divided in four parts.

4.2 Rainfall analysis

With the help of Pettit-Mann-Whitney method we find maximum probability of change year was 2004, 2009 and 2015 from the period of 2000 to 2018 from all 25 rainfall stations (figure 3). In particular these years, there was significant change in mean summer rainfall. This was also confirmed by CUSUM method. Figure 3 represent maximum, minimum, mean and standard deviation values of rainfall for spring-summer (May-August) season from 2000 to 2018 in European Russia. Figure 3 also shows that year 2007 and 2017 have highest rainfall and year 2010 had lowest rainfall in the study area.

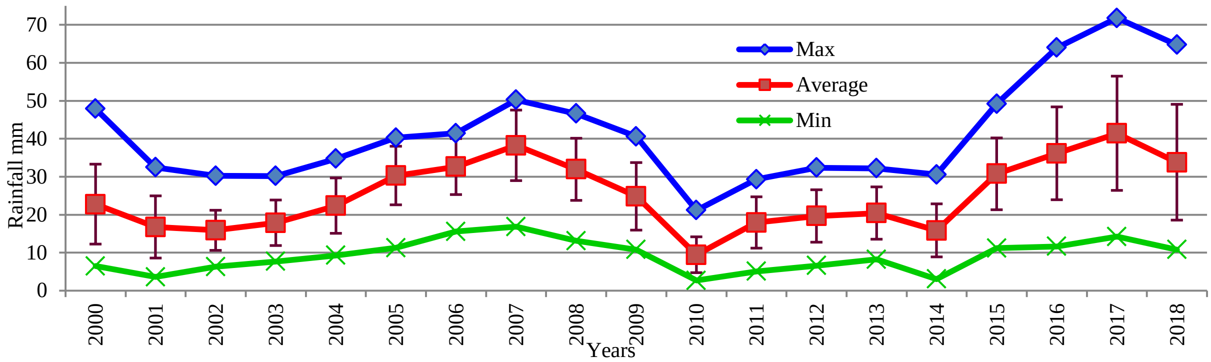


Figure 3. Maximum, minimum, average and standard deviation values of rainfall (mm) for spring-summer (May-August) season from 2000 to 2018.

4.3 Analyses of vegetation cover change

The satellite image analysis of vegetation cover in European Russia from 2000 to 2018 was show significant change in area between vegetation and non-vegetation (figure 4). Total vegetation area (A to G NDVI classes) was continuously increased from 2001 to 2007 and reach 3582036km^2 in 2007 and it was highest as 3681070km^2 in 2017. The non-vegetation area was highest as 982348 and 895479km^2 in 2000 and 2010 respectively (figure 4).

4.4 Analysis of SPI and VIs relationship

Analysis results show that VIs area was increased with increased SPI values and decreased with decreasing SPI values (reducing rainfall or more drought condition). The correlation and coefficients of SPI and VIs have linear regression (R^2) exceeded 0.90. According to SPI values, as year 2010 was the driest year from 2000 to 2018 period and it's also represent by non-vegetation area as it was highest in 2010 (figure 4). When we compare highest values on SPI as it was in year 2007 and 2017, we find that total vegetation cover area was also highest in both years (figure 4). So with this research work we can confirm that SPI values are also associated with vegetation indices (VIs). High SPI values represent high VIs values and vice-versa.

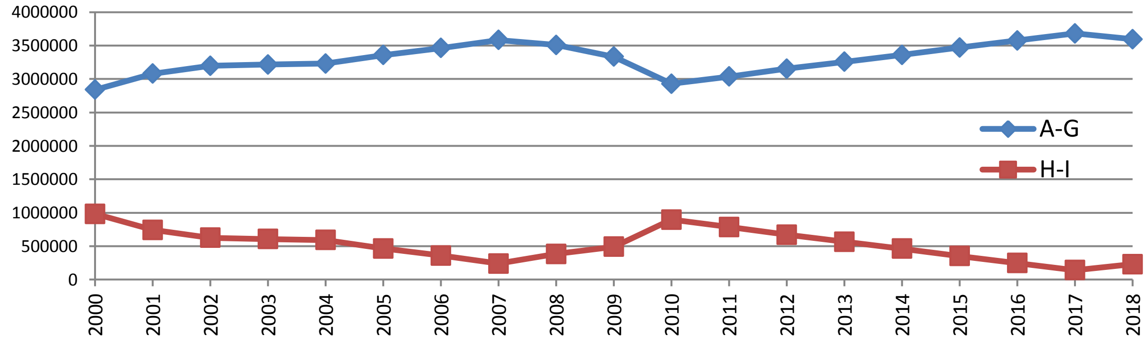
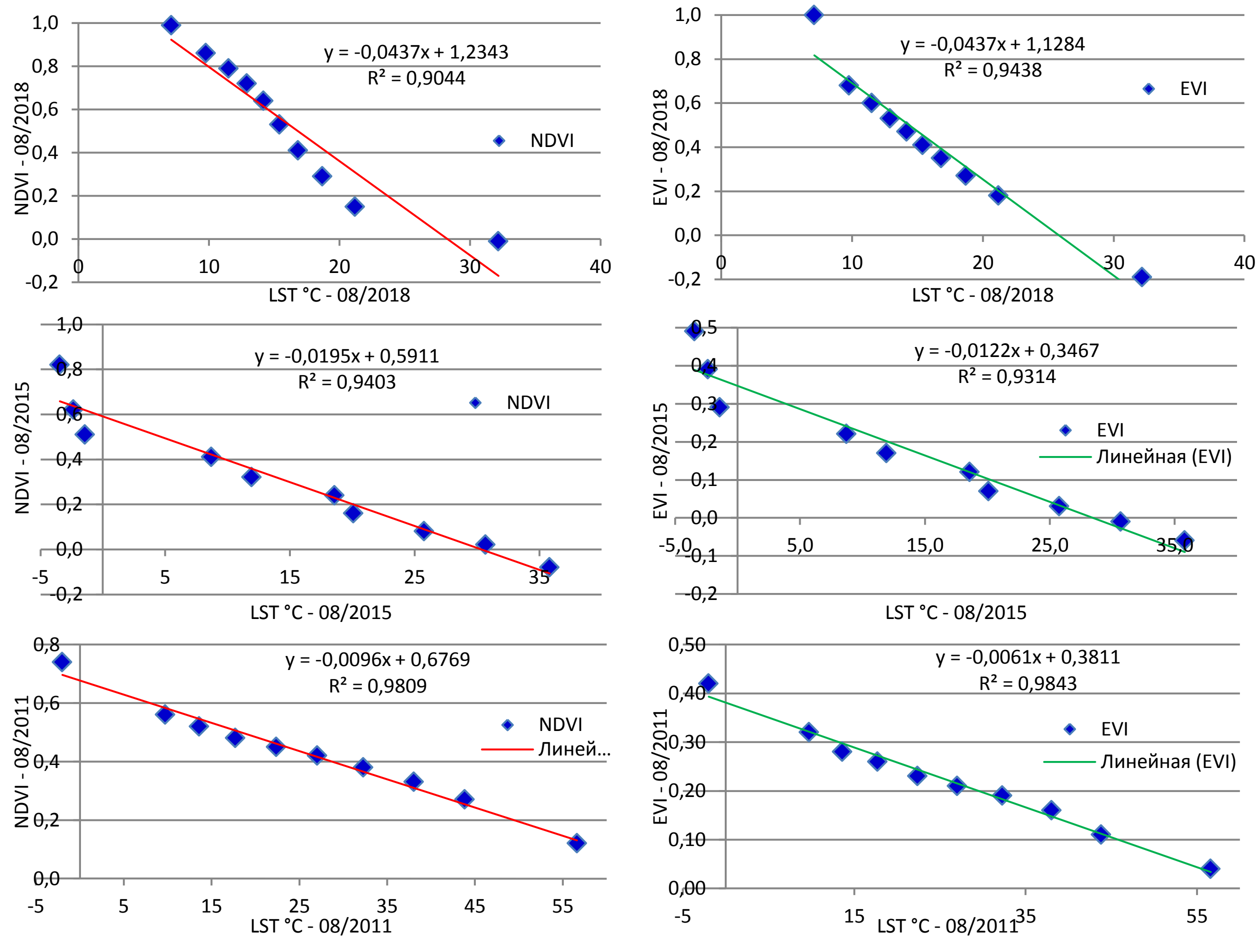


Figure 4. Vegetation and non-vegetation area in ER from 2000 to 2018.

4.5 LST and VIs

To get relationship in between LST and VIs, we use Pearson correlation coefficient during to two decades study period (figure 5) and find clear negative correlation. The correlation coefficient of determination of each linear regression (r^2) exceeded more than 0.90 in all years (figure 5). Extreme temperature show low vegetation and reducing temperature represent increasing high and healthy vegetation condition. Here EVI has high correlation than NDIV as it's not affected by background features effects.



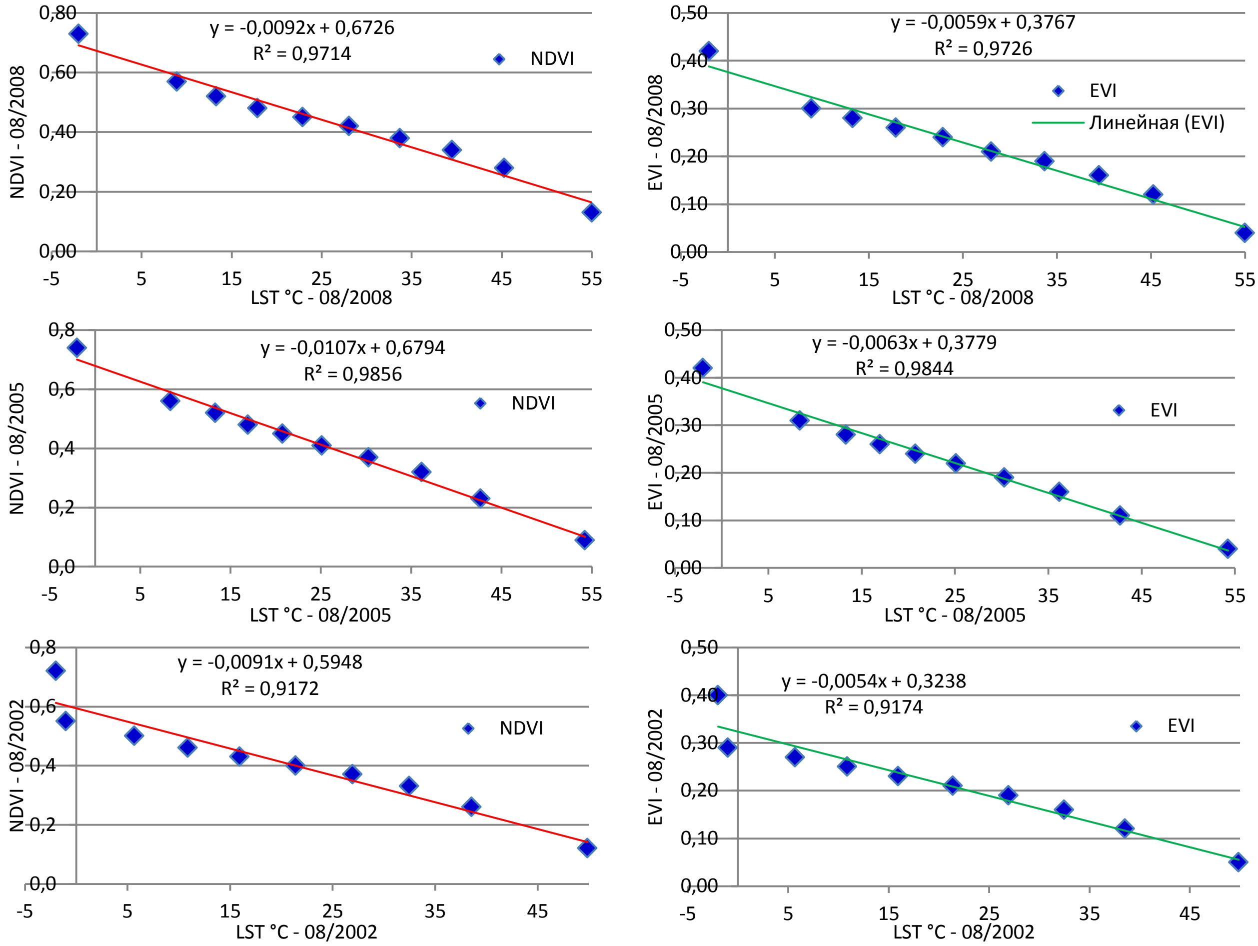


Figure 5. LST and VIs relationship during spring-summer (May-August) season from 2000 to 2018.

Normally VIs represents the land use feature and LST symbolize thermal condition of land surface feature. Figure 4 illustrates the relationships between VIs (NDVI & EVI) for the different years' time period in European Russia from 2000 to 2018. In general, the NDVI value increases with enhanced vegetation coverage. It is easy to understand that higher vegetation coverage would lead to lower LST; however, when the NDVI is below a certain value, the LST appears to increase with the VI.

5. Conclusion

This research work analysis three primary data (Rainfall, LST and VIs) and identify a relationship between climate condition and its direct effect on vegetation through reduction in rainfall, high LST, increasing in drought occurrence and indirectly from human interference. The main work was using time series SPI values from rainfall and detects changes in drought and later on its effect on vegetation covers area and vegetation condition with LST. Especially identification of changing point (2004, 2009, 2015) and extreme wet (2007, 2017) and extreme dry years (2002, 2010) and effects on vegetation with LST relationship in between different time periods. The southern part of the study area is maximum affected by severe drought with high LST and low VIs. Understanding these relationship and the characteristics of droughts is crucial for improving our knowledge of vegetation vulnerability to climate fluctuations and climate change for vegetation drought dynamics.

6. References

[1] Filipchuk, A. Russian forests: A new approach to the assessment of carbon stocks and sequestration capacity / A. Filipchuk, B. Moiseev, N. Malysheva, V. Strakhov // Environmental Development. – 2018. – Vol 26. – P. 68-75.

[2] Zhu, Q. A numerical simulation study on the impact of smoke aerosols from Russian forest fires on the air pollution over Asia / Q. Zhu, Y. Liu, R. Jia, S. Hua, T. Shao, B. Wang // Atmospheric Environment. – 2018. – Vol. 182. – P. 263-274.

[3] Marengo, J.A. Climatic characteristics of the 2010-2016 drought in the semiarid Northeast Brazil region / J.A. Marengo, L.M. Alves, R.C.S. Alvala, A.P. Cunha, S. Brito, O.L.L. Moraes // Anais da Academia Brasileira de Ciências. – 2018. – Vol. 90(2). – P. 1973-1985. DOI: 10.1590/0001-3765201720170206.

[4] Boori, M.S. Supervised and unsupervised classification for obtaining land use/cover classes from hyperspectral and multi-spectral imagery / M.S. Boori, R. Paringer, K. Choudhary, A. Kupriyanov // Proc. SPIE 6th International Conference on Remote Sensing and Geoinformatics of the environment (RSCy). – 2018. – Vol. 107730L. – P. 1-11. DOI: 10.1117/12.2322624.

[5] Palmer, W.C. Meteorological Drought // US Department of Commerce, Weather Bureau, Washington, DC, USA, 1965. – Vol. 30.

[6] McKee, T.B. The relationship of drought frequency and duration to time scales / T.B. McKee, N.J. Doesken, J. Kleist // Proceedings of the 8th Conference on Applied Climatology. – 1993. – Vol. 17(22). – P. 179-183.

[7] Karl, T. Atlas of monthly Palmer hydrological drought indices (1931-1983) for the contiguous United States / T. Karl, R.W. Knight // Natl. Clim. Data Cent, 1985.

[8] Khadr, M. Temporal and spatial analysis of meteorological drought characteristics in the upper Blue Nile river region // Hydrol. Res. – 2017. – Vol. 48(1). – P. 265-276.

[9] Beaudoing, H. NASA/GSFC/HSL, GLDAS Noah Land Surface Model L4 monthly 0.25 x 0.25 degree V2.1, Greenbelt, Maryland, USA / H. Beaudoing, M. Rodell // Goddard Earth Sciences Data and Information Services Center (GES DISC), 2016 [Electronic resource]. – Access mode: https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_V2.1/summary?keywords=GLDAS.

[10] Pettitt, A.N. A non-parametric approach to the change-point problem // Appl. Stat. – 1979. – P. 126-135.

[11] Buishard, T. Tests for detecting a shift in the mean of hydrological time series // J. Hydrol. – 1984. – Vol. 58. – P. 51-69.

[12] Boori, M.S. Land cover classification and build spectral library from hyperspectral and multi-spectral satellite data: A data comparison study in Samara, Russia / M.S. Boori, R. Paringer, K. Choudhary, A. Kupriyanov, R. Banda // ITNT-2018 conference proceeding. – 2018. – Vol. 2210. – P. 390-401.

[13] Boori, M.S. Environmental dynamics for Central Dry Zone area of Myanmar / M.S. Boori, K. Choudhary, M. Evers, A. Kupriyanov // International Journal of Geoinformatics. – 2017. – Vol. 13(3). – P. 01-12.

[14] Giri, C. Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000 / C. Giri, B. Pengra, Z. Zhu, A. Singh, L.L. Tieszen // Estuar. Coast. Shelf. Sci. – 2007. – Vol. 73(1). – P. 91-100.