Climate factors controlling NDVI along Rights-of-Way of petroleum/gas pipelines for planning of revegetation

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Abstract: The main goal of these studies was to determine main climatic factors controlling the regrowth of vegetation cover (VC) along the corridor of BTC and SCP pipelines. Standard multiple, spatial and geographically weighted regression models were used to determine main climate factors controlling VC. Annual precipitation, evapotranspiration and land surface temperature were determined to be main controlling factors of Normalized Difference Vegetation Index (NDVI) over grasslands. Annual precipitation, evapotranspiration and minimum temperature were determined to be main factors controlling NDVI of croplands. Geographically weighted regression model revealed that the regression models are variable along the corridor of pipelines.

KEYWORDS: NDVI, climatic factors, VC, BTC, SCP

1. Introduction

The construction activities of BTC and SCP resulted in the disturbance of grasslands and croplands in Azerbaijan. The 44 m wide and 442 km long oil and gas pipelines passing through Azerbaijan required careful planning of revegetation activities after the completion of construction. In this study, NDVI is used to assess VC because NDVI is a proxy for aboveground biomass and it is highly correlated to green-leaf density (Liu et al. 2010). Better understanding of the controlling climate factors of NDVI is essential for the economic planning and implementation of the revegetation activities.

2. Study area

The study area is 442 km long corridor of BTC and SCP pipelines routed parallel to each other within the 44 m wide Rights-of-Way (RoW) in Azerbaijan. Both of these pipelines are underground and the average depth of cover varies 1–30 m depending on the terrain characteristics (Fig. 1).

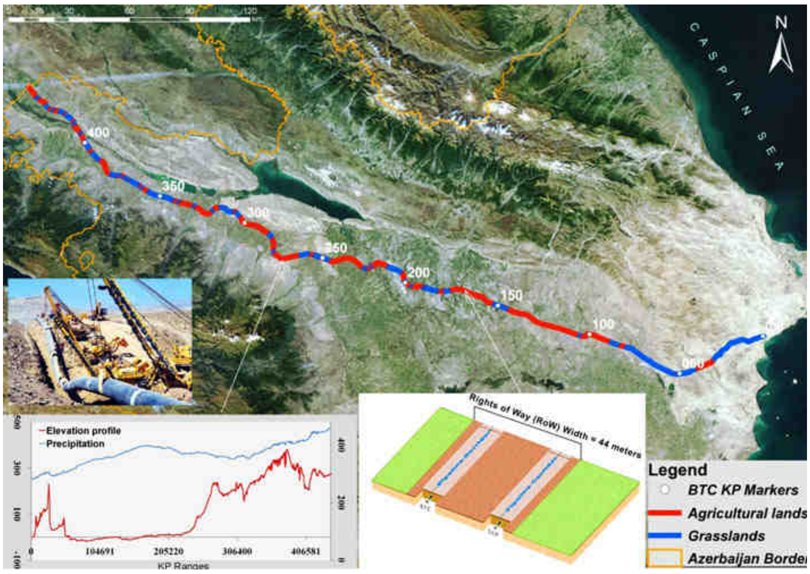

Figure 1. Map of the corridor of BTC oil and SCP gas pipelines passing over Azerbaijan

3. Materials and methods

3.1 Data for statistical analysis

MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI 16-day composite product from NASA with the spatial resolution of 250 m was used in this research to monitor VC along the corridor of pipelines. MODIS LST data for an 8day composite with the spatial resolution of 1 km was acquired for the same vegetation peak months. Digital Elevation Model (DEM) of 10 m spatial resolution was used. The TMIN, TMAX and annual PRECIP were acquired from the WorldClim – Global Climate Data. The MOD16 ET datasets used are estimated using ET algorithm described in Mu et al. (2007). SOLRAD was computed based on the methods from the hemispherical viewshed algorithm developed by Fu and Rich (2002). The IKONOS high resolution multispectral images acquired along RoW in 2007 were used to compute the NDVI with the spatial resolution of 4 m.

100 m long and 44 m wide polygons were created by the division of the RoW corridor. As a result of this, 4410 total polygons were developed along RoW. In each polygon, the pixel values of MODIS and IKONOS NDVIs, precipitation (PRECIP), evapotranspiration (ET), land surface temperature (LST), minimum temperature (TMIN), maximum temperature (TMAX) and solar radiation (SOLRAD) were averaged using the method of zonal statistics. These data was used for running of statistical regression models.

3.2 Standard multiples regression model

A multiple linear regression analysis is performed for grasslands and croplands using the dependent variable NDVI and predictor variables as PRECIP, ET, Tmax, Tmin, LST and SOLRAD. The full linear regression model equation is expressed as follows in Equation 1 (Ji et al. 2004).

$$NDVI_{grass/crop} = \beta_0 + \beta_1(PRECIP) + \beta_2(ET) + \beta_3(TMAX) + \\ + \beta_4(TMIN) + \beta_5(LST) + \beta_6(SOLRAD) + \varepsilon \quad (1)$$

3.3 Maximum likelihood spatial error model

Spatial regression model as simultaneous autoregressive (SAR) models considers spatial autocorrelation of residuals as an additional variable in the regression equation and adds the normalization effect in the estimation of the significance of independent variables (Ji et al. 2004). The parameters for the spatial regression models are estimated based on the maximum likelihood procedure. The SAR model, or the spatial error model, is formulated as follows in Equation 2 (Erener et al. 2010).

$$Y = Xc + \rho Uy + a \quad (2)$$

Where a Vector of errors with zero mean and constant variance σ^2, U Proximity matrix ρ Interaction parameter or spatial autoregressive coefficient, c is the parameter to be estimated due to relationship between the variables.

3.4 Geographically weighted regression (GWR)

Since the relationship between the dependent variable (NDVI) and predictor variables can vary over space, it was also necessary to consider a local modeling technique. GWR estimates parameters along RoW and contributes to the determination of local variations along pipelines. GWR is represented in Equation 3:

$$y = R_0(\mu,\nu) + R_1(\mu,\nu)j_1 + ... + R_n(\mu,\nu)j_n + q \quad (3)$$

where y is the dependent variable; j_1 to j_n are the independent variables; (μ,ν) denotes the sample coordinate in space; and q is the error term.

The parameter R is estimated from:

$$\hat{R}(\mu,\nu) = (X^T W(\mu,\nu) X)^{-1} X^T W(\mu,\nu) y \quad (4)$$

where $\hat{R}(\mu,\nu)$ is the estimate from R, $W(\mu,\nu)$ is the weighting matrix, ensuring that observations near the location have greater influence than those far away.

4. Results and discussions

4.1. Standard multiples regression model and ridge standardized regression procedure for grasslands and croplands

Because of high correlation between the predictor variables, the presence of multi-collinearity was assumed for the regression models of both grasslands and croplands. Based on the ridge standardized regression procedure, the multi-collinearity was eliminated in the subset regression model.

4.2. Global spatial regression model

The spatial regression procedure based on the maximum likelihood procedure showed the predictor variables which were no longer significant at the $\alpha = 0.05$ level. Values > 0.05 are considered to be non-significant in Table 1. The spatial regression for grasslands determined that Tmin is not significant (Table 1). For croplands LST was not significant in the regression model (Table 1). The model was rerun for both grasslands and croplands without Tmin in case of grasslands and LST in case of croplands. The results were $R^2 = 0.70$ for grasslands and $R^2 = 0.47$ for croplands. Equation 5 is the resulting regression model for grasslands, and Equation 6 is for croplands. It can clearly be observed in Table 1 that LST, PRECIP and ET are the most important factors in controlling of NDVI of grasslands. In case of croplands, these factors are PRECIP, ET and Tmin.

Table 1 Coefficient estimates of the spatial regression model for grasslands and croplands (1st and 2nd run)

VARIABLE	Model run	Landuse	Coefficient estimate	Std. Error	t value	Sig.
Intercept	1	Grasslands	100.35	1.86	53.95	0.00
		Croplands	127.60	0.10	127.64	0.00
	2	Grasslands	100.34	1.85	54.26	0.00
		Croplands	127.19	0.97	130.69	0.00
LST	1	Grasslands	-3.19	0.72	-4.45	0.00
		Croplands	0.72	0.45	1.59	0.11
	2	Grasslands	-3.19	0.72	-4.44	0.00
		Croplands	N/A	N/A	N/A	N/A
PRECIP	1	Grasslands	19.50	1.99	9.78	0.00
		Croplands	7.07	1.06	6.64	0.00
	2	Grasslands	19.22	1.96	9.81	0.00
		Croplands	6.72	1.05	6.43	0.00
ET	1	Grasslands	-2.75	0.76	-3.61	0.00
		Croplands	1.57	0.37	4.29	0.00
	2	Grasslands	-2.77	0.76	-3.64	0.00
		Croplands	1.56	0.37	4.26	0.00
TMIN	1	Grasslands	1.26	1.38	0.91	0.36
		Croplands	7.67	1.09	7.06	0.00
	2	Grasslands	N/A	N/A	N/A	N/A
		Croplands	7.91	1.08	7.33	0.00

$$NDVI_{grass} = 100.34 - 3.19\ (LST) + 19.22\ (PRECIP) - 2.77\ (ET) \quad (5)$$

$$NDVI_{crop} = 127.19 + 1.56\ (ET) + 7.91\ (TMIN) + 6.72\ (PRECIP) \quad (6)$$

4.3 Geographically weighted regression (GWR)

The GWR analyses, compared to the global regression results, clearly revealed spatial non-stationary between NDVI of grasslands and croplands and the predictor variables (Table 2). With GWR, R^2 increased markedly to 0.82 and 0.75 for grasslands and croplands, respectively.

Table 2 Local and global regression estimates and diagnostics for grasslands and croplands

Predictor variables	GSRM parameter estimate		GWR parameter estimates	
	Grasslands	Croplands	Grasslands	Croplands
LST	-3.19	N/A	-432.43 to 75.37	N/A
PRECIP	19.22	6.72	-1370.71 to 548.94	-239.88 to 209.78
ET	-2.77	1.56	-75.84 to 89.41	-37.44 to 33.24

TMIN	N/A	7.91	N/A	-110.76 to 148.24
INTERCEPT	100.34	127.19	-35.61 to 743.92	-370.95 to 317.62
Diagnostics				
Adjusted R^2	0.70	0.47	0.82	0.75
AICc	8815.03	17156.1	1219.93	7054.33

5. Conclusions

Standard multiple regression model was not optimal for revealing of the main predictor variables controlling NDVI of grasslands and croplands along RoW. Based on the global spatial regression model, PRECIP, LST and ET were determined as the main climate factors controlling NDVI of grasslands along RoW. In case of croplands, PRECIP, ET and TMIN were determined as the main factors controlling NDVI of croplands. The regression models predicting NDVI for grasslands and croplands were formulated as follows:

$$NDVI_{grass} = 100.34 - 3.19\ (LST) + 19.22\ (PRECIP) - 2.77\ (ET)$$

$$NDVI_{crop} = 127.19 + 1.56\ (ET) + 7.91\ (TMIN) + 6.72\ (PRECIP)$$

The GWR analyses in comparison with the global regression models results clearly revealed that the relationship between NDVI of grasslands and croplands and the predictor variables was spatially non-stationary along RoW.

Quantitative assessment of climate and ground factors controlling VC may provide the possibilities of better planning for the revegetation and erosion control activities along the corridor of pipelines. This may also reduce the investments for the high-resolution aerial and satellite imagery required by the environmental monitoring of restoration activities along the narrow and long-range RoW of pipelines.

6. References

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7. Biography

Emil Bayramov is the Chartered GIS specialist from RGS with 12 years experience. Emil also specializes in RS and Geomatics. Emil holds BSc in Geography, MSc in GIS from Lund University and pursues PhD in Natural Sciences at Dresden University of Technology. Emil works for BP on the position of GIS Coordinator of Oil and Gas pipelines.