EVALUATING TRENDS IN SPATIAL RELATIONSHIP BETWEEN NOAA/AVHRR-NDVI AND RAINFALL AS COMPUTED BY GEOGRAPHICALLY WEIGHTED REGRESSION: A CASE STUDY FROM A DRY REGION IN THE MIDDLE KAZAKHSTAN

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ABSTRACT:

The spatial relationship between vegetation patterns and rainfall as well as its trend over the period 1985-2000 in the shrubland, grassland, and cropland of the Middle Kazakhstan was investigated with Normalized Difference Vegetation Index (NDVI) images (1985-2000) derived from the Advanced Very High Resolution Radiometer (AVHRR), and rainfall data from weather stations. The growing season relationship was examined using a local regression technique known as geographically weighted regression (GWR). Regression models for each pixel and every analysis year (1985-2000) were calculated using this approach. Both the strength of relationship and the regression parameters showed high spatial and temporal non-stationarity. Spatial and temporal drifts of regression parameters and drifts of correlation coefficient were estimated and mapped. There are notable associations between patterns in land cover types and patterns in intercept and slope parameters in the study region. Residuals from the regressions for each pixel and every year were computed. Trend in residual values for each pixel over 16-year period was used to determine a temporal change of conditions of the vegetation cover through the time: pixels with a negative slope are considered to represent ground areas with decreasing amount of vegetation. Four types of trend behaviour were determined and analysed.

1. INTRODUCTION

Climate is one of the most important factors affecting vegetation condition. Therefore, evaluation of the quantitative relationship between vegetation patterns and climate is an important object of applications of remote sensing at regional- and global scales. The Normalized Difference Vegetation Index (NDVI) is established to be highly correlated to green-leaf density and can be viewed as a proxy for above-ground biomass (Tucker & Sellers, 1986). Spatial correlations between NDVI and climatic factors are investigated in many research works. Particularly well correlation in the arid regions show NDVI and rainfall, the relationship between NDVI and temperature are reported to be weaker but also significant (Nicholson & Farrar, 1994; Yang *et al.,* 1998; Richard & Poccard, 1998; Ji & Petters, 2004; Li *et al.,* 2004; Wang *et al.,* 2001).

Regression and correlation techniques were the common empirical approaches used to quantify the relationships in most of these studies. However, the conventional statistical regression method (global OLS regression) assuming the relationship to be spatially stationary is usually not adequate for spatially differenced data, especially by quantifying relationships at regional or global scales. There is many cases that show non-stability of this relationship in space (Brundson *et al.,* 2001; Fotheringham, 1999; Foody, 2003; Wang *et al.,* 2005). The causes of variance of relationship between NDVI and its explanatory variables are known to be spatial variations in properties such as vegetation type, soil type, soil moisture (Wang et al., 2001; Yang et al., 1996; Ji & Peters, 2004; Foody, 2005). The differences between regression models established at different locations can be large with both the magnitude and sign of the model parameters varying.

Local regression techniques, such as space varying coefficients (SVC) method, moving window regression (MWR), or geographically weighted regression (GWR) help to overcome this problem and calculate the regression model parameters varying in space. These techniques provide a more appropriate and accurate basis for modelling relationship between various spatial variables (Pavlov, 2000; Brunsdon *et al.,* 1996; Brunsdon *et al.,* 2001). At the field of remote sensing there are only rare studies applying local regression techniques for analysis of spatial relationships between remotely sensing data and climatic variables (Foody, 2003; Foody, 2005; Wang et al., 2005).

In this paper, we analysed relationship between NOAA/AVHRR-NDVI and rainfall amounts for every year from the study period 1985-2000. Our analysis was based on calculation of local statistics for each pixel through utilization of GWR. In addition, the annually GWR models were used for evaluation of land cover performance. We answered the following questions with regard to vegetation-rainfall relationship at 16-year time-scale: (1) To what extent is vegetation affected by rainfall? (2) What factors predict the spatial variance of regression parameters? (3) Is there any evidence of temporal non-stationarity in NDVI-rainfall relationship over the study period? (4) How can the GWR analysis be used for evaluation of change in vegetation conditions? The aim of the study proposed to answer this questions for each pixel of the study area.

2. 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. In terms of surface structure the study area is divided into two large regions: a plateau of rolling upland in the southern, western, and northern parts with average elevations between 300-700 meter; hills and low mountains in the central and north-eastern parts with elevations 700-1100 meter.

The climate of the region is dry, cold and high continental. 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 relative 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. Dominating vegetation species here are *Artemisia terrae-albae, Artemisia pauciflora, Anabasis salsa, Salsola orientalis*. The northern section of the study is occupied by steppe vegetation, were dominate short grassland species such as *Festuca sulcata, Stipa capillata* and *Stipa lessingiana*. The semi-desert vegetation occupying the mid of the study area represents a complex combination of real steppe turf grasses and semi-shrubs with halophytes.

3. MATERIALS AND METHODS

3.1 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 data for the period were calibrated for post-launch sensor degradation by using methods described by Los (1993). 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 this preparations the NDVI data were ready for the further use in the study.

3.2 Precipitation data

The climate data in the study consist of 10-day rainfall data collected and calculated by the National Hydrometeorological Centre of Kazakhstan for 9 climate stations placed in the study area for the period April-October 1985-2000. The 10-day rainfall data of each year were summed to calculate a sum rainfall value during growing season for every analysis years.
For the preparation of gridded maps of precipitation we summed 10-day rainfall data of each meteorological station for every year. Interpolation of data between stations was made using as gridding method known as the inverse distance to a power. After that all gridded maps were resized to pixel resolution of the NDVI data.

3.3 Regression model

The simple linear regression model, usually fitted by ordinary least squares methods (OLS), is:

$$y = \alpha + \beta * x + \varepsilon \tag{1}$$

Where *a* is the intercept, *β* represents the slope coefficient for variable *x*, and ε is random error.

In this model, the two variables to be related are *y*, the dependent variable (in our model NDVI), and *x*, the independent variable (one of the environmental predictors, such as rainfall, temperature, evapotranspiration etc.). The regression model parameters *a* and *β* derived by the above approach are assumed to be stationary globally over the analysis space. Interpretation of results derived through such model is based on the assumption, that at each point of the study area this model is absolutely representative and the quantified relationship is constantly.

Geographically weighted regression (GWR) is a local regression technique and overcomes the problem of non-stationarity through local disaggregating global statistics and calculates the relationship between NDVI and its predicting variables separately for every point in space of any area. GWR enables local parameters to be estimated and the relationship between the variables can be expressed as:

$$y = \alpha(\Theta) + \beta(\Theta) * x + \varepsilon \tag{2}$$

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

GWR being a local technique works in the way that each data point is weighted by its distance from the regression point. This means, that a data point closer to the regression point is weighted more heavily in the local regression than are data points farther away. For a given regression point, the weight of a data point is at maximum when it has the same location as the regression point, and are more lightly when it has a location at a range of the moving window. The matrix form of parameter estimation for any location point *i* is written as:

$$\hat{\alpha}(\theta), \hat{\beta}(\theta) = (X^T W(\theta) X)^{-1} X^T W(\theta) y \tag{3}$$

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

Spatial weighting function can be calculated using several various approaches. For fixed kernel size, the weight of each point can be calculated by the applying of a Gaussian function

$$w_{ij} = \exp[-1/2(d_{ij}/b)]^2 \tag{4}$$

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

An alternative way is the bi-square function

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

when $d_{ij} < b$ and $w_{ij} = 0$ otherwise.

The weighting of an observation in the analysis is not constant, but a function of location. Data from observations close to point *i* are weighted more than data from observations father away.

In the practice, for each variable from equation (2) its weighting value can be calculated by applying a weighting matrix W(Θ). The weighting matrix is an *n* by *n* matrix whose off-diagonal elements are zero and whose diagonal elements denote the geographical weighting of each of the n observed data for regression point *i*. After that, a local regression at each point in the analysis area can be derived by moving a kernel over the space. A detailed description of geographic weighted regression and its treatments is provided by Fotheringham *et al.* (2002), Brundson *et al.* (1996) and Brundson *et al.* (2001).

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 global 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 therefore how to select an appropriate bandwidth in GWR. The selection of the weighting function can be determined using different methods such as a cross-validation (CV) approach given by Brundson *et al.* (2001), or the generalized cross-validation criterion (GCV), or the Akaike Information Criterion (AIC) described by Fotheringham *et al*. (2002).

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 Fotheringham *et al.* (2002), the equation for the *cross-validation sum of squared errors CVSS* is statistically expressed as:

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

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

As 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 regression model, the bandwidth of 5 pixel was decided to be the most appropriate.

4. RESULTS

Figure 1 provides a visual comparison of NDVI and rainfall amounts in the study area. The spatial distribution of growing season NDVI roughly corresponds to that of rainfall. An analysis at the level of the whole study area based on conventional global OLS regression have established a strong relationship between the both variables. The estimated R^2 ranges from 0.41 to 0.81 over the period 1985-2000 and shows a value of 0.63 with the data relating to averages of all years (Figure 1 (right)). A high degree of inter-annual variations in the regression parameters of OLS was evident but the general nature of the relationship appeared to be relatively stable. Further, the GWR model was applied to disaggregate global statistics and to find spatial variations in the relationships and regression parameters.

4.1 Spatial variations in NDVI-rainfall relationship

The GWR method has been applied for each year of the study period (1985-2000). From the GWR modelling, it was evident that the relationship between NDVI and rainfall displays a high spatial non-stationary.

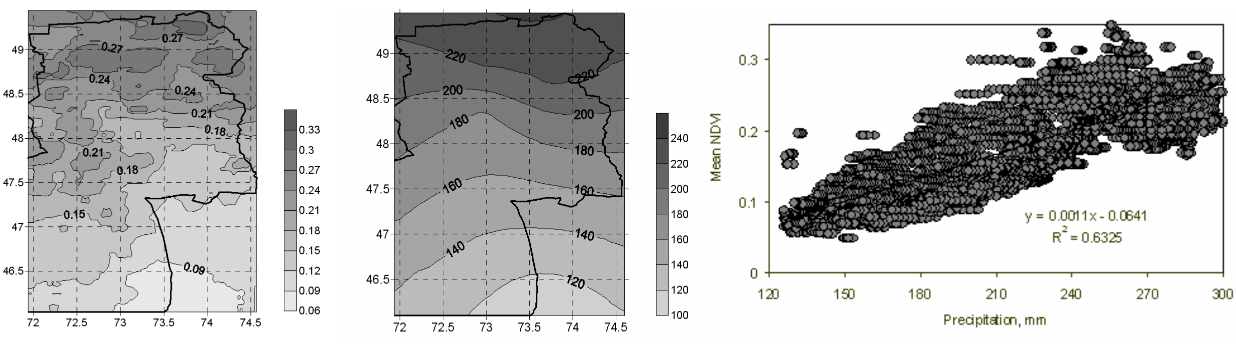

Figure 1. Patterns of NDVI and rainfall in the study area and regression between this both variables: (left) growing season means NDVI determined from 10-day composite images (1985-2000), (centre) growing season rainfall means for the period 1985-2000, (right) graph of the OLS regression between NDVI and rainfall for the data relating to mean values.

The coefficient of determination, R^2, varied in the space over the study area. The strength of the relationship between the both variables increased remarkably, and, accordingly, the amount of variance unexplained is not so large as would be believed from the OLS analysis above. The mean value of R^2 derived from the GWR analysis amount to 0.85, while maximum value achieved 0.96. This suggest that the GWR model significantly improved prediction of NDVI by rainfall over the OLS model. The GWR model demonstrated a very good prediction power: the NDVI residuals ranged from –0.02 to 0.02 over the study area, the standard deviation of NDVI residuals was only 0.0127 or approximately 8 % of the mean NDVI value. Figure 2 summarizes the results derived from the geographically weighted regression analysis between NDVI and rainfall for the data relating to the average values over the 1985-2000.

Generally, the spatial patterns of the mapped intercept and slope parameters 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 values of both regression parameters vary significantly in space, but in the semi-desert zone they are more closer to that of the parameters derived by the OLS regression. Here, the lowest residuals values for GWR are also to note. 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 ($R^2 = 0.70 – 0.92$).

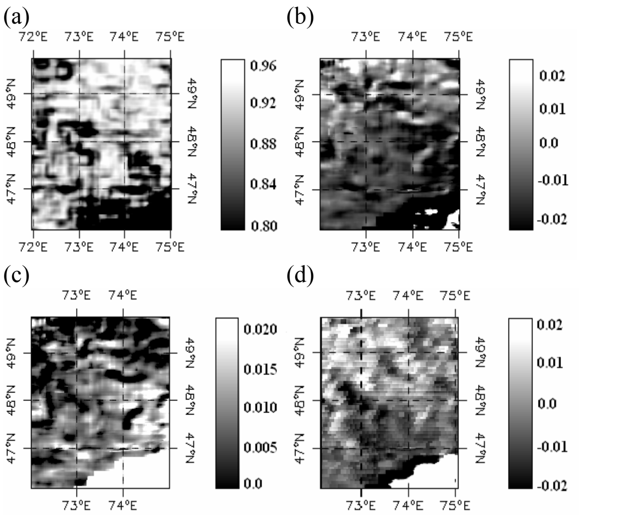

Figure 2. Spatial variations in the parameters of the geographically weighted regression for NDVI-rainfall relationship (mean values for the period 1985-2000). The images show the spatial variation in the local estimate of the coefficient of determination R^2 (a), the intercept (b), the slope (c), and the residuals (d).

4.2 Temporal variation in the GWR parameters over the period 1985-2000

Over in § 4.1, we proved that the relationship between NDVI and rainfall exposes a high spatial non-stationarity. However, there is also a significant temporal non-stationarity in the NDVI-rainfall relationship over the study period. Figure 3 (a) demonstrates the time-series of R^2 for three sites (each has an area of 3*3 pixel) from the main land cover types. The time-series expose that the variance in NDVI unexplained by the geographically weighted regression modelling varied in time during the study period. There is a clear dependence of the inter-annual variability in R^2 on the land cover types: for desert, the R^2 ranged from 0.72 to 0.94, for semi-desert, the R^2 ranged from 0.81 to 0.94, for steppe, the R^2 exhibited the lowest irregularity, its value changed between 0.92-0.96.

We also analysed and mapped the temporal non-stability of the NDVI-rainfall relationship on a pixel-by-pixel basis. Thus, we calculated coefficient of variation of R^2 and linear trend of R^2 for every pixel. Figure 3 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). These results indicate a high temporal changeability in the relationship between NDVI and rainfall in the study area.

There may be many reasons for this phenomenon, relating, for example, to various resilience of vegetation types to inter-annual rainfall variability. 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 (above-ground biomass is only about 30-40% of the entire biomass) capable of holding of great deal of moisture from the preceding 1-2 years that can be released gradually over time. This reveals 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. 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 value, temperature factor plays an important role, and then the value of R^2 is lower.

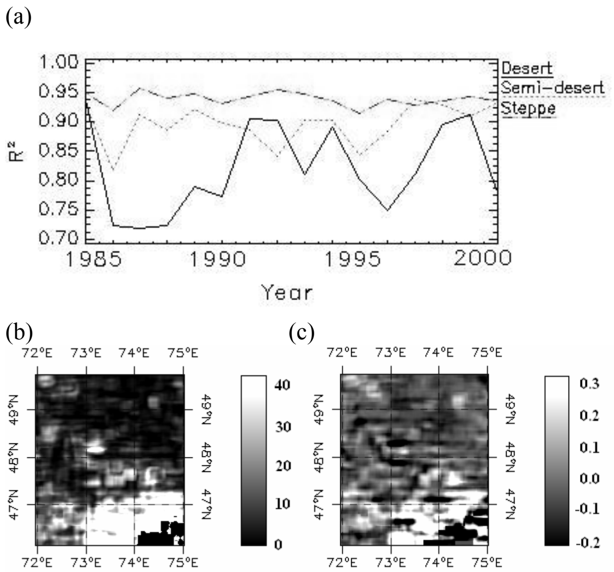

Figure 3. Evidence of temporal non-stationarity in R^2 over the period 1985-2000. (a) Time-series of R^2 for three representative sites; (b) Coefficient of variations of R^2; (c) Linear change in R^2 calculated from the time trend over the 1985-2000.

4.3 Applying GWR analysis to evaluation of land cover performance

Analysis of NDVI-rainfall relationship is also an important object in the studies investigating land cover performance and land degradation in dry regions. Li *et al*. (2004) and Evans & Geerken (2005) applied regression models between NDVI and rainfall for evaluation of land performance and discrimination between climate-induced and human-induced land degradation. The strength of the relationship NDVI-rainfall by itself provides useful information for assessment of land cover performance. Li *et al.* (2004) proved that low positive or slightly negative correlation is associated with potentially degrading areas. The authors analysed outliers from regression between NDVI and rainfall to confirm interpretation derived from the correlation results.

Due to large inter-annual climatic variability in dry regions, any trend in vegetation activities may be correlated with trends in climatic variables, especially in precipitation. In order to identify vegetation changes that are non-dependent on precipitation change, the effect of this climatic component must be removed. It was proposed that after taking away the climatic component, the remaining changes in vegetation activities are attributed to internal factors or human influence. The areas displaying a negative trend over time were considered degrading (Evans & Geerken, 2005).

We used the above GWR calculations for each year to identify climatic component, to remove it, and than to evaluate trend in vegetation activity for every pixel. In order to remove the effect of precipitation, the residuals between the observed NDVI and the regression predicted NDVI was calculated for each year from the study period. Then we calculated for each pixel temporal trend of GWR residuals over the period 1985-2000. It was suggested that any trend in the residuals through time indicates changes in NDVI response not due to climatic component. According to this suggestion, a clear negative trend would indicate increasingly worse response of the NDVI to rainfall. This means that the area experiences human induced degradation. On the other hand, a positive trend would indicate an area with decreased human impact.

Figure 4 displays temporal trends in residuals. It is to be expected that not all pixel would show a linear time-trend in residuals. A rapid change of anthropogenic impact in the early 1990^{s} caused by the collapse of the USSR and the followed economic crisis would influence the permanent residuals trend. This was proved statistically: Figure 5 produces different behaviour of the residual trends calculated for the 1985-2000. Scatter plots 1 and 2 show two "classic" cases with vegetation cover degrading or improving permanently over the study period. Scatter plots 3 and 4 displays two various behaviours of pixels by changing the human impact in the early 1990^{s}. The pixel at graph 3 had been degrading during the time 1985-1992, and was improving since the year 1992. In opposite to this, the pixel at graph 4 had been improving during the period from 1985 to 1991(positive slope of trend), but after the 1991 the trend turned over to negative and we can expect a degrading process in this area.

Positive trends appear in the south, west and central regions of the study area occupied by desert and semi-desert vegetation formations. The land cover of these areas is considered to improve during the period 1985-2000. Areas of negative trend are much more localized. Widely scattered negative areas are located in the north and north central regions where vegetation formation of dry steppe dominates.

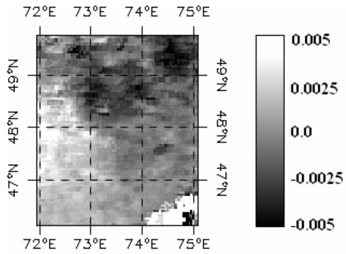

Figure 4. Linear trends in residuals from the GWR over the 1985-2000. Negative trend values indicate poor land cover performance, while positive values indicate improving areas.

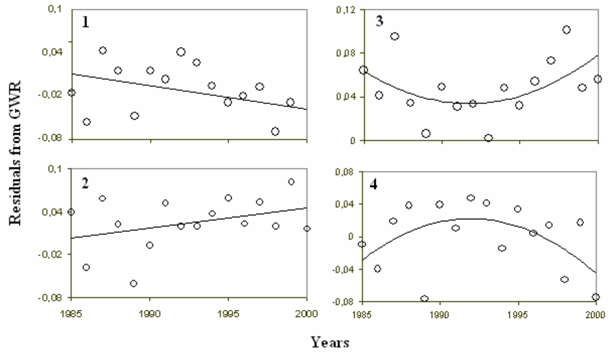

Figure 5. Temporal trends in residuals associated with different behaviour over 1985-2000: (1) The trend slope is negative, that means a change for the worse of the vegetation cover, (2) The trend slope is positive, the vegetation cover is improving, (3) The trend slope was negative than turned to positive, and (4) The trend slope was positive and than turned to negative.

5. CONCLUSION

In our work, we applied both the spatial global OLS regression and the local regression technique, geographically weighted regression, to explore relationship between NDVI and rainfall in desert, semi-desert and dry steppe region of the Middle Kazakhstan for the time period 1985-2000. The results of the statistical analysis proved a high correlation between these variables.

We found that the conventional OLS regression model explains about 63 % of the NDVI spatial variations in the study region for all years. The results of global regression analysis between NDVI and rainfall correspond to the results of studies undertaken in other dry regions of the earth (Ji & Peters, 2004; Wang *et al.,* 2001; Richard & Poccard, 1998; Yang *et al.,* 1998). However, through applying the geographically weighted regression, it was evident that this relationship was non-stationary and that the variations in rainfall could explain a good deal larger amount of the variation in NDVI than was derived from the conventional OLS regression analysis. Taking into account the local variance in the regression parameters, the prediction power of the regression model was drastically improved. The strength of the relationship between NDVI and rainfall increased very significantly, with a mean of 92.3 % of the variation in the NDVI values explained by that in rainfall for all study years. Our study proved that the explanatory power of the GWR is a large amount higher than that of the global OLS

regression. The results of the study are in agreement with the results obtained from similar studies (Foody, 2003; Foody, 2005; Wang *et al.,* 2005).
In order to test whether there is an evidence of temporal non-stationarity in the spatial NDVI-rainfall relationship, we also analysed time-series of the statistics derived by the GWR model. This analysis highlighted presence of temporal variations in both regression model parameters and coefficient of determination R^2 over the period 1985-2000. Patterns in the temporal variation in the slope and in the intercept parameter as well as in the R^2 appeared to correspond with patterns in vegetation cover. The variation was generally large in the areas covered by desert vegetation and low in the areas covered by steppe vegetation. The desert areas also exhibited the highest value of the change in the R^2 over the study period mapped. Here, the coefficient of determination increased for 0.1-0.3 during the 1985-2000. An explanation for the high variation in GWR model parameters and the high increase in R^2 may be a high rainfall variability in this area as well as a remarkable decrease of human influence in the 1990s. Due to economic crises, livestock numbers dropped by more than two-thirds overall in Kazakhstan between 1991 and 2000. This furthers a recovery of scores of desert and semi-desert pastures had been degrading in 1950-1990. The vegetation cover have being recovered from degradation turns out to be more dependent in its patterns on the climatic predictors especially rainfall. This reflected in higher determination of NDVI patterns by rainfall patterns expressed through R^2.

We showed that the GWR analysis can be effectively used for evaluation of land performance and identification of degrading areas. For this, it was necessary to remove climatic signal from the NDVI time-series. This was achieved through calculation of residuals of the GWR model for every year from the study period. After the removing this climatic influence, the remaining changes in NDVI signal are mainly associated with human influence. By looking into changes in the residuals over the study period, we could identify areas with improving (negative trend) or degrading (positive trend) vegetation cover. Some areas demonstrated non-linear changes in the residuals during 1985-2000. The study distinguished four types of trend behaviour.

The technique for removing climate signal from NDVI time-series presented in our work gives new tools for evaluation of land performance and land degradation and enables to improve essentially a discrimination between climate and human-induced changes in vegetation conditions as they were described in related studies by Evans & Geerken (2004) and Li *et al.* (2004).

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