Application of Geographically Weighted Regression Analysis to Assess Human-Induced Land Degradation in a Dry Region of Kazakhstan

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SUMMARY

The primary objective of this study was to assess a human-induced dryland degradation in the cachment basin of the Balkhash Lake in the Middle Kazakhstan based on time series of rainfall data and normalized difference vegetation index (NDVI) for the period 1985-2000. We developed a method to remove the climatic signal from the change in vegetation activity over the study period. By applying a local regression technique known as geographically weighted regression (GWR), relationship between spatial patterns of the growing season NDVI and the growing season rainfall were estimated for every pixel and every year. In geographically weighted regression, the regression parameters are estimated using an approach in which the contribution of an observational site to the analysis is weighted in accordance to its spatial proximity to the specific location under consideration. The weighting is a function of location and it declines the further the observation is from the location for which predictions and parameter estimates are required. The regression models identified a strong dependence of spatial patterns of NDVI on that of precipitation parameter. The relationship between NDVI and the explanatory variable was found to vary spatially and temporally. At local scales, the regression models indicate that over 90% of spatial variations in NDVI is accounted for by the climatic predictor. Deviations in NDVI from this relationship, expressed in regression residuals, were calculated for each year of the study period 1985-2000. Residuals, laying out of the "Standard Error of the Estimate" are regarded as outliers and interpreted as human-induced. The results of the modelling were validated by comparison of the remote sensing data of high spatial resolution (Landsat TM and ETM) and the data from field trips to degrading areas.

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1. INTRODUCTION

Land degradation and desertification has been seen as the major environmental problems in large parts of the arid and semi-arid regions of the earth. Land degradation is considered the result of a series of complex natural and anthropogenic processes that leads to gradual environmental degradation or loss of the lands biological and economical productivity. The processes leading to land degradation manifest in all compartments of ecosystems and are divided into the follows groups: vegetative - degradation of the vegetative cover by removing or destruction on the way of wood cutting and overgrazing; biological – reduction of organic matter content; physical – adverse changes in soil physical properties, such as porosity, bulk density, structural stability and permeability; chemical – soil salinization, acidification and contamination; hydrological – decrease of soil water storage, change in redistribution of surface and soil water and a new threshold for runoff initiation; morphodynamical – water and wind erosion by removal of soil particles by rainfall, runoff or gravity and wind (Darkoh, 1998; Kassas, 1995).

The complexity of the desertification processes demands the use of a wide set of desertification indicators by an attempt to assess and monitor desertification. Indicators usually describe one or more aspects of desertification and provide data on threshold levels, status and evolution of relevant processes. The study specific indicators for some concrete area should be drawn according to a list of criteria, such as reliability, measurability, applicability, cost-effectiveness, and interpretability (Rubio & Bochet, 1998; Babaev & Kharin, 1999).

Since the late 1970s many studies developed methods for deriving individual indicators of desertification from remotely sensed data. The majority of these studies used only one vegetative indicator or its few varieties as the main evaluation aspect (Tucker *et al*, 1991; Weiss *et al*, 2001; Wessels *et al*, 2004). Other recent studies have tried to improve accuracy and objectivity of land degradation assessment by applying a set of various type indicators (Symeonakis & Drake, 2004; Thiam, 2003). However, the most studies assess the complexity of the desertification processes through evaluation of only one indicator type, vegetative. Degrading vegetative cover is the best measurable indicator by remote sensing methods, but it is strongly predicated by macro- and micro-climatic factors, such as global temperature and rainfall distribution change, local topography characteristics etc. Therefore, a discrimination between climate induced and human induced degradation of vegetative cover is very difficult, the neglect of this aspect can lead to mistakes by desertification evaluation (Binns, 1990; Hellden, 1991). A few recent studies have developed methods making possible this discrimination by use of time-series of satellite data and time-series of climatic variables (Holm et al, 2003; Evans & Geerken, 2004; Li *et al*., 2004). These methods have been based on identification of climate signal in inter-annual time-series of vegetation activity. Once the climate signal is identified, it can be removed from the trends in vegetation activity. The remaining vegetation changes are attributed to human influence and those areas displaying negative change over time are considered degrading.

2. STUDY OBJECTIVES

The Normalized Difference Vegetation Index (NDVI) is the most used multi-spectral 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). Remotely sensing derived NDVI data have been used to evaluate climatic and environmental changes at regional- and global scales (Kogan, 1997; Potter & Brooks, 1998; Kowabata *et al.,* 2001; Tucker *et al.,* 2001; Xiao & Moody, 2004). Several previous studies modelled relationships between spatial or temporal patterns of NDVI and that of climatic factors. Particularly strong relationship in the arid regions show NDVI and rainfall (Richard & Poccard, 1998; Nicholson & Farrar, 1994; Wang *et al.,* 2001), NDVI and temperature or growing-degree days (Yang *et al.,* 1998; Li *et al.,* 2002), NDVI and soil moisture (Farrar *et al*, 1994), as well as NDVI and evapotranspiration (Ji & Petters, 2004). The most studies proved the response of NDVI to ecoclimatic factors depends on vegetation types and varies over space. (Li *et al*, 2002; Wang *et al*, 2001,). On the contrary, there are studies (Nicholson & Farrar, 1994) which reported that the response of NDVI to rainfall is more dependent on soil type than on vegetation type. Study results derived by Li *et al*. (2004) for Senegal suggested that the relationship between NDVI and climate, especially precipitation, can be used as a general indicator of land productivity, both for land degradation and land improvements. Evans & Geerken (2004) demonstrated in their study how climatic signal can be identified and removed from NDVI trends.

The object of this study was a detection of degraded areas in the Central Kazakhstan. Vegetation cover in dry regions is very sensitive to climatic variability and climate influences are sometimes stronger than human influences on vegetation condition. It seems likely that it was not able to detect land degradation without taking into account large inter-annual climatic variability in the region. Therefore, an evaluation of land cover performance/degradation in this region should as first task include a quantifying climate influence. This can be achieved by modelling NDVI-climate relationship. The NDVI-climate relation comprises two aspects, a spatial and a temporal. A spatial model between NDVI and climate explains variation in vegetation cover in space predicted by variation in climate factors, while a temporal model deals with variations of variables over time. In this study, we combined the two aspects of NDVI-climate modelling. The combination was achieved through using a set of time-series of spatial models. It means that we derived an individual spatial model for every year from the study period (1985-2000).

Modelling the spatial NDVI-climate relationship one should take into account that he will have to do with a phenomenon of non-stationarity of this relationship in space. However, the conventional statistical regression method (global ordinary least squares regression, OLS) is stationary in a spatial sense. Stationarity means that a single model is fitted to all data and is applied equally over the whole geographic space of interest. This regression model and its coefficients are constant across space assuming the relationship to be also spatially constant. That is usually not adequate for spatially differenced data, especially by quantifying relationships at regional or global scales. The differences between regression models established at different locations can be large with both the magnitude and sign of the model parameters varying. Another large disadventage is autocorrelation of ecoclimatic data. When conventional OLS regression is applied to the analysis of data containing positive autocorrelation, there are two problems: (1) the standard error of the regression coefficient is underestimated, and tests of hypothesis on this coefficient may show that the indicator variable is significant when it really not, (2) the residual mean square may seriously underestimate the variance of the error term, hence the coefficient of determination (R^2) is overestimated (Clifford *et al*., 1989).

An interesting and efficient alternative to the spatial stationarity of the OLS modelling is to allow the parameters of the model to vary with space. Such non-stationary modelling has greater prediction precision because the model being fitted locally is more tuned to local circumstances. Local regression techniques, such as localized OLS (moving window regression) or geographically weighted regression (GWR) help to overcome the problem of non-stationarity and calculate the regression model parameters varying in space. This techniques provide a more appropriate and accurate basis for modelling relationship between various spatial variables and significantly reduce uncertainty in model prediction. For example, the local regression techniques have been effectively used to quantify spatial relationships between different variables at the field of human and economical geography (Brunsdon *et al.,* 1996; Fotheringham *et al*., 1996; Pavlov, 2000; Fotheringham *et al*., 2002; McMillen, 1996), in soil science and climatology (Murray & Baker, 1991; 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, 2004).

After the climatic signal had been identified, we removed that from inter-annual time-series of growing-season NDVI. The remaining negative changes in vegetation cover were associated with human-induced degradation. The study 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) How can the GWR analysis be used for evaluation of human-induced change in vegetation conditions? The results produced a more accurate estimation of the NDVI-precipitation relationship than the previous studies and provided a new technique for determination of human influences on land cover performance.

3. DATA AND METHODS

3.1 Study Area

The study area (Fig. 1) is located in the middle part of Kazakhstan between 46° and 50° northern latitude and 70° and 76° eastern longitude. It comprises the southern margin of the Kazakh Low Hills, North Balkhash gravel desert and the northern part of the Betpak-Dala clay desert. The climate of the region is dry, cold and shows high continentality. Average annual precipitation is above 280 mm per year in the north of the study area, and below 150 mm in the south. The most part of precipitation falls from March to October. The temperature amplitude is 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 region is occupied by steppe vegetation, where dominate short grassland species such as *Festuca sulcata, Stipa capillata* and *Stipa lessingiana*. The semi-desert vegetation complex occupying the mid part represents a complex combination of real steppe turf grasses and semi-shrubs with halophytes.

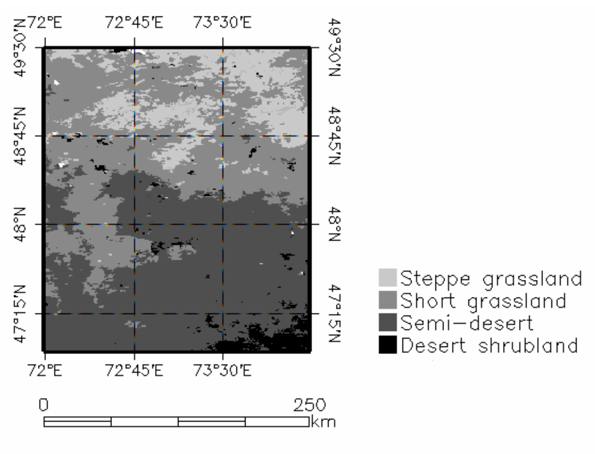


Figure 1. Map of land-cover types in the study area.

3.2 NOAA AVHRR NDVI Data Set

In this study we used 10 day maximum NDVI composites of the AVHRR sensor with a spatial resolution of 8 km. The data cover the period of growing season (April-October) from 1985 to 2000. Using a method described by Los (1993 and 1998) NDVI data were calibrated against three time invariant desert targets located in the Taklamakan Desert. 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 monthly and then to mean growing season values for each year.

3.3 Climate Data

Climate data were retrieved from the yearly statistics by the National Hydrometeorological Centre of Kazakhstan (NHMCK). These data contain 10-day records for growing season (April-October 1985-2001) of precipitation amount (mm) for 9 climate stations placed in the study area. Gridded maps of total precipitation amount over growing season for every year were prepared using ordinary kriging method.

3.4 Analysis Methods

3.4.1 Regression Model

Geographically weighted regression is a local regression technique that significantly improve common regression for use with spatial data. The global regression method assumes a constant (stationary) relationship between spatial variables over a modelling region. Application of a global regression model to the analysis of spatial data containing positive autocorrelation results in positive autocorrelation among regression residuals and makes the model problematic. GWR overcomes the problem of non-stationarity in regression modelling through local disaggregating global statistics and calculates the relationship between spatial variables separately for every point. Local parameter estimates can then be mapped at the locations of the regression points to view possible non-stationarity in the relationship being examined. This results in a more appropriate and more accurate model prediction. GWR analysis has been successful used for ecological modelling (Foody, 2003, 2004). Here we provide only a simple description of GWR, a detailed description can be found by Fotheringham et al. (2002).
GWR focused on deriving local parameters to be estimated. The model can be written as:

$$y = \alpha(\Theta) + \beta(\Theta) * x + \varepsilon \qquad (1)$$

Where a is the intercept of the line on the y axis (where $x = 0$), β represents the slope coefficient for independent variable x, and ε is the deviation of the point from the regression line, Θ indicates that the parameters are to be estimated at a location for which the spatial coordinates are provided by the vector Θ.

GWR 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. 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:

$$\hat{\alpha}(\theta), \hat{\beta}(\theta) = (X^T W(\theta) X)^{-1} X^T W(\theta) y \qquad (2)$$

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*.

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

$$w_{ij} = \exp[-1/2(d_{ij}/b)]^2 \qquad (3)$$

where d_{ij} is the distance between regression point *i* and data point *j*, and *b* is referred to as a bandwidth.
In the practice, for each variable from equation (1) 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.

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. 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:

$$CVSS = \sum_{i=1}^{n} [y_i - \hat{y}_i(b)]^2 \qquad (4)$$

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 GWR model, the bandwidth of 5 pixels was decided to be the most appropriate.

3.4.2 Identification of Areas Experiencing Human-Induced Degradation

Because of high inter-annual variability in climate in dry regions, any trend in NDVI over time is correlated with trends in climatic factors, especially precipitation (Tucker *et al*, 1991; Tateishi & Ebata, 2004; Richard and Poccard, 1998). Therefore, each temporal change in NDVI can be attributed to two explanatory factors, climatic component and anthropogenic component. In order to identify change associated with human influence, the climate component must be removed from the NDVI trend. Recent studies worked out different techniques to identify and to remove climate signal from NDVI time series (Li et al, 2004; Evans and Geerken, 2004).

We solved this problem through identification of the climatic component in spatial distribution of vegetation for every year. The solution of the problem was based on the use of geographically weighted regressions between NDVI and precipitation. These regressions describe the expected (predicted) NDVI, abbreviated as $NDVI_{pred}$, for any particular climatic signal. The observed NDVI, abbreviated as $NDVI_{obs}$, may show deviations from the regression line. We suggested that positive deviations indicate better response of vegetation to climate while negative deviations indicate worse response. When these deviations lay under/over defined threshold values, they are considered to be anomalous and may be associated with influence of other factors (non-climatic). The threshold value for every pixel and every year has been computed using standard error of prediction, SE, which is expressed as:

$$SE = \frac{s}{\sqrt{n}} \qquad (5)$$

where,

$$s = \sqrt{\frac{\sum (NDVI_{obs} - NDVI_{pred})^2}{n-1}} \qquad (6)$$

In order to monitor vegetation cover performance, we computed running sum of outliers over the study period. If the negative outliers show a large sum, it means that the response of vegetation to climate becomes worse and worse. This may indicate a decrease of vegetation cover and a land cover performance getting worse.

4. RESULTS

4.1 Patterns in NDVI and Precipitation in the Study Region

Vegetation and rainfall spatial distribution in the study area display similar spatial patterns. Average growing season precipitation increased markedly from south to north: from about 100 mm in the desert to over 260 mm in the steppe zone (Figure 2, left panel). The 16-year average of growing season NDVI ranges from less than 0.05 in the southern part of the study region to more than 0.35 in the north (Figure 2, right panel). A visual comparison of the spatial patterns in NDVI and precipitation gives an impression that there is a strong relationship between spatial patterns of these variables. The spatial distribution of NDVI roughly corresponds to that of rainfall.

For all GWR models, the NDVI-precipitation relationship was strong and highly significant (99% level of confidence). However, it was apparent from the results that relationship derived for each year from the period 1985-2000 was significantly non-stationary. The relationship varied over the study region. High local variability of regression parameters reflects variance in the NDVI-precipitation relationship.

4.2 Geographically Weighted Regression Modelling

GWR analysis was carried out for every year from the study period. Figure 3 summarizes the results derived from the geographically weighted regression analysis between NDVI and rainfall related to average values of these variables. Panel a shows spatial distribution of the intercept which had a median value of –0.022 and a range of –0.2 to 0.2. Large positive values are distributed mainly in the north of the region where short grassland and steppe grassland dominate while low values are mainly found in the mid and in the south. Here dominate semi-desert and desert vegetation.

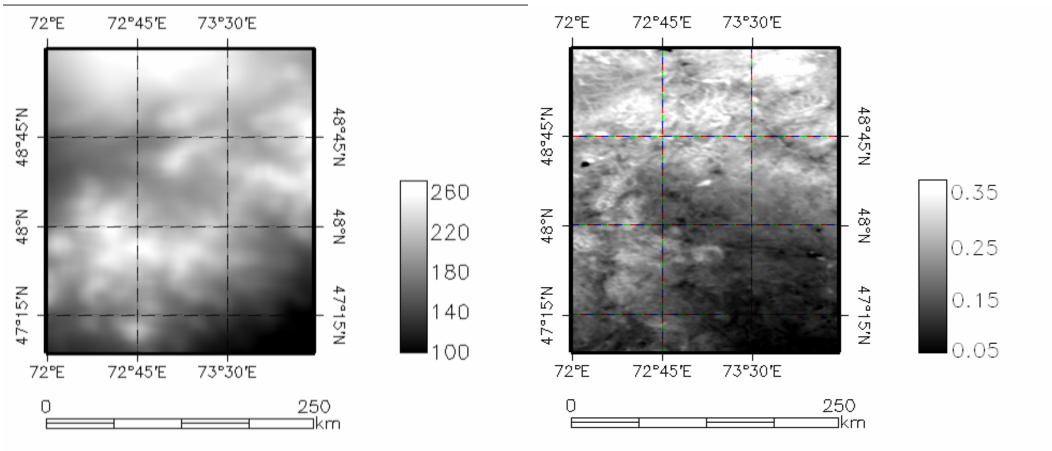


Figure 2. Mean growing season rainfall and average NDVI for the period 1985-2000.

Panel b shows spatial variation in the slope parameter. This parameter had a mean of 0.0418 with a range of 0.00023 to 0.002 and a standard deviation of 0.0002. Negative values of the slope parameter indicate that in some locations NDVI decreases when precipitation increase. Negative values are mainly in the northern and western parts of the study region where crop fields/grassland mosaics dominate. The valley bottoms in the north-east also exhibit negative values of the slope parameter. Panel c displays the spatial variation in the strength of the relationship. The goodness-of-fit, measured by the coefficient of determination, R^2, varied in the space and ranged from 0.016 to 0.99, with $R^2 > 0.75$ for eighth-tenth of the study region. Low values of R^2 are mainly distributed in the south and over a swath of land from the east to the north-west in upper part of the map. The entire model performance was very high with about 96% of the variation in NDVI values explained by that in rainfall. Figure 4 shows the scatter plot between measured NDVI and predicted NDVI using the GWR model. Panel d in Figure 3 indicates regression residuals which have been used as a guide to prediction accuracy. Value of regression residuals ranged locally from –0.025 to 0.025. the standard deviation of NDVI residuals was only 0.0127 or approximately 8 % of the mean NDVI value. This suggest that the GWR model demonstrates a very good prediction power. The spatial patterns in the parameter estimates from the GWR analysis illustrate the geography of the relationship. Generally, the spatial patterns in the intercept and slope parameter appear to correspond with some patterns in land cover distribution. The intercept parameter increases in order from desert, to semi-desert, to short grassland 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). For semi-desert vegetation formation, the R^2 ranges from 0.80 to 0.92 with the mean value of 0.90. Desert vegetation correlates much lower with the patterns of rainfall (R^2 = 0.70-0.80). The large spatial variation in the regression parameters suggests that spatial non-stationarity exists and that there are different responses of vegetation to precipitation not only between the land-cover types but also within every land-cover type.

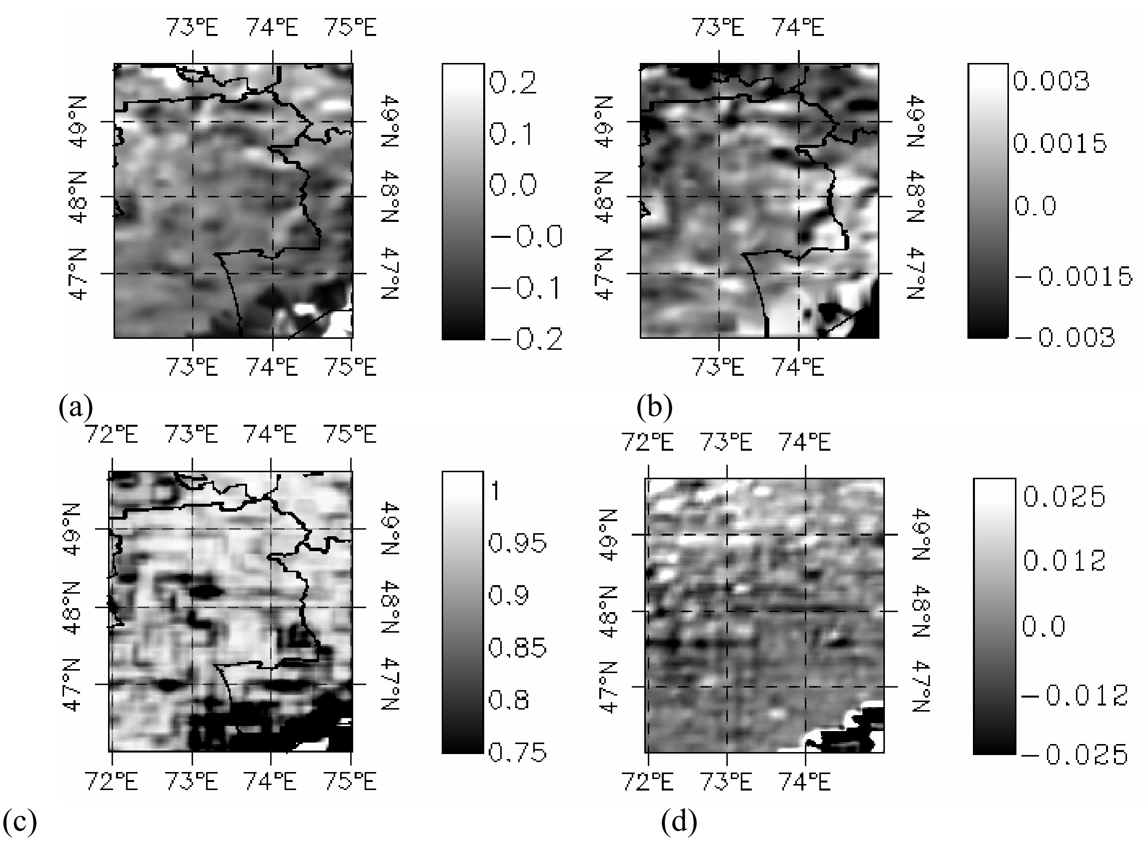
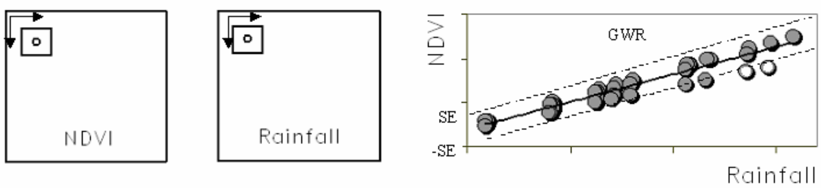


Figure 3. Results of the geographically weighted regression for the data related to average values. The images show the spatial variation in intercept (a), the slope parameter (b), the local estimate of the coefficient of determination, R^2, (c), and the residuals (d).

4.3 Identification of Areas Experiencing Human-Induced Land Degradation

Due to large inter-annual climatic variability in the study region, 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 removing the climatic component, the remaining changes in vegetation activities are attributed to internal factors or human influence. In the above geographically weighted regression calculations for each pixel, a mean of rainfall as the main explanatory factor for NDVI spatial and temporal dynamics was highlighted and statistically measured. The regression models for individual years predicted locally from 76% to 96% of spatial variation in NDVI explained by rainfall pattern. An example for one local regression shown in Figure 4, describing the expected NDVI for any particular rainfall amount. The scatter plot shows a strong trend of increasing NDVI with increasing precipitation value. Although climate significantly affects NDVI, a significant part of variation in NDVI is not explained by this example model. The scatter of points about the regression line suggests different response to the precipitatied rainfall amount. Using the technique describing by Li *et al.* (2004), we estimated treshold value, expressed in standard error estimate (SEE), above/under which a point is regarded as an outlier. If the point is greater or less than+1/-1 SEE, respectively, this point is regarded as an outlier. This process was repeated for every pixel and every year. On this way, we derived maps of outliers for every year from 1985-2000 (Figure 5). The outliers can be defined as anomalius behaviour regarding the NDVI-rainfall relationship. Negative outliers indicate those pixels that exhibite worse response of NDVI to rainfall. These pixels have low NDVI values and high precipitation for the local area. Standard error of estimation was derived for each pixel within the study region for each year. When a pixel shows worse response longer than 2-3 or more years, this pixel would indicate an area experiencing degradation. In order to define degrading pixels across the study region, we computed running sums of negative outliers over 1985-2000 (Figure 6).



$$SE = \frac{s}{\sqrt{n}} \qquad S = \sqrt{\frac{\sum (NDVI_{obs} - NDVI_{pred})^2}{n-1}}$$

Figure 4. Calculation of GWR outliers using Standard Estimation Error, SEE. For every pixels and each year, SEE was computed and comprised with the residual from the GWR derived for the defined pixel. If this pixel is greater or less than +1/-1 SEE, respectively, the pixel is considered as a negative/positive outlier for the GWR. In the graph, two open circles represent negative outliers.

5. CONCLUSION

In general, climate is an environmental factor of high importance in determining vegetation conditions. Various studies from arid region of the earth brought evidence of high correlation between climatic parameters and vegetation growth and production. Large-scale climatic prediction of vegetation conditions can be statistically quantified by analysis of the spatial and temporal relationships between satellite-derived vegetation indices, NDVI, and precipitation (Tucker et al., 1986; Yang et al., 1998; Richard & Poccard; 1998; Ji & Peters, 2004). In our work, the spatial regression models between NDVI and precipitation for every year from 1985-2000 were constructed using a local spatial regression procedure, known as geographically weighted regression. These models expressed the quantitative relationship between vegetation and rainfall distribution at regional scale for each of the analysis years. The results of the statistical analysis proved a strong relationship between these variables. 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.

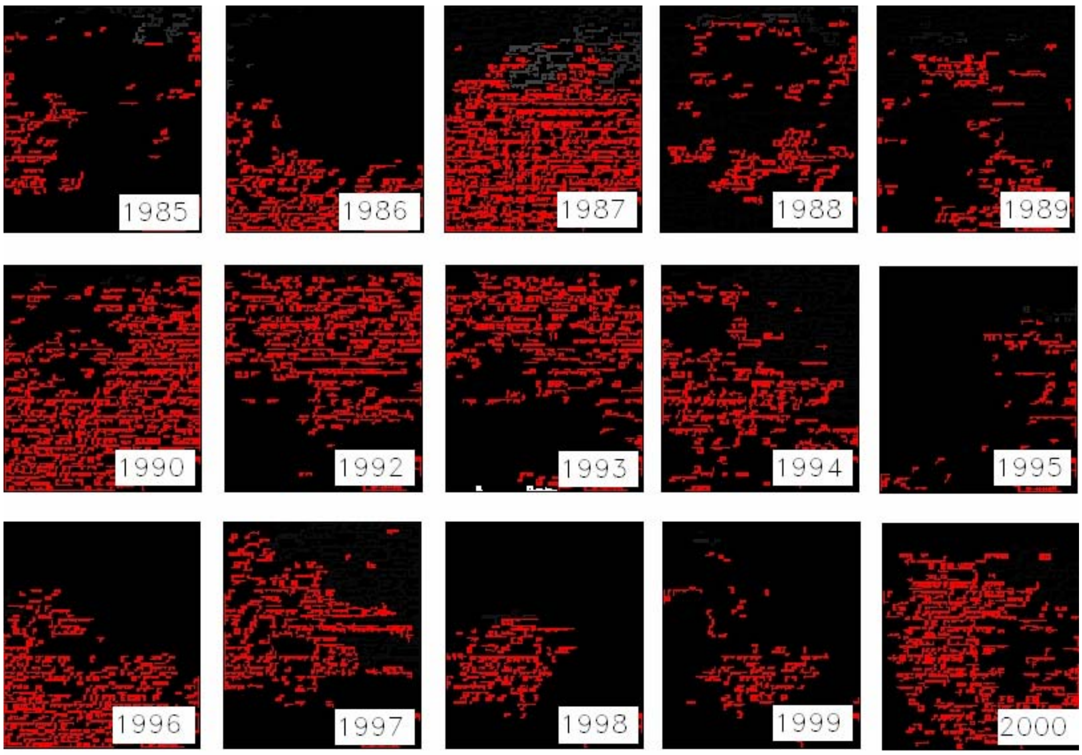


Figure 5. Maps of negative outliers (< 1 SEE) from the geographically weighted regression for every year, 1985-2000.

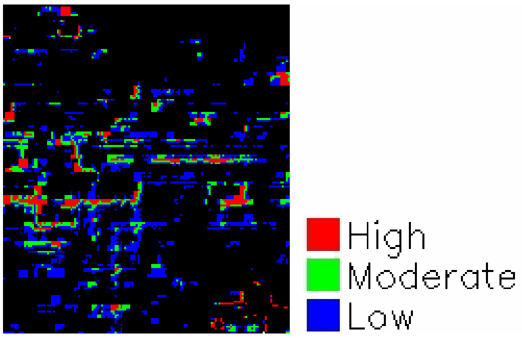


Figure 6. Running sum of outliers from the GWR over 1985-2000. Pixels with high value of outliers indicate severe degradation, pixels with moderate sum indicate moderate degradation, while pixels with low running sum of outliers present areas of slight degradation.

The technique for removing climate signal from NDVI time-series presented in our work gives new tools for evaluation of land performance/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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