Land Use Change Factors in Kathmandu Valley: A GWR Approach

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1. Introduction

Understanding the causes and consequences of land use change (LUC) to explore the extent and location of future landscape changes are very important. The driving factors that influence the magnitude and extent of LUC are often related to the functioning of local and regional policies and demographic conditions. Kathmandu Valley which is the most populous metropolitan region in Nepal, has been facing rapid urbanization over the last three decades (Thapa et al. 2008). The transformation of agricultural land into urban/built-up areas in the valley was escalated in 1991-2000 (Thapa and Murayama 2009). The urbanization pressure led to a population influx, an increase in motorized transport, a loss of agricultural land, and ultimately an alteration to the land use patterns in the valley. Therefore, identifying relationship between the LUC and associated factors is essential for understanding the urbanization process in the valley. This paper aims to explore LUC factors in the valley applying Geographically Weighted Regression (GWR). Kathmandu, a bowl shaped valley is a unique case to study as it imposes topographic constraints for horizontal urban expansion but faces rapid urbanization. A broad range of environments from highly urbanized to suburban to very rural areas in a complex mountainous area are existed where GWR can provide better insights to understand the urbanization process.

The conventional model such as Ordinary Least Squares (OLS) conveys only a single set of parameter estimates assuming to apply equally to all parts of the region (eq. 1).

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad (1)$$

where y_i is the estimated value of the dependent variable for observation *i*, β_0 is the intercept, β_k is the parameter estimate for variable *k*, x_{ik} is the value for the *k*th variable for observation *i* and ε_i is the error term.

In OLS, the parameter estimates β_k are assumed to be spatially stationary. But in reality, there will be intrinsic differences in relationships over space which may be non-stationary character. The non-stationary problem can be measured using GWR (Fotheringham et al. 2002, Platt 2004). Conceptually, the GWR permits the parameter estimates of a multiple linear regression model to vary locally (eq. 2).

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \qquad (2)$$

where (u_i, v_i) denotes the coordinates of the *i*th location of the observation *i* (Fotheringham et al. 2002).

2. Data and Method

The map of land use changes in 1991-2000 (fig. 1) of Kathmandu Valley was taken from Thapa and Murayama (2009) which is dependent variable in this study. The study area comprises of 5 municipal urban centres and 97 surrounding villages creating a total of 102 administrative polygons within the valley. LUC is an interactive function of biophysical and socioeconomic factors. Identifying explanatory factors that explain the LUC in the valley is the most challenging task. We assessed many explanatory variables such as population change, the distance to road, existing built-up surface, industrial estates, and rivers, the agricultural, forest and shrubs lands for the year 1991, slope, and five more, using scatter-plot, correlation, OLS (eq. 1), and spatial autocorrelation analysis techniques. Highly correlated variables were filtered out after examining correlation and scatter-plot results. The eq.1 was run to identify the contribution of each explanatory variable, statistically significance, and multicollinearity. After several combination tests performed, the following combination (eq. 3) provided best indication for local regression modelling (table 1).

$$LUCM2_i = \beta_0 + \beta_1 Popch01\_91 + \beta_2 Agarea91m2 + \beta_3 Mslope\_pct + \beta_4 Frstshrb91 + \beta_5 Md2wat91 + \beta_6 Md2road91 + \varepsilon_i \qquad (3)$$

where, *LUCM2*: LUC (1991-2000) in m^2, *Popch91_01*: Population changed in 1991-2001, *Agarea91m2*: Agricultural area in m^2 (1991), *Mslope_pct*: Mean slope in %, *Frstshrb91*: Forest and shrubs land m^2 (1991), *Md2wat91*: Mean distance to water areas in m (1991), *Md2road91*: Mean distance to road in m (1991).

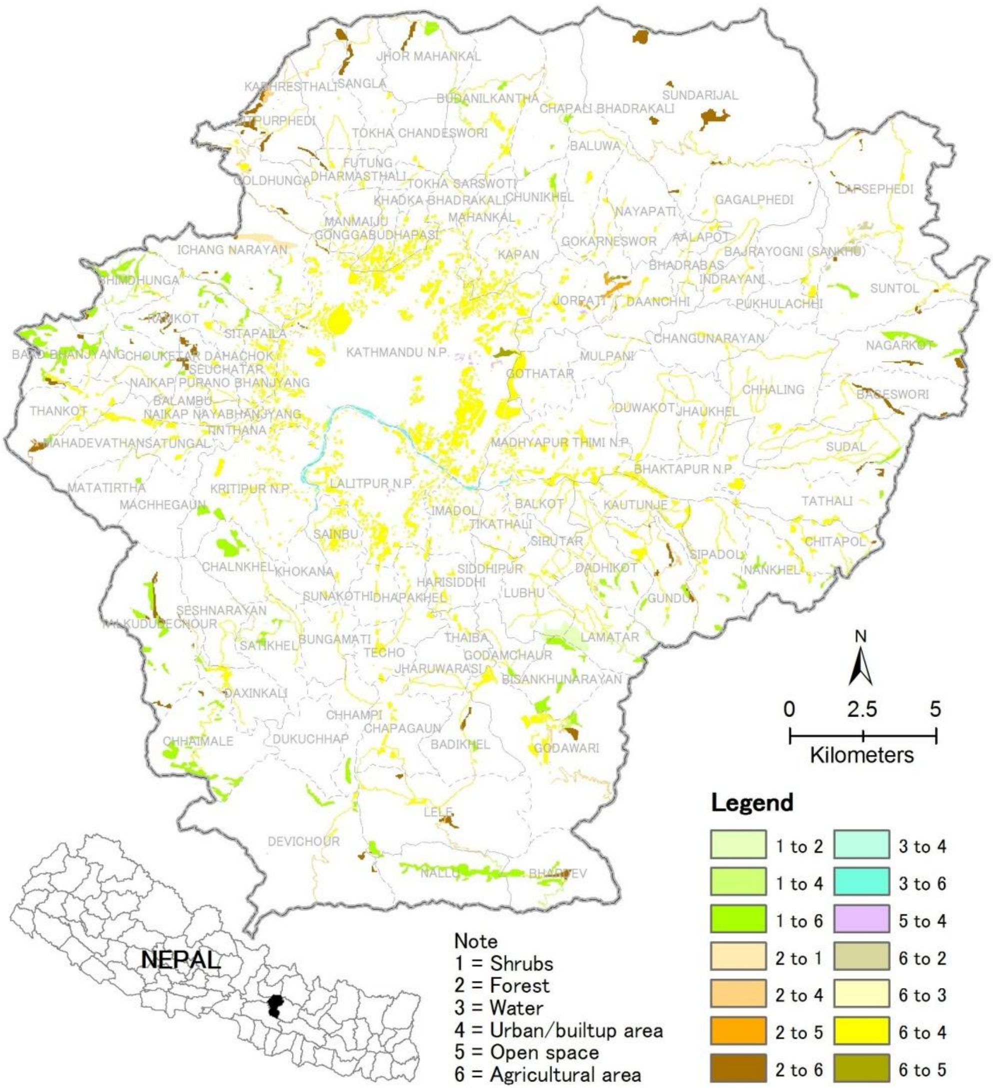

Figure 1. Land use changes in Kathmandu Valley, Nepal (1991-2000)
(Source: Thapa 2009)

Variable	Coefficient	StdError	t-Statistic	Probability	VIF[1]
Intercept	-30501.897	55811.810	-0.546	0.585998	--------
Popch91_01	35.164	1.0847	32.416	0.000000*	1.512
Agarea91m2	0.029	0.010	2.718	0.007799*	1.494
Mslope_pct	6035.260	2462.808	2.450	0.016087*	1.852
Frstshrb91	0.029	0.007	3.861	0.000211*	1.740
Md2wat91	133.365	60.168	2.216	0.029035*	1.125
Md2road91	-14.386	24.682	-0.582	0.561368	1.661
Akaike's Information Criterion (AIC)					2809
Adjusted R^2					0.945

*Statistically significant at the 0.05 level. [1]Variance Inflation Factor

Table 1. Summary of OLS Results

High explanatory power evident by adjusted-R^2 (0.94) (table 1), comparatively low AIC (2809), and no multicollinearity noticed with lower VIF (<2) have shown the best model performance. All the variables, excluding Mdroad91 are statistically significant at 0.05 level. The coefficient values further justify the relationship contribution of each variable to LUC. The spatial autocorrelation test revealed Moran's-I with 0.07 which is, of course, a little evidence of any autocorrelation but the pattern may be due to random choice. Although the OLS model produces a single set of parameter estimates but it provided several clues for GWR modelling. The model eq. 3 was calibrated using GWR (eq. 2).

3. GWR Results and discussion

The model result is improved while calibrating in GWR with the adjusted-R^2 of 0.96. However, the R^2 values varied spatially ranging from 0.53 to 0.99 (fig. 2.a). The AICs estimate similar to OLS which is increased by 1; a minor increase in AICs is fine on local modelling (Fotheringham et al. 2002). The spatial patterns of residuals in fig 2.b show some under prediction and over prediction. Some villages such as Baad Bhanjyang in the west and Devichour in the south are in extreme over predictions and under predictions respectively. However the model exhibits no spatial autocorrelation as evidenced by Moran's-I (0.01), which means the residuals of the over and under predictions are randomly distributed.

The GWR model has the highest explanatory power (R^2>0.97) in the urban centres and some northern adjacent villages, Kathmandu, Lalitpur, and Kritipur urban centres, Gonggabu, Dhapasi, Khadka Bhadrakali, Mahankal, and Budhanilkantha villages, for example. The eastern and southern villages: Devichour, Nallu, Bhardev, and Lele have lowest (<0.66) explanatory power. It shows the parameter estimates varied locally based on explanatory variables existence. Looking at the coefficient maps (fig. 2.c-h), the agricultural area in 1991 seems more prevalent in the urban centres and the nearby villages. Much of the agricultural land in these areas welcomed development projects in the 1990s giving higher impact to LUC from agricultural to built-up surface. However, this is not the case in far northern villages where the LUC is promoted by road, river, slope, and population increase. The influences of slope and population change are also observed in the southern villages but model performance in these areas is a bit poor. The LUC in the western villages are mainly influenced by the forest and shrubs lands in 1991. Agriculture encroachment over forest and shrubs lands occurred during the period. The overall result has a little contradiction with the LUC study of Ogneva-Himmelberger et al. (2009) where they found lowest explanatory power in the major cities in Massachusetts.

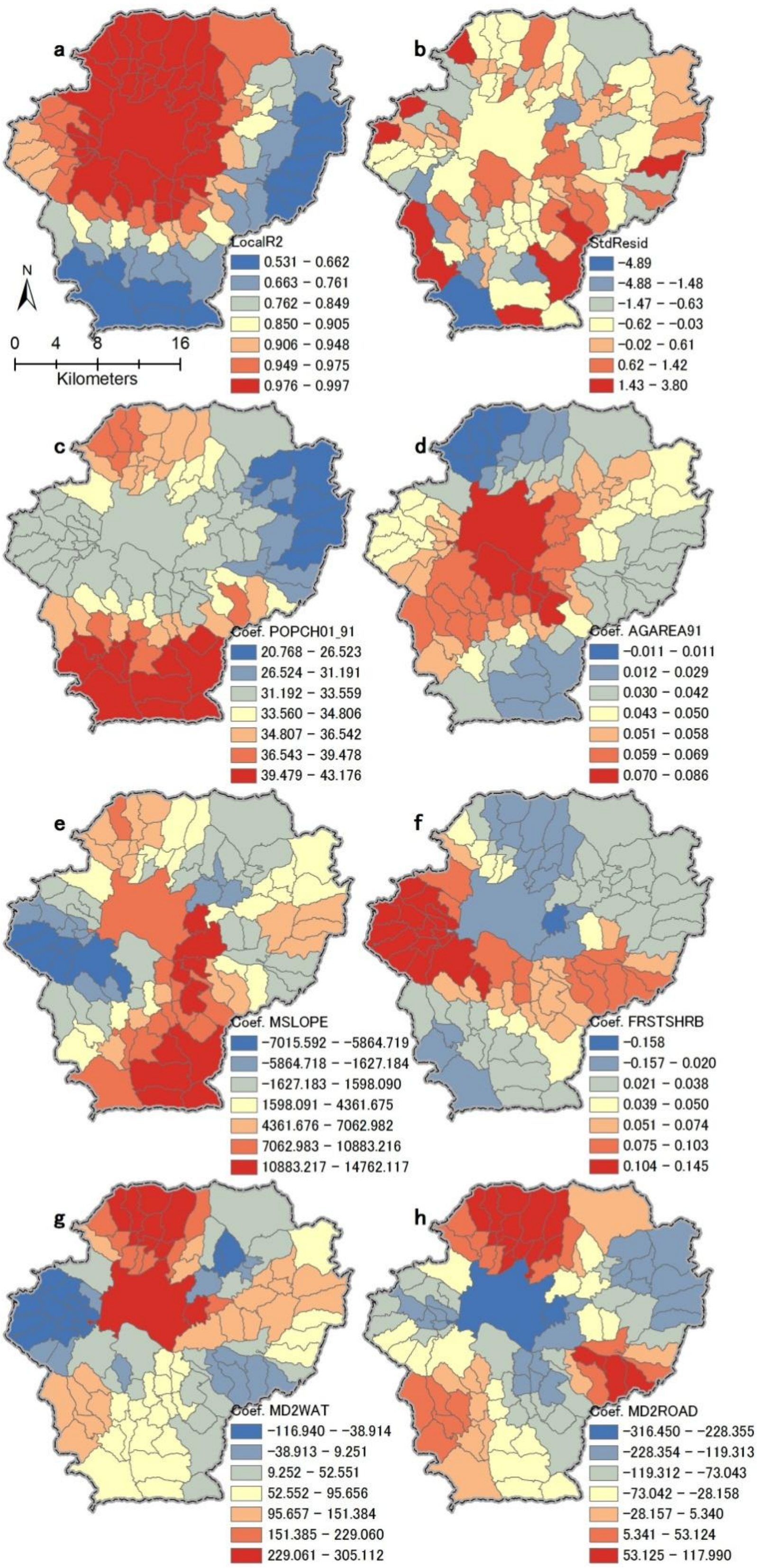

Figure 2. Parameter estimates of GWR: a. Local R^2, b. Std. Residuals, c. Popch91_01, d. Agarea91m2, e. Mslope_pct, f. Frstshrb91, g. Md2wat91, and h. Md2road91

4. Conclusion

The causes of LUC in the Kathmandu valley are examined using GWR approach. The LUC in the valley is influenced by available agricultural and forest/shrubs lands, population influx, slope of land, access to water and roads. However, the degree of influence of each variable varied at different location. The GWR model explained considerably more variance in the relationship of the explanatory factors compared to conventional OLS models. The random distribution of standard residuals confirmed that the probability of missing variables to explain LUC in the valley is very low, which further strengthen the model. The localized regression estimates exhibited the relationships between the dependent and explanatory variables varied spatially. In general, models tend to predict better in major cities and adjacent villages where the gradient of change in values from one village to next is low.

The LUC exploration model developed in this research is passed several bottle-neck parameter estimates from conventional model to local model demonstrating a unique example of local spatial modelling, especially to understand the urbanization process in traditional city developed in complex mountain terrains.

5. Acknowledgement

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