SPATIO-TEMPORAL DRIFTS IN AVHRR/NDVI-PRECIPITATION RELATIONSHIP AND THEIR LINKAGE TO LAND USE CHANGE IN CENTRAL KAZAKHSTAN

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ABSTRACT

Spatial relationship between vegetation patterns and precipitation in drylands of Kazakhstan was investigated with Normalised Difference Vegetation Index (*NDVI*) derived from the Advanced Very High Resolution Radiometer (AVHRR) and climate records from weather stations. A local regression technique known as geographically weighted regression (GWR) was used to model the growing season relationship between these variables at the local scale. GWR models were established for each pixel and every analysis year during the period of 1985-2000. The models exposed spatial and temporal non-stationarity of the *NDVI*-precipitation relationships. This non-stationarity was estimated for each pixel and each year and mapped. We traced at the per-pixel basis the vegetation response to precipitation over the period of 1985-2000 and compared it with land use/land cover change that happened in the study region. For the four cases investigated the study proved that any temporal drift of this response is a result of any land use/land cover change. The areas with clear signs of land degradation displayed either extraordinary low response of *NDVI* to rainfall or a permanent decrease of this response throughout the observation time. On the contrary, the areas associated with improvement of vegetation cover are characterised by an increase of the vegetation response to precipitation. The results of this study improve our understanding of the interaction between the vegetation cover, the climatic components and human activities of dryland's ecosystem in Central Asia.

Keywords: NDVI, climate, GWR model, drylands, Kazakhstan.

INTRODUCTION

Vegetation cover is a very sensible natural system, which is regulated by a large complex of endogenic, and exogenic, natural or anthropogenic factors such as climate, geology, soil characteristics, underground water regime, land use etc. Conditions of vegetation cover and its dynamics can be explained by the joint effect of these factors. In general, vegetation cover reacts very sensitively on changes of precipitation particularly in dry regions. If the response of vegetation to precipitation remains constant, increase/decrease of vegetation activity should exactly reflect changes in precipitation. That is the rule for undisturbed vegetation cover. However, the strength of vegetation response to climate factors will be significantly altered by external forces such as human impact. Disturbance of vegetation cover can be seen in change of its response to climate. It means that a weaker response of vegetation to climate may indicate a degradation of vegetation cover caused by non-climatic factors (e.g. human impact), while a stronger response may indicate an improvement of vegetation conditions (1).

Investigation of relations between vegetation patterns and its explanatory factors is an object of applications of remote sensing at regional and global scales. The Normalised Difference Vegetation Index (*NDVI*) is established as a good measure of landscape patterns of primary productivity and can be used as a general surrogate for many conditions of vegetation cover such as overground biomass, leaf area index (*LAI*), fraction of photosynthetically active radiation (*fPAR*) (2,3,4). Remotely sensing derived NDVI data have been successfully used for monitoring of vegetation activity and environmental changes at regional and global scales (5,6,7), detection of droughts (8), desertification and land degradation studies (9,10).

Temporal and spatial relationships between *NDVI* and climatic factors in inter-annual and intra-annual time-scales are investigated in many research works. *NDVI* correlates with climate variables, especially rainfall and temperature, particularly strong in the arid regions. Recent studies showed that the strength of the relationship depends on vegetation type or land cover/land use: study (11) demonstrated that both abandonment and introduce of agricultural land were clearly reflected in the vegetation response. Landscapes with grass vegetation exhibit higher coefficients of correlation; on the contrary, areas of forest vegetation demonstrate only weak response to climate factors (12,13,14,15,16). (17) reported about very weak relationship between *NDVI* and precipitation at locations undergoing process of land degradation. With exception of forested areas, the reason of poor response to climate might be related to physical nature of the land resources (naturally unproductive soils or geological constraints), but a decreased correlation in an otherwise responsive area could be caused by human activity and influence. It is clear that degraded areas show very weak or no response to climatic variables. Therefore, the correlation coefficients calculated in these areas might be either very low or negative. This fact has been supposed in studies published recently (18,19). Some studies have used the coefficient of correlation between *NDVI* and precipitation as a general indicator of performance of vegetation cover and developed monitoring systems of land degradation based on the monitoring of the *NDVI*-precipitation relationships (20,9).

In view of that, the response of vegetation cover to climate factors is individual for every land cover type and can indicate the performance of the vegetation cover. Consequently, a monitoring of the vegetation response may be a powerful tool to identify the alterations happening in the vegetation cover. The main idea of this study was to use the correlation between *NDVI* and precipitation for detection of the land use land cover change (LULCC) in a semi-arid region of Kazakhstan. We supposed that the rapid change in land use caused by the constitutional change in Kazakhstan after the collapse of the Soviet Union in 1991 could be reflected in the response of vegetation to rainfall. Therefore, temporal trends in the vegetation response may be useful for detection of areas undergoing LULCC. The goals of the study were to examine trends in the vegetation response to precipitation and to reveal possible linkages between them and LULCC. In order to achieve the study goals, the work was done in three steps, which also define the structure of the paper. First, the relationships between *NDVI* obtained from the Advanced Very High Resolution Radiometer (AVHRR) and precipitation were modelled at per-pixel scale using a local statistical technique known as geographically weighted regression (GWR). The first step examined spatial variance in the *NDVI*-rainfall relationships for a number of years. The results of this modelling were the correlation coefficients between *NDVI* and precipitation for each pixel in the study region and each year from 1985 to 2001, the period covered by the source data sets. Secondly, we examined historical trends in the *NDVI*-precipitation relationships over 16 years, and analysed temporal variance of them. This examination was made with regards to vegetation type and spatial patterns in vegetation cover. Thirdly, we described four specific case studies, where the historical trends in the *NDVI*-precipitation relationships could be linked to land use/land cover change.

STUDY AREA

The study area is located in the middle part of Kazakhstan between 46° and 50° northern latitude and 72° and 75° eastern longitude (Figure 1a). In terms of surface structure the study area is divided into two large regions: a plateau of rolling upland in the south, in the west, and in the north with average elevations between 300-700 metres; hills and low mountains in the central and north-eastern parts with elevations 700-1100 metres.

The climate of the region is dry, cold and high continental. The average annual precipitation is above 250-300 mm per year in the north of the study area, and below 150 mm in the south. The most part of precipitation falls during warm period from March to October. The temperature amplitude is relatively high: average January temperature is below –12°C and average July temperature is about 26-28°C.

The south of the study region is vegetated by sagebrush and perennial saltwort associations (Figure 1c). Dominating vegetation species here are *Artemisia terrae-albae, Artemisia pauciflora, Anabasis salsa, Salsola orientalis.* The northern section of the study region is occupied by steppe vegetation, where short grassland species such as *Festuca sulcata, Stipa capillata* and *Stipa lessingiana* dominate. The semi-desert vegetation complex occupying the mid of the study area represents a complex combination of real steppe turf grasses and semi-shrubs with halophytes. The vegetation cover in the study area exhibits high variations in density. The fraction of the vegetation cover varies from about 0.05 in the desert zone to more than 0.60 in the steppe areas. The fraction of the vegetation cover at 23 test sites was estimated from the nadir photos by a digital camera made in the field during our field survey in July 2005. Figure 2 presents some examples of the cover observed in different vegetation types. The estimation of the fractional vegetation cover from the digital photos was made visually using the common cards of fractional cover.

During the Soviet Era the study area was extensively used for agricultural production. The areas of steppe were cultivated for production of wheat and barley. The wide areas of semi-desert and desert zone in the southern part of the region served as natural pastures. After the collapse of the socialistic economic system in 1991, the degree and spatial patterns of anthropogenic impact experienced a drastically change. Generally, the anthropogenic impact was reduced: about 2/3 of cropland was abandoned, the livestock number dropped also dramatically.

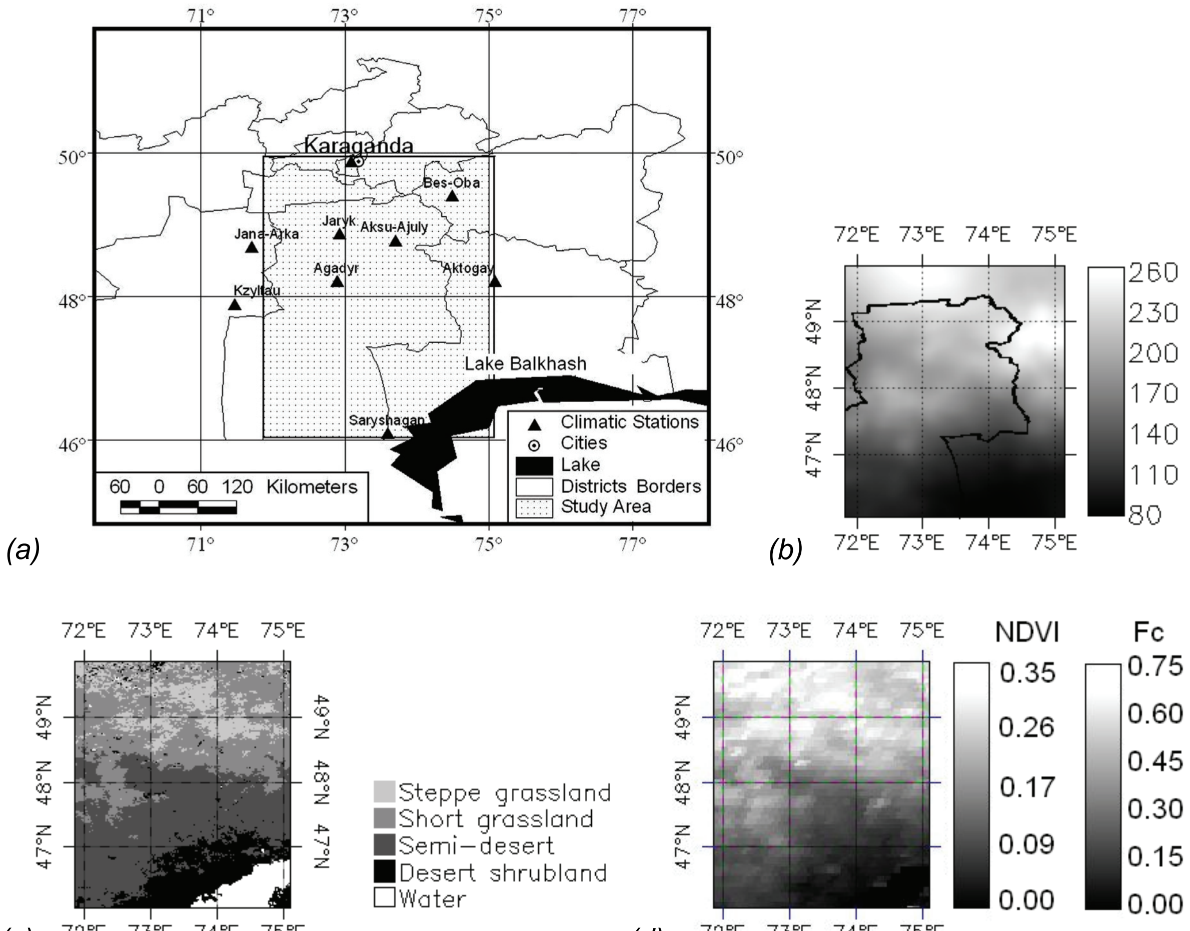


Figure 1: A map of the study region with locations of the climate stations (a), average rainfall amount in mm (c), land cover types (c), average growing season NDVI and fraction of vegetation cover Fc (d). The line in image (b) indicates the administrative boundaries of Shetsky district.

However, some places, particularly located near large rural settlements, experienced an increase of anthropogenic impact after the collapse of the Soviet Union. The reason for this was the process of the abandonment of the crop fields and pastures located far away from settlements and intensification of the human activity at the fields and pastures located around the settlements.

DATA USED IN THE STUDY

AVHRR NDVI data

The *NDVI* images used in this research represent 10-day Maximum Value Composites covering the study area for the years 1985-2000. The spatial resolution of the original data was 8 km. The data for period were calibrated for post-launch sensor degradation by using methods described by (21). In addition to that, we removed noisy pixel areas characterized by exceptionally low *NDVI* values relatively to their pixel neighbourhood. This pixels represented large cloud areas and were replaced by a mean value calculated from the temporal neighbouring *NDVI* layers. The 10-day *NDVI* composites were integrated to mean monthly and then to mean growing season values for each of the analysis years. After all of these preparations the *NDVI* data were ready for further use in the study.

The spatial distribution of the mean growing season *NDVI* is presented in Figure 1d. The *NDVI* value ranges from more than 0.35 in the northern part of the study area to about 0.03 in the south. We were aware of the limitations of the *NDVI* concerning the low sensitivity of this index in the case of sparse vegetation cover. Therefore, the results of this study in the areas of low vegetation cover, especially in the desert zone, should be considered with caution.

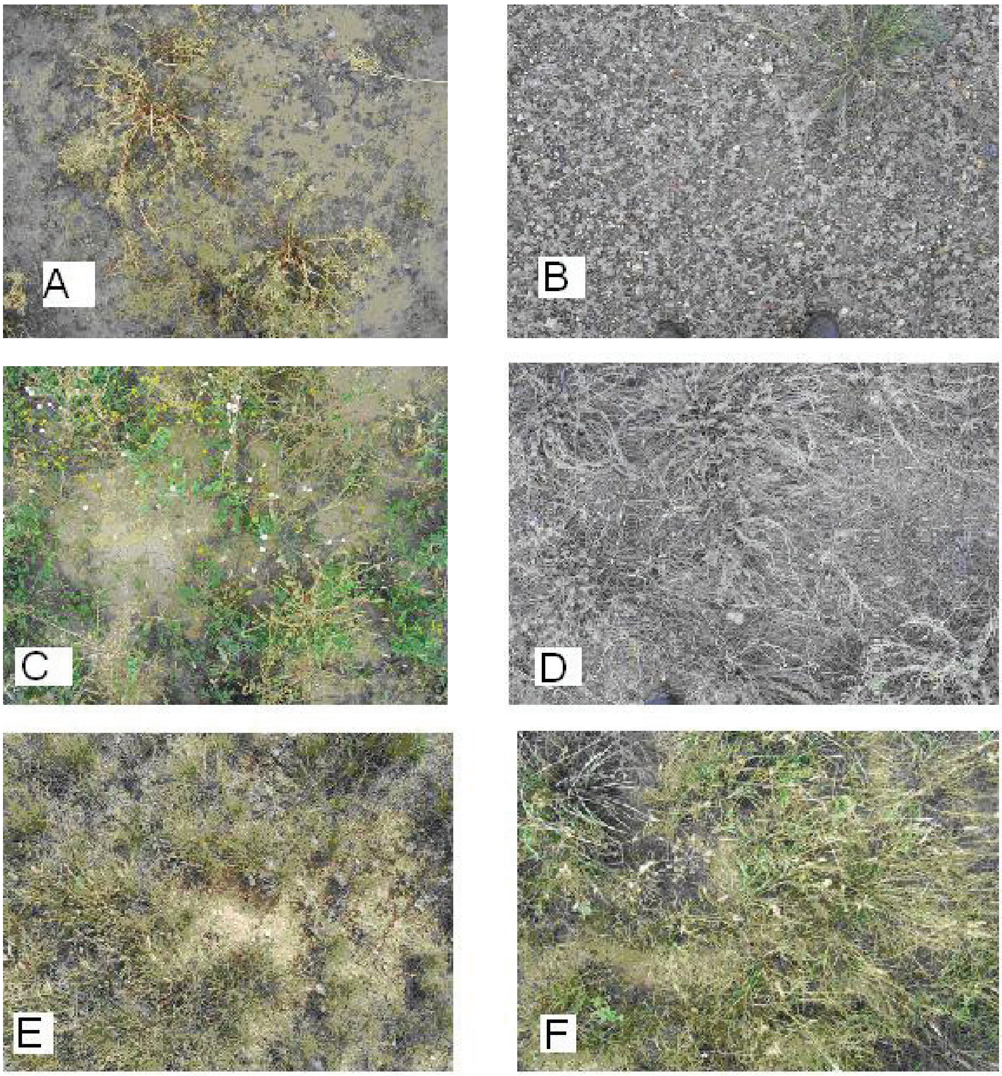


Figure 2: The fractional vegetation covers as observed in the field: nadir photos acquired in July 2005. Images (a) and (b) represent different types of desert; images (c) and (d) show photos acquired in the semi-desert zone; (e) and (f) demonstrate vegetation covers in short grassland.

The original source data for computation of the AVHRR *NDVI* product were digital numbers of the 1 and 2 channels. The Normalised Difference Vegetation Index is a dimensionless variable which is computed using the equation:

$$\frac{NIR - R}{NIR + R}, \tag{1}$$

where *R* is the first and *NIR* is the second AVHRR band. Certainly, as long as the NDVI is not calibrated to field observations, the values of *NDVI* given in Figure 1d provide little information. The key issue for the understanding of the information contained in the “raw” values of the *NDVI* can be the fractional vegetation cover as observed in the field. However, our estimations of the fractional vegetation cover obtained for 23 sample plots could not be directly compared with the 8-km *NDVI* data because of the huge difference between the size of an individual plot and the spatial resolution of an AVHRR pixel. We modelled the fractional vegetation cover by the approach widely used in recent studies (25,26). According to this approach, rearranging and representing the background and vegetation reflectance by the minimum and maximum values of the *NDVI* yields the fractional vegetation cover, *Fc*. The equation is the following:

$$Fc = \frac{NDVI - NDVI_{\mathrm{min}}}{NDVI_{\mathrm{max}} - NDVI_{\mathrm{min}}}, \tag{2}$$

A common method to retrieve maximum and minimum *NDVI* values is through time-series analysis. We used the minimum and maximum *NDVI* values for each individual year to compute the fractional vegetation cover. The map in Figure 1d represents the averaged fractional vegetation cover calculated from 16 individual images of the annual *Fc*. The obtained average *Fc* is strong linearly related to the average *NDVI*. With regard to the individual vegetation types, the modelled values of *Fc* correspond generally to that observed in the field. The fractional vegetation cover shows a strong gradient from 0.01-0.10 in the desert zone to more than 0.60-0.70 in the zone of steppe grassland.

Precipitation data

Precipitation data were retrieved from the annual statistics by the National Hydrometeorological Centre of Kazakhstan (NHMCK). These data contain 10-day records of 9 climate stations placed in the study area for growing seasons (April-October 1985-2004). The location of the climate stations is presented on the map of the study area (Figure 1a). Gridded maps of 10-day precipitation were prepared for the growing season and every study year of the period 1985-2001. Gridded maps of growing season rainfall and mean growing season temperature were calculated from the 10-day gridded maps. These results were obtained using an interpolation method known as kriging with external drift (KED) (27). There are prominent anomalies in the patterns caused by the influence of relief on the climate. The magnitude of elevation in the study region is about 700 m, the altitude ranges from 350 m to over 1000 m. Therefore, this external explanatory factor for spatial distribution of climate variables had to be incorporated in the kriging model by preparing gridded maps. In order to assess the accuracy of the data preparation, we randomly reserved 3 weather stations from the interpolation for one of the 10-day from every year and recorded values. Average error resulted in a value less than 6%. It means that the approach of kriging with external drift worked very effectively. The root mean squared error (*RMSE*) was also used as a guide to the accuracy of the prediction. For KED, the *RMSE* was 8.3 mm for 9 climate stations. For these data, there appear to be benefits in using kriging with external drift.

There is a strong north-south gradient in the distribution of rainfall across the study area. The mean average amount of growing season rainfall varies from above 260 mm in the north to less than 100 mm in the south (Figure 1b).

METHODS

General premise of the study

Climate has a substantial control on vegetation pattern through annual rainfall and temperature. This control is reported to be predictable in every point of a space to be investigated and at every time-point. The degree of the climate control is accounted for by vegetation response to climate predictors and can be quantified through correlation/regression analysis. Generally, a statistical model comprises one of the indicators for vegetation activity as a dependent variable on the one hand and climatic factors as explanatory variables on the other hand. Specifically, this work focused on the use of *NDVI*-rainfall correlation for the monitoring of the land cover/land use change in a dry region of Kazakhstan where vegetation production is strongly dependent on precipitation pattern (23,24). Our premise was that the strength of the relationship between *NDVI* and precipitation for a certain vegetation cover should remain constantly if there is no change of environmental conditions such as geological/morphological constraints, soil characteristics, underground water level, species composition of the vegetation communities etc. A change of these environmental conditions should cause a change of vegetation response to precipitation and, as a consequence, a modifying of the correlation between *NDVI* and rainfall. A rapid change of the environmental conditions is thought to be possible only as a result of human activity and influence on the environment. Therefore, when observing dynamics of the relationship between *NDVI* and rainfall we can monitor dynamics of human activity in the study region and trace the human impact on vegetation cover. The use of time series of NOAA AVHRR *NDVI* enabled us to monitor this relationship during the last two decades of the 20th century. Correlation analysis comprised the 16-year period and was implemented with yearly time-step. We considered that the change in the strength of the *NDVI*-precipitation relationship within a year is not representative o long-time monitoring of land cover/land use change.

A general framework of the data analysis is provided in Figure 3. The entire work could be clearly divided into three work steps. The further description of methods and results will follow according to this structure. The first step was to model spatial variance in the vegetation response across the study region. The outputs from this modelling were correlations between *NDVI* and precipitation at the per-pixel basis for every year from the study period. The second step was to model the temporal dynamics in the vegetation response to precipitation. The inter-mediate products of this work step were the time-series of the *NDVI*-precipitation correlation for each pixel. These time-series were further used for modelling temporal variance of the vegetation response. In the final step of the work we examined trends in the *NDVI*-precipitation relationships at four test sites with regard to land use and land cover change. In these four specific case studies we tried to find how LULCC influenced the direction and the magnitude of the trends in the *NDVI*-precipitation relationship.

Modelling spatial variance in NDVI-precipitation relationships

The first step was an investigation of variance in the vegetation response to precipitation at per-pixel basis. For this purpose, we utilised a local regression technique known as geographically weighted regression (GWR). Here, we give only brief descriptions of GWR, for a full description with all details see (22). The GWR disaggregated global statistics and calculates the relationship between *NDVI* and its predicting variables at local scale for every point of a space to be analysed. The regression model is calibrated on all data that lie within the region described around a regression point and the process is repeated for all regression points. The resulting local parameter estimates can then be mapped at the locations of the regression points to view possible non-stationarity in the relationship being examined. GWR focused on deriving local parameters to be estimated. The GWR model can be written as:

$$y = \alpha(\theta) + \beta(\theta) \cdot x + \varepsilon \quad (3)$$

where θ indicates that the parameters are to be estimated at a location for which the spatial coordinates are provided by the vector θ.

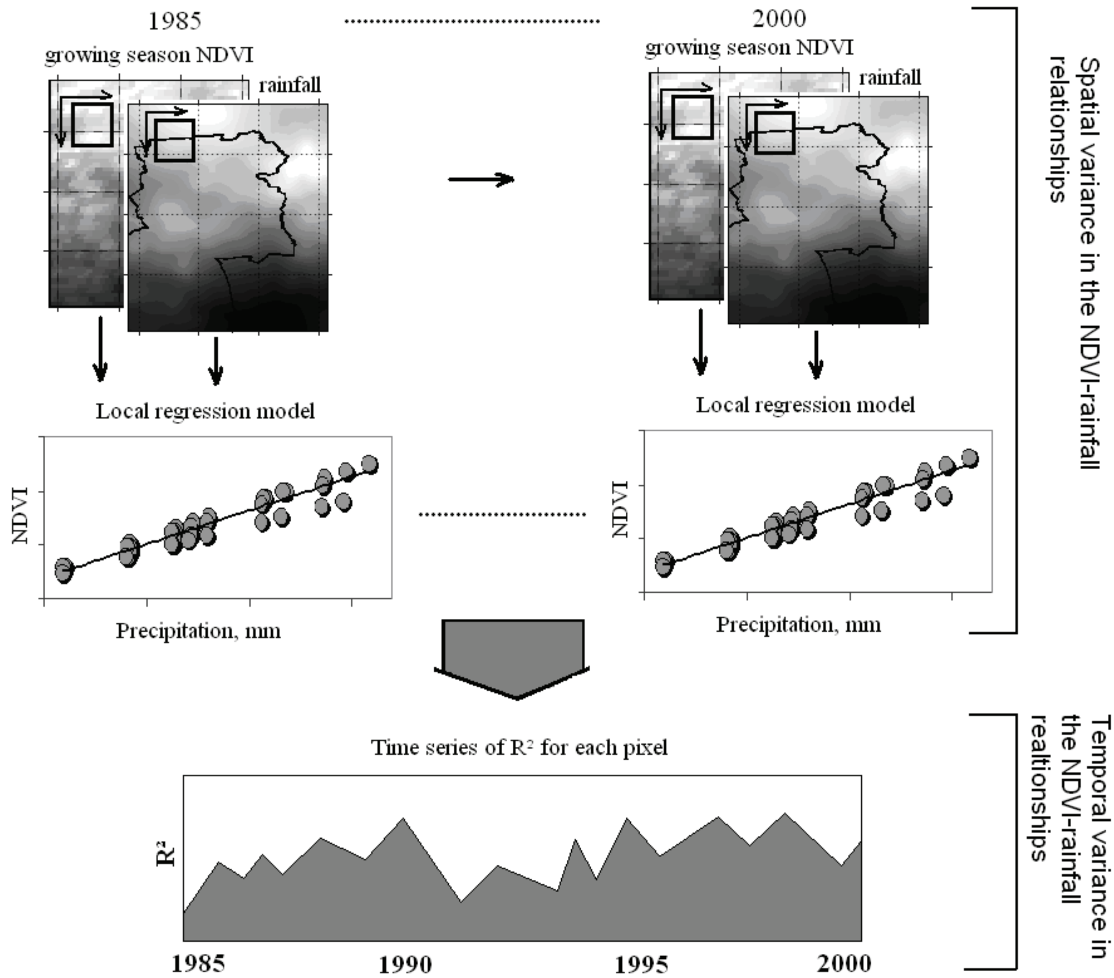


Figure 3: Modelling the temporal dynamics of the vegetation response to precipitation for each space point through calculation of local regression at the per-pixel basis. Time series of R^2 between NDVI and rainfall amount derived for each pixel could be used to indicate at each locality the process of change in human activity during the study period.

GWR works in the way that each data point is weighted by its distance from the regression point. In GWR an observation is weighted in accordance with its proximity to location *i* so that the weighting of an observation is no longer constant but varies with *i*. The matrix form of parameter estimation for *i* is expressed as:

$$\hat{\alpha}(\theta), \hat{\beta}(\theta) = (X^T W(\theta) X)^{-1} X^T W(\theta) y \tag{4}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are intercept and slope parameter in location *i*; and $W(\theta)$ is weighting matrix whose diagonal elements represent the geographical weighting associated with each site at which measurements were made for location of *i*.

The spatial weighting function can be calculated by several various methods. For fixed kernel size, the weight of each point can be calculated by applying a Gaussian function

$$w_{ij} = \exp\left[-1/2(d_{ij}/b)\right]^2 \tag{5}$$

where d_{ij} is the distance between regression point *i* and data point *j*, and *b* is referred to as a bandwidth.

Estimated parameters in geographically weighted regression depend on the weighting function of the kernel selected. As the bandwidth, *b*, becomes larger, the closer will be the model solution to that of the global ordinary least squares regression (OLS). Conversely, as the bandwidth decreases, the parameter estimates will increasingly depend on observations in close proximity to regression point *i* and will have increased variance. The problem is how to select an appropriate bandwidth in GWR. To establish an appropriate bandwidth, *b*, we used the cross-validation approach (CV) which determines *b* by minimisation of the sum of squared errors between predicted variables and those observed. According to (11), the equation for the cross-validation sum of squared errors *CVSS* is statistically expressed as:

$$CVSS = \sum_{i=1}^{n} \left[y_i - \hat{y}_i(b) \right]^2 \qquad (6)$$

where y_i is the observed value and $\hat{y}_i(b)$ is the fitted value of y_i for bandwidth *b*.

As a general rule, the lower the *CVSS*, the closer the approximation of the model to reality. The best model is the one with the smallest *CVSS*. For our GWR model, the bandwidth of 9 pixels was decided to be the most appropriate.

Exploring temporal variance in NDVI-precipitation relationships

We applied GWR models for every year and derived a set of maps showing the spatial variance in the *NDVI*-rainfall relationships across the study area. The results of outputs from the GWR models included the following variables: intercept, slope, determination coefficient R^2, and standard error terms. We considered that the value of the determination coefficient R^2 of the regression between *NDVI* and precipitation amount is the most suitable parameter to represent the response of vegetation cover to precipitation. Thus, a greater value of R^2 indicating stronger relationships between *NDVI* and precipitation would represent a higher response of vegetation to precipitation. On the contrary, a lower R^2 value would be a sign of a weaker response of vegetation to precipitation. Certainly, the response of vegetation to climate at any point of space (e.g. pixel) may not be constant and may experience a temporal change. We used the value of R^2 parameter for exploration of the temporal variance in *NDVI*-precipitation relationships. It means that the change in the value of R^2 during the study period was associated with the change in the response of vegetation to precipitation. In order to quantify the temporal change in the value of R^2, a set of descriptive variables from univariate statistic was proposed: the minimum value of R^2, the maximum value of R^2, and the coefficient of variation of R^2 during the study period. The descriptive statistics were obtained for each pixel, the results were mapped and interpreted with respect to vegetation type.

We also drew time-series of R^2 for locations in different vegetation types where no significant LULCC was happened and interpreted them. The profiles of these R^2 time-series served as reference basis for the modelling at the specific test sites described in the next section.

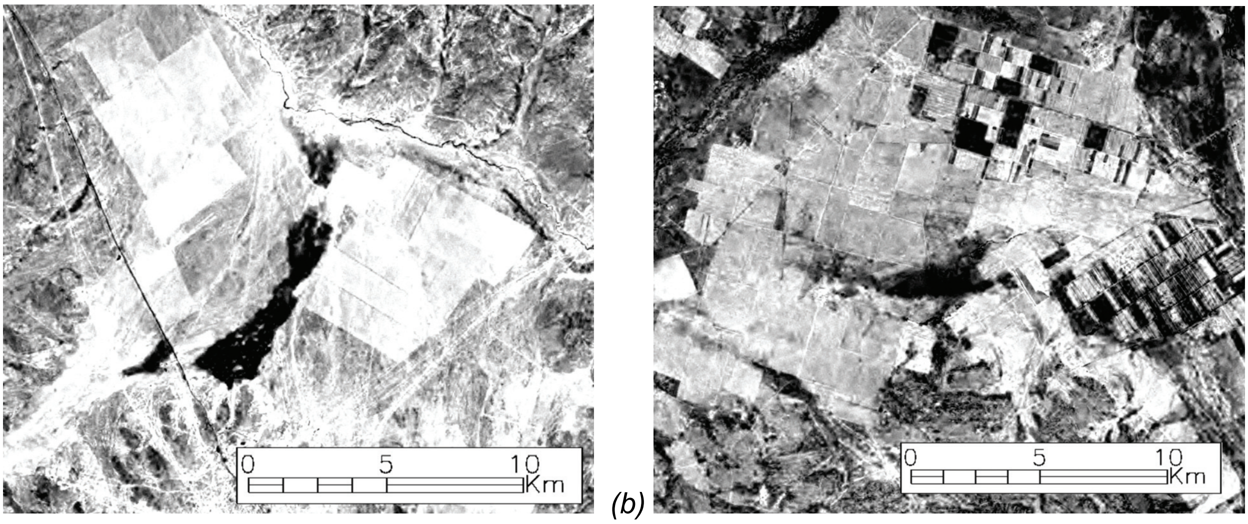
Specific case studies

Four specific test sites that experienced strong LULCC were selected for a thorough analysis of the linkages between the vegetation response to precipitation and LULCC. The test sites are located in Shetsky district and were selected on the basis of local expert knowledge and analysis of a multi-temporal Landsat imagery. In terms of the land cover type, two of the test sites belong to short grassland and two to steppe grassland. The following criteria were used for the selection of the test sites:

LULCC should be considerable during the period of investigation (1985-2000). It was important that the magnitude and direction of this change differed between the individual sites.

Vegetation cover should be sufficient (from 30% to 70%) that the use of *NDVI* as indicator of vegetation activity would be not limited.

The size should correspond to the spatial resolution of the NOAA AVHRR data. We tried to find test sites which size approximately matches to one pixel of the *NDVI* data. Generally, the size of the agricultural land in the study region varies from about 3-4 km to about 8-10 km. It was not possible to find the fields for the specific case studies which have the spatial dimension of at least 3 pixels of the AVHRR *NDVI*. Taking into account other criteria for the selection of the test sites, we did our best to find test sites with the size of not less than (8-10)×(8-10) km. Two examples facilitating the spatial dimensions of the agricultural land in the study region are presented in Figure 4. Certainly, the results derived with these case studies should have a lower accuracy and should be considered with caution. However, the results of this paper will demonstrate that, even though the size of the specific case studies was less than 3×3 pixel of the AVHRR *NDVI*, there were significant differences between the temporal behaviour of the R^2 in the test sites and in the surrounding area.



(a) (b)

Figure 4. Landsat images of the sites selected for the specific case studies. The images demonstrate the common size of the agricultural land in the study region.

A number of different sources and methods were used to derive information about vegetation cover performance and LULCC at each test site. The sources for this information were as follows: statistical reports, interviews of local authorities, satellite imagery of fine resolution with acquisition year of 1978, 1982, 1988, 1992 and 2001. We also visited each of the test sites during field campaigns in 2004 and 2005 and assessed the contemporary degree of land degradation using the following curriculum of desertification indicators: fractional vegetation cover, species composition of vegetation, visual signs of wind and water erosion on the soil surface, carbon content in the upper soil horizon, water content in the upper soil horizon.

After locating the test sites at the multi-temporal composition of *NDVI* images we processed time-series of the coefficient of determination R^2 and constructed temporal profiles of this variable for each test site. Then we looked into the derived time-series and analysed them in combination with the information about land cover performance and the land use/land cover change. Looking into time-series of annual values for R^2, the ability of the land surface to respond to rainfall over the time period can be implied. Thus, a decrease of R^2 over the study period would indicate a decreasing dependence of the vegetation cover on rainfall patterns and an increasing dependence on others factors such as temperature patterns or human influence. This negative trend would indicate an area with vegetation cover being damaged. On the contrary, an increase of R^2 over time may indicate a surface with an increasingly better response of the vegetation cover to rainfall and a decreasing role of other predictive factors. There is no doubt, that any change in land cover or in land use would be reflected in a change of R^2 value. So, abandonment or expansion of cultivated areas as well as taking virgin land into agricultural use should be noticeable in the time-series of R^2.

For interpreting the results from the case studies it was important to compare the dynamics of the vegetation response in them with that in the surrounding area. For such a comparison, a number of reference sites were selected in the surrounding area of the specific case studies. Two criteria for the selection of the reference sites were used: first, the reference sites should belong to the similar vegetation type, and second, the reference sites should reveal no significant land use land cover change during the study period.

RESULTS & DISCUSSION

Spatial variance in NDVI-climate relationship

The GWR model comprising *NDVI* and precipitation has been applied for each pixel and for each year from the study period (1985-2000). From the GWR modelling, it was evident that the relationship between *NDVI* and the explanatory variable displays a high spatial non-stationarity. The coefficient of determination, R^2, as well as the intercept and the slope parameters calculated for the GWR models between *NDVI*-rainfall and *NDVI*-temperature varied in the space over the study area. The mean value of R^2 derived from the GWR analysis amounts to 0.92. Figure 5 summarizes the results of the GWR between *NDVI* and precipitation averaged over the period of 1985-2000.

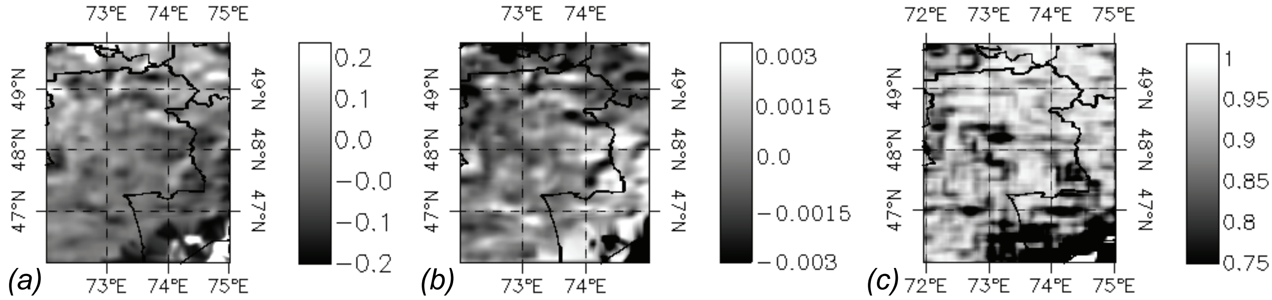


Figure 5: Summary results of the geographically weighted regression between NDVI and precipitation calculated with mean values of the variables over the period 1985-2000. The images display: (a) the intercept, (b) the slope, (c) the coefficient of determination R^2.

Generally, the spatial patterns of the mapped parameter estimations appear to correspond with some patterns in vegetation and land cover distribution. The intercept parameter increases in order from desert, to semi-desert, and to steppe, while the slope parameter decreases in the same direction. The coefficient of determination R^2 tends to display the highest values in the north of the study area where steppe vegetation dominates (R^2 = 0.92 - 0.96). Desert vegetation correlates much lower with the patterns of rainfall (R^2 = 0.75 – 0.85).

Temporal variance in the NDVI-climate relationship

The study found not only spatial non-stationarity of the *NDVI*-rainfall relationship but also high temporal variance. Figure 6 demonstrates the time-series of R^2 for four independent sites which were considered to be representative of vegetation types (each area is 3×3 pixel large). The sites were selected in the areas where no any land cover/land use change could be proved over the study period. It is to note that temporal variability in R^2 differs between land cover types. The highest changeability of vegetation response to climate factors is observed in desert shrubland. There, the R^2 ranged from 0.50 to 0.89. This gives a coefficient of variation equal to 35%. For shrubs with grasses, variability in the R^2 is lower; it ranges between 0.66 and 0.87 with a value of variation coefficient of 28%. The variability of R^2 rapidly decreases by increasing presence of grass species in the vegetation cover and by increasing vegetation cover percentage. For short grassland, the changeability of vegetation response to climate factors is only about 12%. For steppe, the R^2 exhibited the lowest irregularity; its value changed between 0.84-0.96 and showed a variation coefficient with a value of 6%.

We also analysed and mapped coefficient of variation of the *NDVI*-climate relationship at the per-pixel scale. Figure 7 shows the results of our calculations. Spatial patterns of the coefficient of variation of R^2 appear to correspond exactly with patterns in land cover: variability of R^2 decreases from desert vegetation in the south of the study area (coefficient of variation = 30-40), to semi-desert (10-20), and to steppe vegetation in the north (<10).

There may be many reasons for this phenomenon. For example, it can be a different sensitivity of vegetation to inter-annual rainfall variability observed by various vegetation types. Some vegetation communities may react to inter-annual variations in rainfall more sensitive than others. An explanation may be that the steppe vegetation has well-developed root systems (the above-ground biomass in steppe amounts to about 30-40% of the entire biomass) capable of holding of great deal of moisture from the previous 1-2 years that can be released gradually over time. This is reflected in a very low inter-annual variability of R^2. Semi-desert vegetation and desert shrub lands, on the contrary, have much shallower root systems and vegetation growth here is affected to a significant degree by inter-annual variations in rainfall and temperature. In the years with high rainfall amount, the prediction of *NDVI* patterns by rainfall is larger and the R^2 is higher. On the other hand, in the years with low rainfall values, temperature factor plays an important role, and then the value of R^2 is lower.

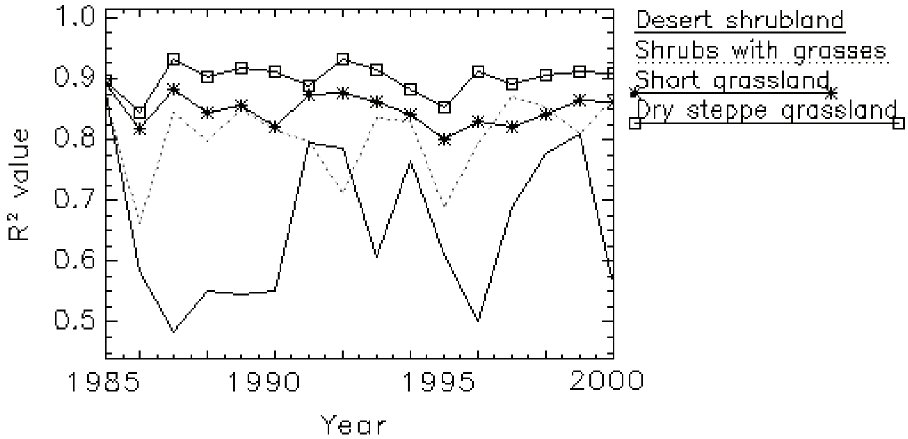


Figure 6: Time-series of the GWR R^2 between NDVI and precipitation over 1985-2000 for the reference sites in different vegetation types.

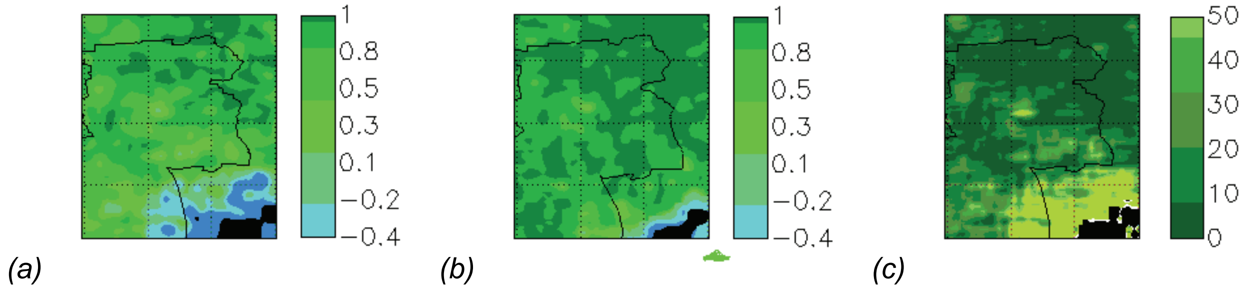


Figure 7: Maps demonstrating variability in NDVI-precipitation relationship during 1985-2000. (a) Minimum value of the determination coefficient, R^2, (b) maximum value of R^2 and (c) coefficient of variation of R^2.

Case studies: trends in NDVI-climate relationship and their linkages to land use/land cover change

In order to determine linkages between the vegetation response to precipitation and LULCC, we processed time-series of the determination coefficient R^2 for the four specific test sites and interpreted them with regard to the LULCC found at each individual site. We also processed time-series of the R^2 in the reference sites located in the surrounding area of the specific case studies. By interpretation of the results from each case study we compared the variation of the R^2 in it with that in the corresponding reference site. If the variations of the R^2 in a case study site and the surrounding area were different, an impact of the LULCC on the vegetation response in this case study could be considered to take place. Figure 8 shows the results of the case studies. In order to facilitate the understanding of the linkages between the dynamics of the R^2 and the LULCC, we also placed at the diagrams the time-series of the R^2 value in the corresponding reference sites and the mean value of the R^2 in each of the test site.

In terms of the temporal variance of the vegetation response to precipitation, the specific case studies showed the generally larger changeability of the R^2 value than that observed in the surrounding area. Thus, in the case study (a) the value of R^2 ranged from 0.75 to 0.95, while in the corresponding reference site it ranged from 0.85 to 0.92. The coefficient of variation of the R^2 was

28% and 9% for the test site and the reference site, respectively. The R^2 value in the other three case studies was also characterised by higher temporal variances than in the corresponding reference sites: 41% versus 11%, 32% versus 11%, and 26% versus 10%, in the case studies b, c, and d, respectively. Even though the case studies were located in the zones of short grassland and steppe grassland, the magnitude of the observed variations of their R^2 is like that of the shrubland and the desert in Figure 6. These results suggest that agricultural use significantly enlarges the inter-annual variability of the vegetation response to precipitation. The case studies demonstrated that the vegetation cover of the agriculturally used land is more sensitive to the inter-annual rainfall variability. This means a larger susceptibility of the vegetation to climatic hazards such as drought.

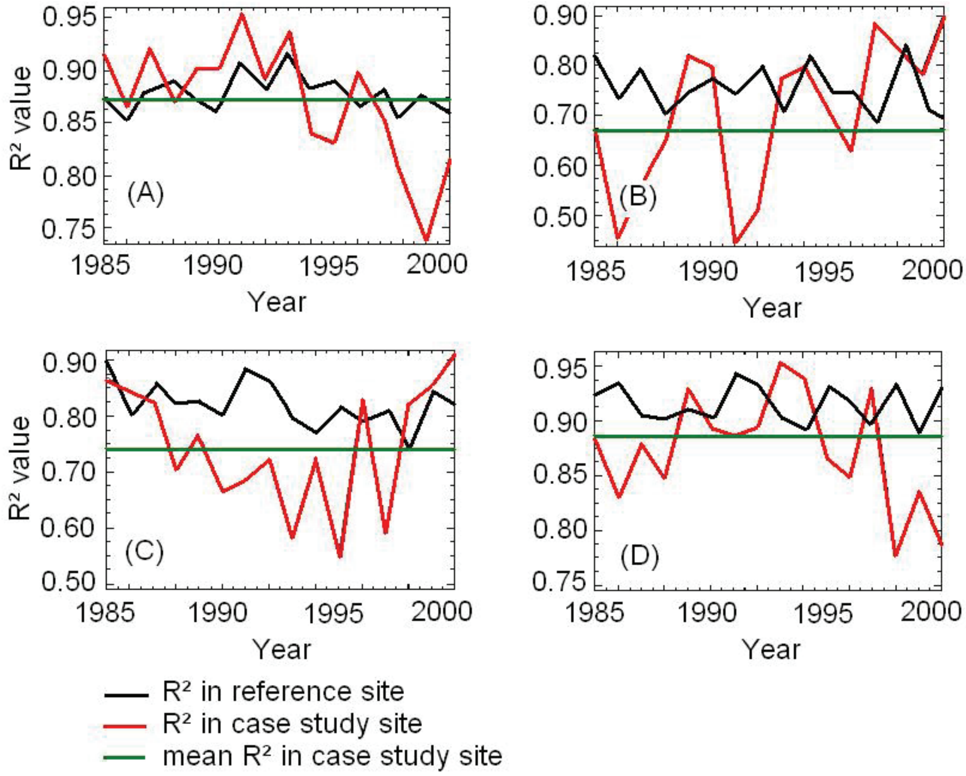


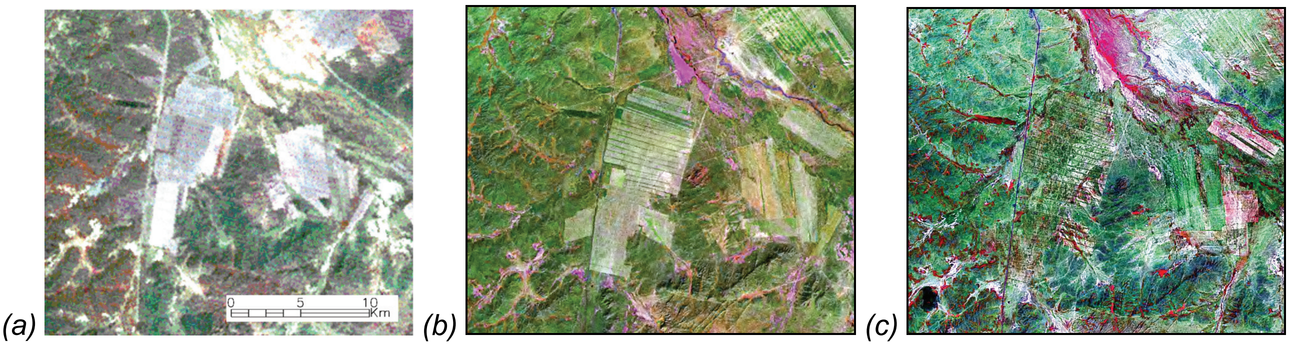
Figure 8: Time-series of R^2 for the specific case sites demonstrating typical linkages between the NDVI-climate relationship and land use/land cover change. The first two sites belong to the zone of dry steppe grassland, whereas the second two sites belong to the zone of short grassland. The time-series of R^2 for the corresponding reference sites are represented with the black line. The green line shows the mean value of the R^2 over the period of 1985-2001 in each of the case study sites.

Four behaviour types of trend in the R^2 could be considered at the test sites. The results proved that the profiles of R^2 strongly depend on the magnitude and direction of the LULCC. Figure 8 displays temporal patterns of R^2 time-series for the test sites.

Panel (a) shows a site in which agricultural use was evident during the entire study period. The R^2 value in this site shows inter-annual oscillations with a magnitude which is significantly higher than that observed in the corresponding reference site. During the first half of the observation period, the direction of these oscillations corresponded with the direction in the surrounding area. In the second half of the observation period the direction of the R^2 trend in this test site differed from the direction recorded in the reference site. This site is characterized by the mean value of the R^2 which is similar to that in the surrounding area. This fact could suggest the generally good performance of the vegetation cover during the period of 1985-2001. However, a comparison of the profiles for the R^2 in the test site and in the reference site reveals a decrease of the R^2 in the second half of the study period. In the main, for this site, the strength of the NDVI-rainfall relationship decreased from 1993 to 2001, implying a decreased ability of the land surface to respond to precipitation. The magnitude of the R^2 variance increased significantly after 1992. As suggested above, the high variability of the vegetation response to precipitation is characteristic of the lands with disturbed vegetation cover. Signs of increasing land degradation were identified on the Landsat images. These signs were then confirmed by the field trips.

Panel (b) shows a site located in the steppe section which was used as pasture. The mean value of the determination coefficient R^2 was clearly below the R^2 values in the surrounding area revealing the generally worse performance of the vegetation cover, even though, the performance of the vegetation cover significantly improved during the sub-period of 1992-2001. The clearly positive trend in R^2 after 1991 is associated with a rapid reduction of livestock in the study area that caused a rehabilitation of the pasture land. This case study also supported our above suggestion about the relationships between the magnitude of the R^2 variance and the degree of human impact on the vegetation cover. The inter-annual changeability of the R^2 was very high during the first half of the observation period and significantly decreased during the second half, when the number of livestock was strongly reduced.

The clearest trends are related either to the abandonment of cultivated areas or to newly established cultivated areas. Panel (c) represents a site that had been intensively cultivated until 1993 and then was abandoned. The extensive cultivation of the site caused land degradation and a permanent decrease of vegetation response to rainfall during 1985-1993. The abandonment of the cultivated field enhanced a rapid recovery of the vegetation cover and the positive trend in R^2, although there were two years with exceptionally low R^2 values. Corresponding Landsat imagery is presented in Figure 9. In this case study site, the value of the R^2 averaged over the whole study period was significantly below the R^2 values recorded in the surrounding area. This suggests a generally weaker response of the vegetation cover to precipitation in comparison to the vegetation cover of the undisturbed area. However, visual analysis of the R^2 profiles in panel c reveals that at the beginning and at the end of the study period (1985-88 and 1998-2001) the response of the vegetation cover in the test site was like that in the reference site. We could consider that the degradation of the vegetation cover in this test site took place in the sub-period from 1990 to 1997. These years were characterised by the low values of the R^2. This sub-period (1990-1997) is also characterised by a higher magnitude of the inter-annual R^2 variance.



(a) (b) (c)

Figure 9: Expansion and abandonment of agricultural land at the third test site 3: (a) Landsat MSS image from 1975, RGB = Band 4,1,2. (b) Landsat TM image from 1992, RGB = Band 4,7,2. (c) Landsat ETM+ image from 2001, RGB = Band 4,7,2. The corresponding time-series of R^2 are displayed in Figure 8 (c).

Panel (d) shows a process, which is reverse to that described for Panel (c). The site of this panel had experienced no or very slight human influence in form of grazing during 1985-1992 and was taken into intensive agricultural use after 1992. The ploughing up of the grassland on this site enhanced degradation of the upper soil layer caused by wind erosion and was expressed in a decrease of R^2 values over the 1992-2000.

CONCLUSIONS

This study investigated spatial and temporal drifts in the relationship between NOAA AVHRR-NDVI and rainfall in drylands of Kazakhstan. We also explored linkages between NDVI-precipitation relationships and LULCC at a number of test sites. The relationship for each growing season from the period of 1985-2000 was modelled at the per-pixel basis using geographically weighted regression.

The vegetation response to rainfall was found to vary spatially and temporally. The spatial patterns in the vegetation response showed some correspondence with the distribution of vegetation types. The strength in the *NDVI*-precipitation relationships increased from desert shrub land, to semi-desert, to short grassland, and to steppe grassland. The results from the specific case studies demonstrated that the vegetation response to precipitation depends on the performance of the vegetation cover. Thus, in the specific case studies undergoing degradation the *NDVI*-precipitation relationship was significantly weaker than that in the corresponding reference sites. These results proved the fact that the undergoing degradation processes decreased the vegetation response to precipitation.

The study also highlighted the presence of temporal variations in the coefficient of determination R^2 between *NDVI* and precipitation over the period 1985-2001. The variation was generally large in the areas covered by desert vegetation and low in the areas covered by short grassland and steppe vegetation. The temporal variance of the R^2 in the four case studies demonstrated a higher magnitude than that in the reference sites. The variance magnitude was like that observed for desert vegetation. The results showed associations between the magnitude of the temporal variance of the R^2 and the performance degree of the vegetation cover. Thus, the vegetation cover with a low performance is characterised by a higher magnitude of the R^2 variance. On the contrary, the non-degraded vegetation cover commonly shows a low variability of the R^2. The variance magnitude in the degraded lands increases towards the values observed in the semi-desert and desert zones. We propose that the increase of the changeability of the R^2 is caused by a decrease of the vegetation fraction. The processes of degradation reduce the vegetation fraction in the affected areas making it similar to the vegetation fraction in the desert and semi-desert zones. Therefore, the magnitude of the R^2 variance changes in the direction of the corresponding values. Our conclusion from these results is that the temporal variance of the vegetation response to precipitation is an indicator o performance of the vegetation cover and can be used for evaluation of land degradation.

For the four specific case studies the analyses of R^2 time-series revealed a strong dependence of the vegetation response to rainfall on LULCC. At all sites analysed, the response of vegetation cover to precipitation was increased with a decrease of the anthropogenic impact. On the contrary, an increase of the human influence was reflected by a diminishing response of vegetation to precipitation. The processes of degradation and rehabilitation of the vegetation cover were proved to be also recognisable through analysis of the dynamics of vegetation response: A decreasing response of vegetation to precipitation indicates a damage process happening in the vegetation cover.

Our general conclusion is that, for the four specific case studies, the response of vegetation cover to rainfall factor serves as a good indicator of land cover performance. Its spatial and temporal variance may serve as representative indicators of land use/land cover change in drylands.

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