ANALYSIS OF THE RELATIONSHIP BETWEEN NDVI AND CLIMATE VARIABLES IN MINNESOTA USING GEOGRAPHICALLY WEIGHTED REGRESSION AND SPATIAL INTERPOLATION

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ABSTRACT

In order to better understand the effects of climate change on ecosystems, the relationship between Normalized Difference Vegetation Index (NDVI) and atmospheric constituents have been explored widely by scientists using the global technique of Ordinary Least Squared (OLS) regression analysis. However, recent studies exploring such relationships at different spatial scales have revealed that local statistical approaches are more appropriate when the assumption of spatial stationarity is invalid. This study aims to explore the relationships between NDVI and the local level atmospheric constituents consisting of precipitation and temperature in the state of Minnesota from 1990 to 1997 using Geographically Weighted Regression (GWR) and spatial interpolation techniques. The analysis focuses on the summer months, when such relationships are more apparent in northern mid-latitude regions. In comparison to traditional OLS, there is a substantial improvement in the analysis using GWR with the average r^2 value improved from 0.24 to 0.67. The overall relationship between the different atmospheric constituents and NDVI were broadly consistent with the different types of land uses across the state with the highest correlation located in forested areas. The spatial patterns of the association between different climatic variables and NDVI in the form of regression coefficients were not very consistent over the years as result of inter-annual variations in the local climate.

INTRODUCTION

The role of prevailing climatic conditions on vegetation activity, especially the relationship of Normalized Difference Vegetation Index (NDVI) to climatic variables, has been widely validated across different regions of the world. At the regional scale, various studies have focused on arid or semi-arid areas where NDVI is highly sensitive to climatic fluctuations. For instance, Nicholson et al. (1990) compared the vegetation response to precipitation in Sahel and East Africa during 1982 to 1985 and found out that the spatial patterns of annually-integrated NDVI closely reflected mean annual precipitation. Nicholson and Farrar (1994) examined the variability of NDVI over semiarid Botswana during the period 1982-1987. Their study demonstrated a linear relationship between precipitation and NDVI when precipitation was less than approximately 500 mm/yr or 50-100 mm/month. Similar results were also found by Wang et al. (2003), who examined the temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA in Kansas and concluded relationship between precipitation and NDVI is strong and predictable when viewed at the appropriate spatial scale. There are also a number of different studies that have analyzed the influence of precipitation, temperature, atmospheric circulation on vegetation dynamics and biomass at high latitudes. In particular, Dye and Tucker (2003) studied the seasonality and trends of snow-cover, vegetation index, and temperature in northern Eurasia. Vicente-Serrano et al. (2006) analyzed the spatial distribution of the inter-annual variability of vegetation activity in central Siberia and its relationship with atmospheric circulation variability. The strongest relationships between the atmospheric circulation variability, climate and the NDVI variability were found in areas where the climatic characteristics are more limiting for the vegetation development.

At the global scale, Kawabata et al. (2001) analyzed inter-annual trends in annual and seasonal vegetation activities from 1982 to 1990 and its relationships to temperature and precipitation. Their study indicated increased vegetation activities over extensive regions in the northern middle-high latitudes, because of gradual increase in temperature. The empirical association between annual climate and seasonality of NDVI were also explored by Potter and Brooks (1998), who reported a time lag of 1 to 2 months in the monthly timing of NDVI extremes that is closely associated with seasonal patterns in maximum and minimum temperature and precipitation. They also concluded that regions in which NDVI seasonal extremes are not accurately predicted are mainly high latitude zones, mixed and disturbed vegetation types, and other remote locations where climate station data are sparse. Moreover, the geographical distribution of global greening trends and their climatic correlates was investigated by Xiao and Moody (2005). They reported that temperature was the primary climatic factor associated with greening in the northern high latitudes and Western Europe while precipitation was a strong correlate of greening in fragmented region only, while decreases in greenness in southern South America, southern Africa, and central Australia were strongly correlated to both increase in temperature and decreases in precipitation.

In majority of these studies, the global technique of Ordinary Least Squared (OLS) regression analysis was utilized. The OLS regression is based on the assumption of spatial stationarity, therefore, the use of this global technique over relatively wide areas is constrained by local level spatial variability of the observed relationships (Maselli, 2002). Compared to the OLS method, Geographically Weighted Regression (GWR) is a relatively new method that takes into consideration spatially varying relationships in a regression analysis (Fotheringham et al. 2002). The potential use of GWR to the remote sensing community has been revealed by Foody (2003).

The objective of this research study is to explore the relationships between NDVI and climatic variables (temperature and precipitation) at the local level in 225,000 km^2 Minnesota using GWR in comparison to the standard OLS regression. Minnesota has a centroid coordinates of 95.33^{o}W longitude and 46.03^{o}N latitude. Its monthly average temperatures range from a high of 28.6^{o}C to a low of -19.4^{o}C, with typical annual precipitation varying from more than 32 inches in southeast corner to less than 20 inches in the upper northwest area. The diverse vegetations and their spatial heterogeneity make Minnesota an ideal case study for analyzing local level vegetation dynamics in response to climatic variables using GWR analysis.

METHODOLOGY

Minnesota has a relatively short growing season restricted mainly to the summer season. We used biweekly summer Normalized Difference Vegetation Index (NDVI) composites from 1990 to 1997 that were obtained from the USGS Earth Resources Observation and Science (EROS) data center. These biweekly NDVI values were generated from 1-km NOAA AVHRR (Advanced Very High Resolution Radiometer) images. Daily climatic data were collected at the station-level for maximum and minimum temperatures, and precipitation from the Global Daily Climatology Network (GDCN) dataset 9101 v 1.0 (NCDC, 2006). For the entire state of Minnesota, the daily data for maximum and minimum temperatures, and precipitation were continuously and simultaneously available for about 68 stations. GAP land cover data, created for use in the US Geological Survey's Gap Analysis Program (GAP) project, were used as the weight variable in GWR analysis.

Both the OLS method of multiple linear regression (Equation 1) and GWR analysis (Equation 2) are examined and compared.

$$NDVI = \beta_0 + \beta_1 T_{Max} + \beta_2 T_{Min} + \beta_3 P + \varepsilon \quad (1)$$

where T_{max} and T_{min} are the summer season maximum temperature and minimum temperature. P is summer average precipitation. β_0, β_1, β_2, and β_3 are the slopes and ε is the residual.

$$NDVI(u,v) = \beta_0(u,v) + \beta_1(u,v)T_{Max} + \beta_2(u,v)T_{Min} + \beta_3(u,v)P + \varepsilon(u,v) \qquad (2)$$

where *(u,v)* are the coordinates of location of a particular point in surface.

From above equations we can see, the GWR method takes into consideration the local variations in rates of change with resulting coefficients calculated by the model that is specific to each location (u, v). The GWR analysis was conducted using an adaptive kernel method in cases where the bandwidth associated with the regression points were widely spaced was greater than where the regression points were more closely spaced. Land cover data were used as weight variables. The analysis also included the calculation of Monte Carlo significance test used for determining the levels of significance in spatial non-stationarity (Brundson et al., 1996). The results of GWR analysis, consisting of the local r-squared values, and regression coefficients for the different independent variables, were next mapped using ordinary kriging, which was selected over other methods of surface interpolation due to its lower root mean square error and best representation of the interpolated surface.

ANALYSIS AND RESULTS

Daily climate data and NDVI values were compiled into annual summer season averages recorded at 68 stations. For each year a separate matrix, NDVI, average precipitation, maximum, and minimum temperatures over the summer season were created for each station. The average biweekly summer season maximum temperatures for the entire station network over the eight year time period was 22.7^{o}C while the seasonal average minimum was 10.5^{o}C. The spatial patterns for the distribution of temperatures showed an overall north to south gradient. The spatial patterns of precipitation across the state also showed similar patterns with a relatively greater amount of summer biweekly precipitation occurring in the southern parts of the state that was about 4.8 inches with an average value for the entire state of 3.2 inches. The spatial and temporal patterns of NDVI values ranged from approximately 100 for water bodies to the highest value of around 171 for highly vegetated areas 1990 to 1997 for most of the years extending from 1990 to 1997. The average biweekly NDVI also demonstrates spatial patterns. The highest NDVI values are concentrated in the northeast corner (Figure 1).

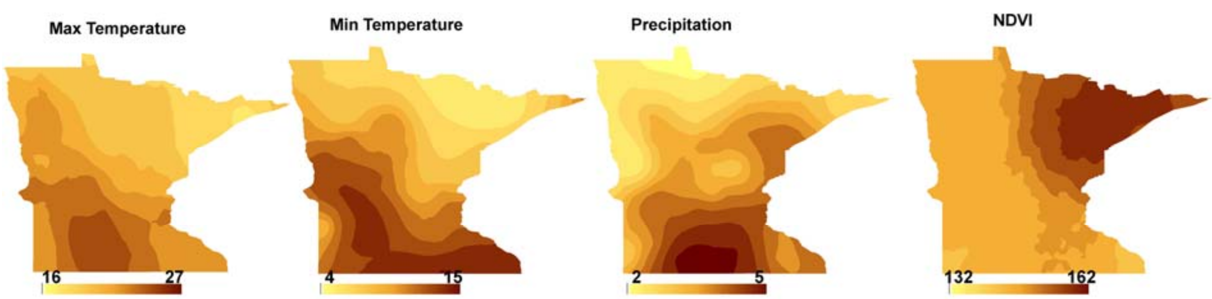

Figure 1. Average biweekly values for the climate variables and NDVI

A comparative summary of the results from OLS and GWR analyses are summarized in Table 1. It is evident there was a substantial improvement in the analysis using GWR since the average r^2 value improved from 0.24 to 0.67. These results reveal apparent spatial non-stationarity in the relationship between the NDVI and the atmospheric constituents. The overall improvement in residuals between the two analyses also verified importance of micro level processes in the relationship among different variables. In addition, Table 1 shows the significance level for the different independent variables calculated by Monte Carlo simulation exhibited the highest significant role of precipitation during 1991 and extreme temperatures during 1997 on the resulting NDVI values with nearly 0.0 p-value. On the contrary, the lowest significant value was observed in 1992 with a p-value of 0.99 for maximum temperatures. The overall spatial patterns of NDVI showed the strongest response to the prevailing precipitation conditions except for the case of 1996. In contrast, the responses of NDVI patterns to temperatures were more variable from year to year. Compared to minimum temperatures, the maximum temperatures showed higher impact on the dependent NDVI patterns.

Table 1. Comparative summary of results from OLS and GWR analysis.

Year	OLS R^2	GWR R^2	Monte Carlo Significance Level (p-value for independent variables)		
			T_{min}	T_{max}	Precipitation
1990	0.22	0.61	0.96	0.60	*0.13*
1991	0.23	0.67	0.86	0.84	**0.00**
1992	0.09	0.62	0.34	0.99	0.23
1993	0.26	0.65	0.23	0.30	*0.11*
1994	0.09	0.66	0.32	0.79	*0.12*
1995	0.41	0.74	0.97	0.20	*0.14*
1996	0.33	0.64	0.77	0.94	0.83
1997	0.30	0.75	**0.00**	**0.00**	0.40

The overall spatial patterns for the local r^2 values are broadly similar across the state during the study period for the 8 years. The eight-year average local r-square values across the entire state between NDVI and climatic variables were interpolated and mapped in Figure 2. The lowest local r^2 values can be found in the southeastern and northwestern parts of the state, whereas the greatest explained variance concentrated in the northeast-southwest central axis across the state.

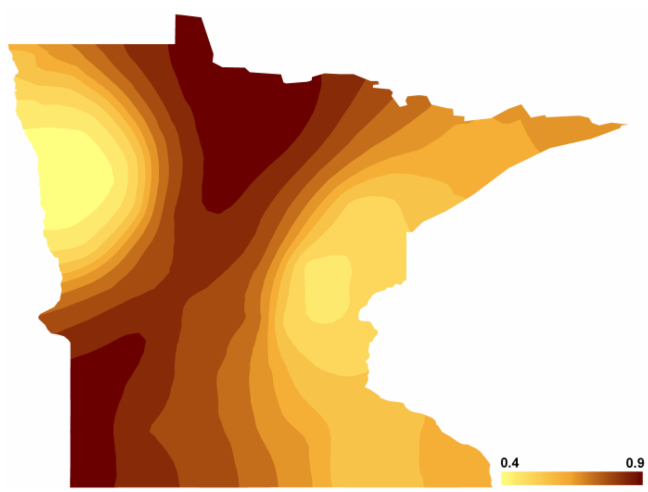

Figure 2. Spatial patterns of average local R-squared value from 1990 to 1997 calculated by GWR analysis.

In view of the objective of the present study to determine the relative role of selected independent variables on seasonal level NDVI values, regression coefficients for each of the independent variables were also interpolated and mapped in Figure 3. Generally, similar coefficient patterns can be found in the wet years including 1991, 1993, and 1995, while more variable patterns were demonstrated in dry years of 1992 and 1996. The responses of NDVI to maximum temperatures were mostly positive during 1994 and 1997. However for the rest of the years, negative associations are predominant. Comparatively, the southern cultivated region of the state was more variable over the years. For the roles of minimum temperature on seasonal NDVI values, the generally negative coefficient values implies that higher the summer minimum temperatures, the worse the NDVI for our study area. The unusual years of cool and dry 1992, and dry 1996 demonstrated spatially different coefficient patterns.

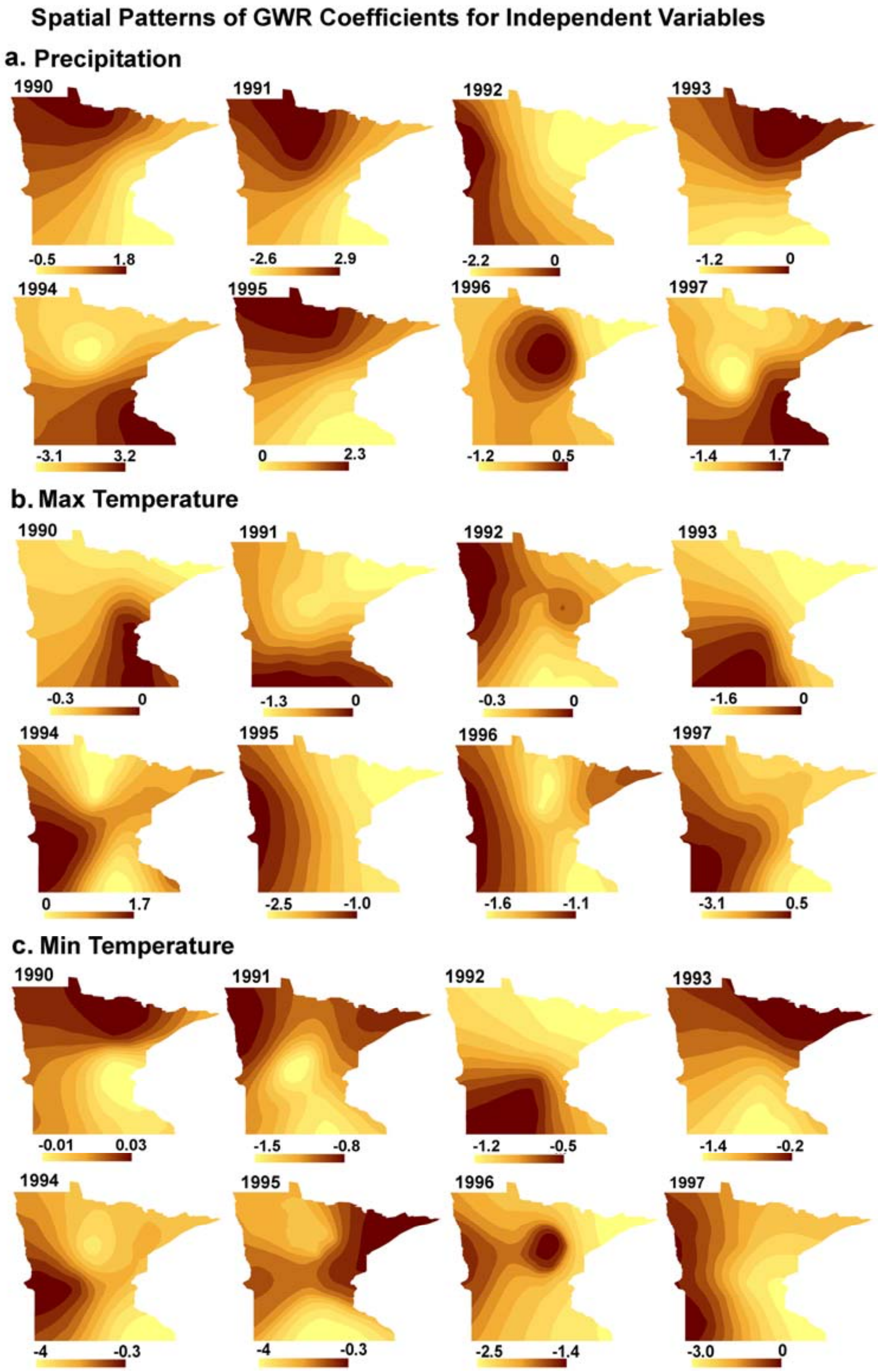

Figure 3. Spatial patterns of regression coefficients showing the strength of the relationship between NDVI and climatic variables.

CONCLUSIONS

This study explores the role of atmospheric constituents specifically precipitation, maximum and minimum temperatures on the spatial patterns of NDVI across the state of Minnesota. Our results indicate the relatively better predictive capacity of GWR in detecting the role of local level processes on the resulting spatial patterns. The overall relationship between the different atmospheric constituents and NDVI were broadly consistent with the land use types, with the highest correlation located in northeast forested areas and lowest associations located in the predominantly developed areas in northwestern and southwestern Minnesota. The inter-annual variations of the spatial patterns of coefficients between climatic variables and NDVI were decided by the yearly changing weather conditions. GWR may be an effective method of analyzing spatially varying relations between NDVI and climatic variables.

REFERENCES

Dye, D. G., and C. J. Tucker, 2003, Seasonality and trends of snow-cover, vegetation index, and temperature in northern Eurasia. *Geophysical Research Letters*, 30 (7): Art. No. 1405

Foody, G. M, 2003, Geographical weighting as a further refinement to regression modelling: An example focused on the NDVI–precipitation relationship. *Remote Sensing of Environment*, 88: 283-293.

Fotheringham, A. S., Brunsdon, C., and M. E., Charlton, 2002, *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*, Chichester: Wiley, pp282.

Kawabata, A., Ichii, K., and Y. Yamaguchi, 2001, Global monitoring of interannual changes in vegetation activities using NDVI and its relationships to temperature and precipitation. *International Journal of Remote Sensing*, 22(7): 1377-1382.

Maselli, F., 2002, Improved estimation of environmental parameters through locally calibrated multivariate regression analyses. *Photogrammetric Engineering and Remote Sensing*, 68: 1163– 1171.

Nicholson, S. E., M. L. Davenport, and A. R. Malo, 1990, A comparison of the vegetation response to precipitation in the Sahel and East Africa, using normalized difference vegetation index from NOAA AVHRR. *Climatic Change*, 17(2-): 209-241.

Nicholson, S. E. and T. J. Farrar, 1994, The influence of soil type on the relationships between NDVI, precipitation, and soil moisture in semiarid Botswana. I. NDVI response to precipitation. *Remote Sensing of Environment*, 50(2): 107-120.

Potter C. S. and V. Brooks, 1998, Global analysis of empirical relations between annual climate and seasonality of NDVI. *International Journal of Remote Sensing*, 19(15): 2921-2948.

Vicente-Serrano, S. M., Grippa, M., Delbart, N., Toan, T. L., and L. Kergoat, 2006, Influence of seasonal pressure patterns on temporal variability of vegetation activity in central Siberia. *International Journal of Climatology*, 26: 303-321.

Wang, J., P. M. Rich, and K. P. Price, 2003, Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. *International Journal of Remote Sensing*, 24(11): 2345-2364.

Xiao and Moody, 2005, Geographical distribution of global greening trends and their climatic correlates: 1982 – 1998. *International Journal of Remote Sensing,* 26(11): 2371-2390.