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Original Article

Land use intensity dynamics in the Andhikhola watershed, middle hill of Nepal

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Abstract: Land use intensity is a valuable concept to understand integrated land use system, which is unlike the traditional approach of analysis that often examines one or a few aspects of land use disregarding multidimensionality of the intensification process in the complex land system. Land use intensity is based on an integrative conceptual framework focusing on both inputs to and outputs from the land. Geographers' non-stationary data-analysis technique is very suitable for most of the spatial data analysis. Our study was carried out in the northeast part of the Andhikhola watershed lying in the Middle Hills of Nepal, where over the last two decades, heavy loss of labor due to outmigration of rural farmers and increasing urbanization in the relatively easy accessible lowland areas has caused agricultural land abandonment. Our intention in this study was to ascertain factors of spatial pattern of intensity dynamism between human and nature relationships in the integrated traditional agricultural system. High resolution aerial photo and multispectral satellite image were used to derive data on land use and land cover. In addition, field verification, information collected from the field and census report were other data sources. Explanatory variables were derived from those digital and analogue data. Ordinary Least Square (OLS) technique was used for filtering of the variables. Geographically Weighted Regression (GWR) model was used to identify major determining factors of land use intensity dynamics. Moran's I technique was used for model validation. GWR model was executed to identify the strength of explanatory variables explaining change of land use intensity. Accordingly, 10 variables were identified having the greatest strength to explain land use intensity change in the study area, of which physical variables such as slope gradient, temperature and solar radiation revealed the

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highest strength followed by variables of accessibility and natural resource. Depopulation in recent decades has been a major driver of land use intensity change but spatial variability of land use intensity was highly controlled by physical suitability, accessibility and availability of natural resources.

Keywords: Explanatory variable; GWR model; Land use intensity; Multivariate analysis; Spatial statistics

1 Introduction

Traditional approaches of land use study often examine one or a few aspects of land use intensity, disregarding the multidimensionality of the intensification process in the complex land system (Lambin and Meyfroidt 2011). Analysis and monitoring of land use intensity require an integrative conceptual framework that focuses on inputs to the land, outputs from the land, and the human induced, but unintended outcomes of land use intensification (Erb et al. 2013). Traditional insensitive subsistence farming system of Nepal combines both crop farming and livestock rearing, where natural resources such as arable land (both private and public), forest, grazing/ grassland and water play a crucial role (Malla and Chidi 1997). Thus, disturbance on one of these resources and activities upsets the whole integrated farming system. Agricultural landscape is human driven in which socioeconomic and biophysical variables of the land use and land cover change are often considered as driving factor (Barton et al. 2010). This is why land use/land cover is a significant element for the interconnection of human activities and environment monitoring (Halimi et al. 2018). A typical strategy for analyzing the spatial distribution of land use/land cover starts with revealing the land transitions, quantifying the pattern of change, and identifying the processes of change (Macleod and Congalton 1998). The spatial pattern of land use intensity is very essential to monitor the various factors of land use change (Kuemmerle et al. 2013). Therefore, quantification of land use and its intensity are the basic requirement for scientific analysis of land use and land cover with its multiple determining factors. Geographers have developed Geographically Weighted Regression (GWR) model which is non-stationary data-analysis technique (Oshan and Fotheringham 2018) differing from the stationary OLS regression giving local variability of determining factors. This model accounts local heterogeneity of relationship between response variable and its explanatory one in which the relationship between variables decreases with increasing spatial distance. This model has been used to analyze the spatial variability of relationship among variables (Li et al. 2019; Liu et al. 2019).

Remote sensing image data due to efficient, cost effective and higher accuracy are widely applied for land use/land cover change analysis. These data can be used for monitoring even in the mountainous and remote areas (Andualem et al. 2018; Chaikaew 2019). High resolution satellite image is often useful for land use and land cover change detection (Bashir et al. 2018; Wang et al. 2017). Finer resolution image data exhibits higher level of detail feature than those of preceding sensor from which details of land cover information can be detected (Myint et al. 2011). Recent advent of Object Based Image Analysis (OBIA) on high-resolution satellite image has improved the accuracy of land use and land cover mapping (Blaschke et al. 2014). This technique is more accurate for land use/land cover extraction combining with spatial and spectral information (Blaschke 2010) as compared to only the spectral values of pixels. Available studies indicate that the OBIA technique is more suitable for land use/land cover extraction especially on high resolution image (Hurskainen et al. 2019). Additionally, Geographical Information System (GIS) is used to create geo-database and integrate land cover data extracted from satellite images and available statistical data (Halimi et al. 2018). However, land use/land cover change analysis using high resolution satellite image in the mountain region is still lacking in different countries of the world.

Traditional agricultural system in the hills of Nepal integrates livestock, cultivated land, vegetated area and other natural resources. In the past, there was high population pressure on the traditional agriculture in the hills of Nepal (Blaikie et al. 2007; Ives and Messerli 1989; Paudel 2006). But over the recent decades, the situation has been changed due to outflow of rural farmers (Chidi 2016). Out-migration of the hill farmers to lowland, cities and abroad has caused a change in landscape at the watershed level (Awasthi et al. 2002). Decreasing population in the rural hill areas is creating a labor shortage in agriculture and as a result, agricultural land abandonment in those areas is increasing, which has also affected to change in vegetation covers such as forest, shrubs and grassland. Rural depopulation in the hills of Nepal was also due to outmigration of the people during the Maoist insurgency from 1996 to 2006, causing farmland abandonment (Manandhar 2014). Next, increasing rate of school going age groups of population was also a cause of labor deficit (Suwal and Dahal 2014) resulting in sharp decline in economically active population in the agricultural sector (Satyal 2010) and therefore livelihood in the rural areas was quite poorer than the urban areas (Chaudhary et al. 2018). New generations are less attracted toward the agricultural sector due to poor agro-infrastructure and profitability. The total effect of declining agricultural labor has resulted in overall landscape change in the hills of Nepal. Available studies show that there has been a broad level of change in the land use/land cover in the hills of Nepal over the last two decades (Chapagain et al. 2018; Chaudhary et al. 2018; Pradhan and Sharma 2017), showing multiple implication such as food supply, land management and environmental sustainability. Greenery has increased since the last four decades across the hills of Nepal due to successful implementation of the community forestry (Gurung et al. 2011) also. There have been formulated several agriculture development and land management policies in Nepal, but their poor implementation has caused improvement of neither the agricultural condition to an expected level nor the land use management (Basnet 2016; GoN 2013; Paudel et al. 2017). Thus, the problem of land use management in the hills has not been solved but rather the condition has deteriorated. This study has two- fold aims: one to analyze the land use intensity change and another to identify its major determining factors.

2 The Study Area

This study area covers the northeast part of the Andhikhola watershed of Syangja district, which is located in the middle hill region of Nepal (Fig. 1). The study area extends between 28°03'40" N to 28°11'02"N latitudes and 83°49'30" E to 83°56'51" E longitudes, occupying 97.75 km^2. The elevations range from 779 to 1566 masl. Over half (52.53%) of the study area is steep hill slope with a gradient range of 5° to 30° and about 30% land is less than 5° slope. Over 34% of the hills has slope with over 30°. There are limited lowland basins, most of which are occupied by river channel and river floods. Of the slope aspect, north, south and west facing slope areas account for over 81%, while the east facing slope area occupies below 19%. Of these, the eastern, southern and western facing slopes are agriculturally important due to sun facing slope, but at the same time they also expose to more vulnerable to landslides and soil erosion due to intensive human activities. The climate types of subtropical to warm temperate region prevail in the study area (GoN 2017). The area receives an average annual precipitation of 2800 mm; 80% of which occurs during the summer season (June to September). The rainfall is often characterized by torrential downpour in limited duration, causing soil erosion and landslide along the steep slopes and floods in the downstream areas. The average temperature ranges with a maximum of 21°C in summer and a minimum of 5°C in winter. The study is drained by the Andhikhola and its tributaries such as the Phedikhola, Bhadhkhola, Araudikhola, Rangkhola and Sumrakhola flowing through the eastern part and the Chisyarkhola and Baidikhola flowing through the west.

The Siddhartha highway is the main thoroughfare running through this area, connecting it to other parts of the country and local roads connect the scattered villages with this highway. Most of the human settlements are located along the eastern, southern and western hill slopes, but the lowland river basins have large villages and towns. Putalibazaar, the district headquarters town is the biggest urban center located in the middle part of the study area. Other towns are Phedikhola, Badhkhola, Naudanda, Setidobhan and Rangkhola. Cultivable land has occupied 62.46% of the total watershed area, of which only 21.6% has perennial irrigation facility, 14% has seasonal irrigation facility and remaining area were rain-fed (DADO 2013). Majority of the population with 73% were involved in the agricultural activities and the average land holding size for the farm households was 0.51 hectares (CBS 2013). The farming system is a typically traditional type and the agricultural activities are of integrated farming type, consisting of both crop farming and livestock rearing, which are squarely dependent on available surrounding natural resources such as forest, grazing land and water resources (Waceke and Kimenju 2007). According to the 2011 population census, the average population density was 324 persons per sq. km, ranging from 30 persons to 3404 persons per square km. There was an increased growth rate of population during the past decades, for instance, with

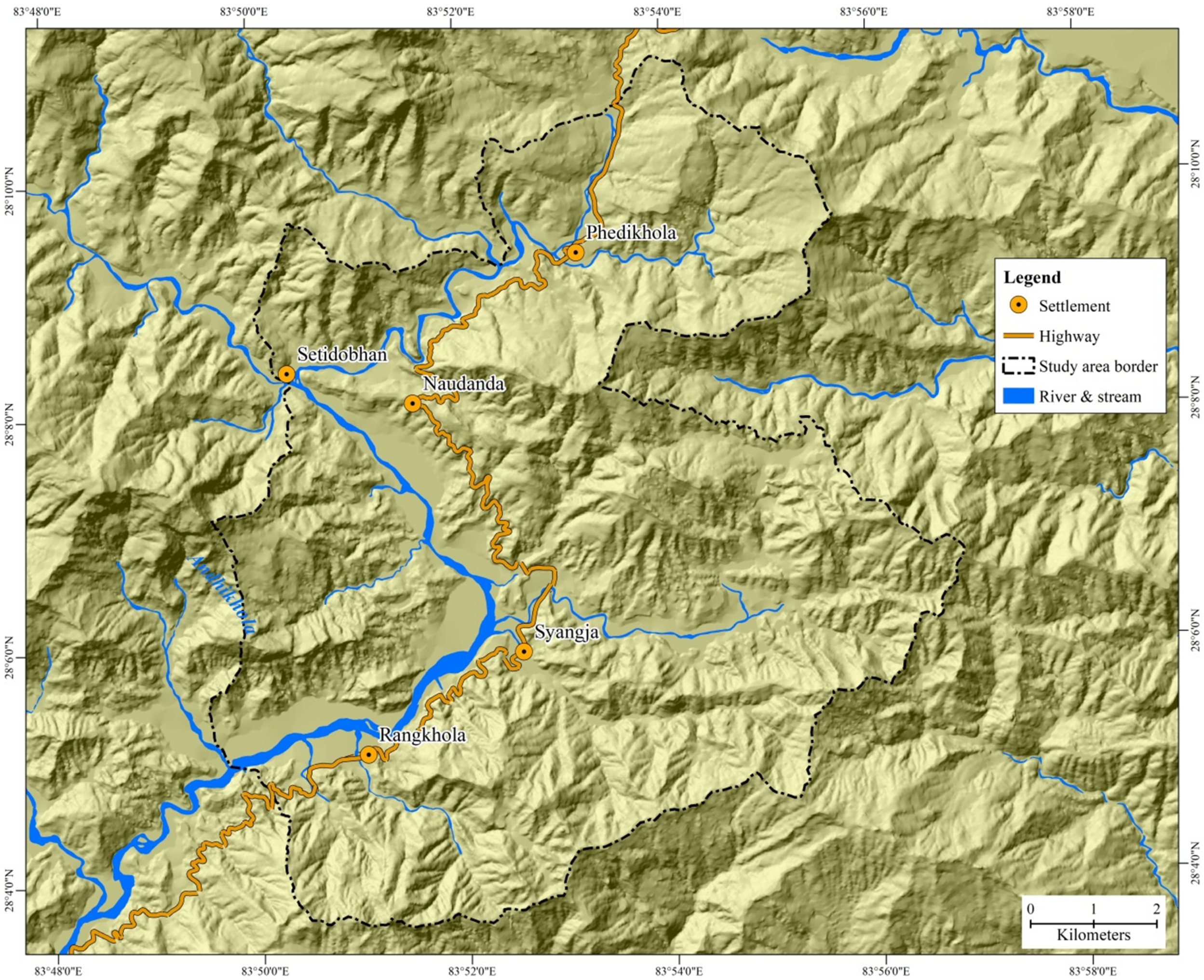


Fig. 1 The northeast part of the Andhikhola watershed of Syangja district in the Middle Hill of Nepal.

0.77% annual growth rate during the years 1981-1991 and with 0.78% annual growth rate during the years 1991 to 2001. And the population decreased at the annual growth rate of -0.93 during 2001-2011 census years and during the same decade, more than half of the households had at least one family member being absent (CBS 2012). Recently long practicing of traditional subsistence agricultural system has been transformed into intensive commercial production in the urbanizing lowland areas having road facility.

3 Methods and Material

3.1 Data Collection

This study has been based on both primary and secondary data sources. Analogue maps such as aerial photos of 1996, topographic maps 1996, land capability map 1986 were collected from the Survey Department of Nepal and WorldView2 image was acquired from the DigitalGlobe. Other secondary information was gathered from the profile reports of local administrative units, district level government and non-government agencies. Intensive field study was carried out in the study area for verification of data outputs generated from those analogue and digital maps in terms of correction, modification and assessment of the ground reality. Reality Check Approach (RCA) was used to verify the changed phenomena or incidents with the local resource persons (Pain et al. 2014). Seventeen locations representing different geographical areas including towns and rural villages of the low land, hill slope and the ridge of the hills were selected for the collecting data from the field using RCA approach. Three households from each of the selected locations representing high, middle, and poor-income households were interviewed by administrating structured questionnaires. Informal discussions were also held with the government officials, local leaders, teachers, elder persons and farmers to furnish additional information.

3.2 Data Processing

Photomap of aerial photos of 1996 was developed by orthophoto generation process (ERDAS 2010) having two meter spatial resolution. Land use map of 1996 was derived from the orthophoto of 1996 and the land use information of 2016 was derived from the WorldView2 image of 2011 (acquire date 28th Nov., 2011) with intensive field verification in 2016 and correcting from Google Earth image of DigitalGlobe. Multispectral image of the WorldView2 with 8 bands (coastal, blue, green, yellow, red, red edge, Near IR1 and Near IR2) and 2 m spatial resolution and 11-bit radiometric resolutions was used and processed. This image also included panchromatic image of 0.5 m spatial resolution. Multispectral bands were resampled with panchromatic image to increase spatial resolution of multispectral image into 0.5 m. Land use information with higher accuracy was acquired by OBIA on a high-resolution image and this OBIA method with threshold algorithm was developed for image classification on the WorldView2 image in eCognition software (Blaschke 2010; Randall et al. 2019; Yurtseven and Yener 2019). The land use was classified into forest, shrubs, grassland, cultivated land, sandy area and water body. The land surface temperature was calculated (Das 2015; Suresh et al. 2016) from the thermal band (band 10 and 11) of Landsat8 image. The acquired date of this image was December 2014 for winter and June 2015 for summer. Average land surface temperature was calculated on the basis of winter and summer land surface temperatures. Digital Elevation Model (DEM) was developed from the 20 m interval contours of topographic map from which different slope characteristics and solar radiation were also calculated (ESRI 2012). As land use/land cover is highly controlled by elevation, slope gradient and slope aspect in most of the hill and mountain areas (Birhane et al. 2019), land use/land cover and its change in this study were calculated in terms of elevation, slope gradient and slope aspects.

3.3 Deriving Variables

Water body, sand and degraded lands were removed from the map to derive land use intensity because these land use changes were unintentional in the context of human activities in the study area. Weight for land use intensity on the basis of input to land, output from the land and unintentional outcome from the land was used. This technique has been used by several studies but the weighting system found to be different according to local variability (Wang et al. 2010). Different weights ranging from highest to lowest were given to different land use/land cover classes such as 5 for built-up area and 1 for vegetated area on the basis of intensity of input and output (Table 1). For explanatory variable, land capability was also weighted with 4 to 1 such as 4 for Class I and 1 for Class IV. Perennial, seasonal and rain fed cultivated lands were weighted with 3, 2 and 1 respectively to derive the irrigation variable. Built up variable was derived by the kernel density tool (Kim and Scott 2012) by using built up points on the topographic maps of 1996. Similar kernel density surface maps for each variable of road and service centers were also developed by using certain weights assigned to their hierarchical categories. Roads were weighted by type, such as 6 for highway, 3 for district road, 2 for major road and 1 for other roads. Weights to the towns were given based on their population size, i.e., high weight to large size and low weight to small size. Other services such as health, education and

Table 1 Weight given to different land use categories

Types	Uses	Input	Outcome	Weight
Built-up area	All time protection of life and property including commercial activities in urban area.	Construction and maintenance cost	Rent, business	5
Perennial irrigated cultivation	Three crops, most time under cultivation	Agriculture inputs and protection of crops	Three seasons' agriculture products	4
Seasonal irrigated cultivation	Two crops fallow in winter dry season	Agriculture inputs and protection of crops	Two seasons' agriculture products	3
Rain fed cultivation	One season crop with mixed cropping	Agriculture inputs and protection of crops	One season's agriculture product	2
Vegetated area	Sometime used for grass, fodder, grazing and timber	Fencing of land to protect from grazing livestock.	Timber, non-timber products	1

postal service were given weights according to their hierarchical order. Ward area-based raster surface maps of demographic, food sufficiency and ethnicity were also developed.

Observation unit of this study was grid of 500m×500m ground area. From the test of different grid size, it was identified 500m×500m grid size as the best suitable grid size on the basis of map scale and details of land use information. Thus, the study area was divided into 426 square grids (500m×500m) to derive the quantitative value for each variable by grid. The average value of each grid of land use intensity of 1996, land use intensity of 2016, irrigation facility, land capability data were calculated from the vector data model using the formula given below (Bracken 2008).

$$\text{Intensity} = \sum A_i \,.\, W_i \qquad (1)$$

where, A_i is the area proportion of particular category of land use/land cover in the square grid, W_i is the given weight for particular category of land use/land cover.

Raster based variable were derived using the zonal statistical tool from already developed raster surface of the variables. Grid based land use intensity change variable from 1996 to 2016 and other 29 explanatory variables were also derived. Data standardization was carried out for the consistency of different scales data in multivariate analysis (Gupta 2017). Land use intensity change from 1996 to 2016 was considered as dependent variables and other derived 29 variables were used as explanatory variables for statistical analysis.

3.4 Dependency Analysis

It is crucial for how to apply regression technique for dependency analysis which needs to know whether the data are balanced before including interaction (Zuur et al. 2010). Multicollinearity among variables in multivariate analysis is problematic and so, variable should be filtered to make free of multicollinearity among variables (Chatterjee and Hadi 2013). OLS regression can identify the multicollinearity giving Value Inflation Factor (VIF) more than 7.5 which has the multicollinearity with other variables (Daoud 2017; Igwenagu and Alma 2014). Five variables were removed from the total 29 variables for consideration in this study due to the multicollinearity among variables. Therefore, only 24

Table 2 Bivariate results of Geographically Weighted Regression (GWR) model of individual explanatory variables

Factor	Variable	R^2	Z-Score of Moran's I	p Value
Physical	Slope gradient	0.57	1.23	0.22
	Land surface temperature	0.54	1.65	0.10
	Solar radiation	0.53	1.96	0.06
	Elevation	0.52	0.55	0.59
	Flow accumulation	0.49	2.24	0.03
	Rainfall	0.46	1.63	0.10
Accessibility	Built-up	0.57	0.21	0.83
	Education institute	0.51	0.45	0.66
	Urban	0.50	0.49	0.63
	Road	0.49	0.90	0.37
	Post office	0.48	1.15	0.25
	Health institute	0.48	0.89	0.37
Resource	Irrigation	0.53	0.72	0.47
	Land capability	0.53	1.03	0.31
	Water sources	0.49	1.17	0.24
Ethnicity	Dalit	0.51	1.20	0.23
	Bahun& Chhetri	0.50	1.13	0.26
	Janajati	0.50	1.65	0.10
Food sufficiency	More than 9 month	0.52	1.20	0.23
	Less than 6 month	0.50	1.51	0.13
	Food surplus	0.48	1.57	0.12
Demography	Population change	0.51	1.01	0.32
	Household size change	0.50	1.76	0.08
	Sex ratio change	0.49	1.28	0.20

explanatory variables (Table 2) were used for the analysis. Most geographic data have normality problem and violate the assumption of the parametric statistical techniques. In this situation, semi parametric technique like GWR is very useful. According to the Tobler's first law of geography (Tobler 1970), it is a kind of local technique to estimate regression models with spatially varying relationships (Lu et al. 2011). This technique assumes the non-stationary relationships between response and explanatory variables. It generates a single equation for each spatial unit and consequently allows regression coefficients to vary across the study area. The equation is defined as follows.

$$Y_i = \beta_0(\mu_i, v_i) + \sum_k \beta_k(\mu_i, v_i) X_{ik} + \varepsilon_i \qquad (2)$$

where,

Y_i is the dependent variable at location I,

X_{ik} is the value the k^{th} explanatory variable at location i,

$\beta_0(\mu_i, v_i)$ is the intercept parameter at location i,

$\beta_k(\mu_i, v_i)$is the local regression coefficient for the k^{th} explanatory variable at location i,

(μ_i, v_i) is the coordinate of location i,

ε_i is the random error at location i.

Firstly, bivariate GWR analysis was executed with 24 explanatory variables to identify the strength of individual variables predicting land use intensity change. Then, variables were categorized into six factors such as physical, natural resource, accessibility, ethnicity and food sufficiency. Multivariate GWR was executed with the explanatory variables of six factors separately to identify the prediction strength of the different factors. Again, frequent GWR model were executed with different combination of 24 explanatory variables to identify the maximum strength of explanatory variables. Finally, combinations of ten variables were identified having the maximum strength of explaining land use intensity change. Those ten variables were slope gradient, built-up, land surface temperature, solar radiation, irrigation, land capability, elevation, education institute, population change and urban center.

Table 3 Area and percentage of land use/land cover in 1996 and 2016, and their changes during that period.

Land use/land cover	Area (km²)		Area proportion (%)		Change (%)
	1996	2016	1996	2016	
Forest	30.10	38.12	30.80	39.00	26.6
Shrub	5.92	26.77	6.06	27.39	352.0
Grass	3.44	2.50	3.52	2.56	-27.3
Cultivation	55.48	26.48	26.79	27.40	-52.9
Built-up	0.70	1.45	0.72	1.48	105.6
Degraded	0.01	0.09	0.02	0.09	350.0
Sand	1.54	1.50	1.57	1.53	-2.6
Water body	0.56	0.54	0.58	0.55	-5.2
Total	97.75	97.75	100.00	100.00	

Standard residual derived by GWR model is a significant indicator of uncertainty of prediction accuracy because of autocorrelation of spatial variables (Propastin et al. 2008). Moran's I is a commonly used indicator of spatial autocorrelation (Fu et al. 2014) which measures the degree of spatial autocorrelation (Anselin 1995). In each step of GWR analysis, Moran's I were used on standard residuals to identify model validity. The Z-Score and p-value of Moran's I are measures of statistical significance, indicating whether or not to reject the null hypothesis. For this tool, the null hypothesis states that the values associated with features are randomly distributed. The concern of spatial autocorrelation of standard residual is to identify whether the distribution is clustered or not. Value of Z-Score derived from the Moran's I should be less than 1.96 to be acceptable reliability of prediction of GWR model at 95% confidence level which means that the standard residual value derived from GWR model is reliable. Additionally, prediction result may be unreliable if the condition number is more than 30 in each observation. Out of total 426 observations, more than 46 percent of them had more than 30, which indicates the suspicious of local prediction of ten explanatory variables. Therefore, only six explanatory variables were used for GWR model removing four explanatory variables among ten.

4 Results

4.1 Land use and change

There is a significant change of land use/land cover in the study area. Higher portion of cultivated land is found to be converted into forest and shrubs. Greenery has increased highly in 2016 than in 1996. Conversion of cultivated land into greenery is mostly in highland remote areas. Instead, in low land area, built-up area is found highly increasing, encroaching upon the cultivated land. However, this conversion is limited to urban areas (Fig. 2). In 1996, cultivated land with nearly 57% was the largest coverage in the study area, followed by forest, which together occupied nearly 88% of the total area. The vegetated area comprising forest, shrubs and grass land occupied more than 40% of the total area. The land use coverage by major categories in 2016 was just reverse. Forest coverage was the highest at 39%, and the next was cultivated land with 27.4% (Table 3). The shrub coverage increased drastically from 6% in 1996 to slightly over 37% in 2016.

There was a significant change in land use/land cover categories in the study area between 1996 and 2016. Shrub area increased tremendously with over 352% during this period, followed by forest and built up areas. In 1996, it was found that more than 29% of total cultivated land was converted into shrubs and in 2016 its nearly 20% was converted into forest (Table 4) in which higher proportion of conversion from cultivated land into forest and shrubs was in the higher elevation, steeper slope gradients and north and west facing slopes. More than 34.6% of shrub was converted into forest mostly in the higher hills slopes during that period. Conversion of cultivated land into shrub was mainly due to the agricultural land abandonment. Conversion of shrubs into forest was the result of successful implementation of community

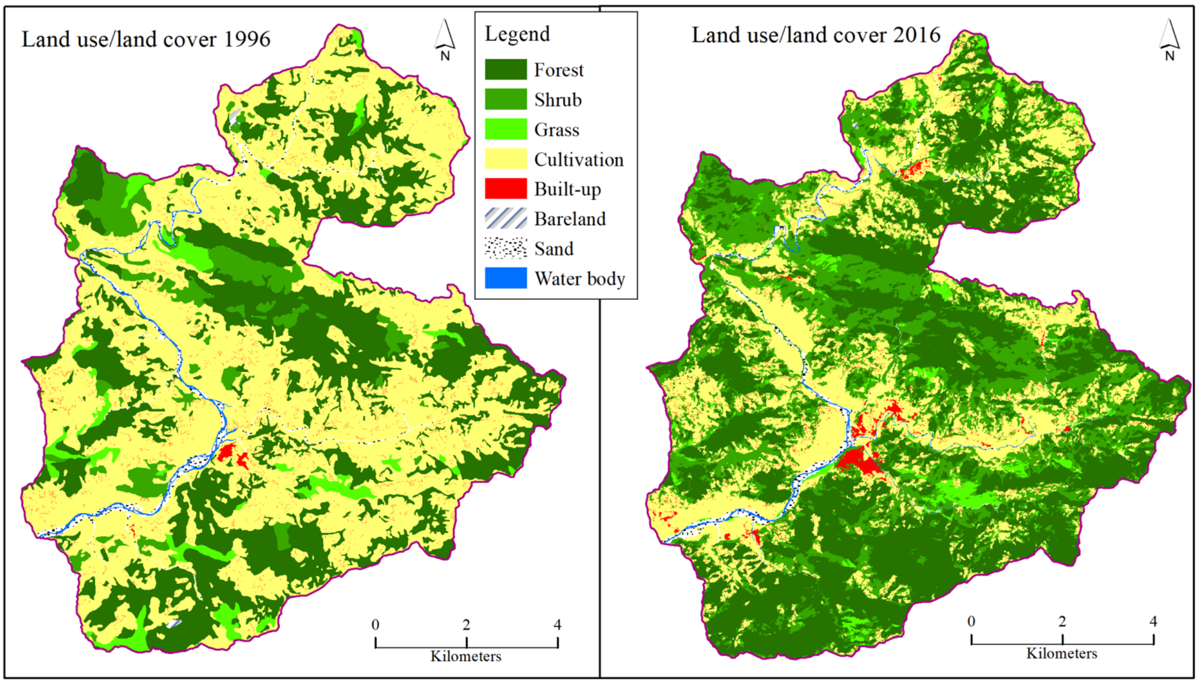


Fig. 2 Land use/land cover in 1996 and 2016 in the study area.

Table 4 Percent of land use/land cover transformation (in row) from one category to another from 1996 to 2016.

Land use/land cover	Cultivation	Built-up	Forest	Shrub	Grass	Sand	Water
Cultivation	45.45	2.18	19.95	29.06	2.20	0.90	0.26
Built-up	45.78	29.14	8.01	16.43	0.57	0.06	0.01
Forest	2.11	0.08	80.06	17.30	0.38	0.05	0.02
Shrub	2.07	0.05	34.61	60.84	2.13	0.14	0.17
Grass	2.04	0.07	26.86	43.15	27.71	0.08	0.09
Sand	24.13	0.37	2.80	11.32	4.04	42.86	14.46
Water	16.43	0.44	0.34	15.06	3.18	42.46	22.08

forest and decreasing number of domesticated livestock for grazing in the shrub and forest. Built-up area became more than double, which is confined to lower plain and accessible area because of urbanization along the highway.

This result of agricultural land abandonment and increasing greenery can be compared with the mountain and the hill regions of the Saptakoshi and the Narayani watersheds of eastern and central Nepal (Chaudhary et al. 2018; FRTC 2017; Pandey et al. 2014; Paudel et al. 2014; Pradhan and Sharma 2017) but the rate of change in the study area is much higher than most of the other areas.

4.2 Land use intensity and its change

The distribution pattern of land use intensity found to be more random in 1996 as compared to it in 2016. The intensity is clustering in limited parts in 2016. Most of the areas have the decreasing condition of land use intensity and higher rate of decreasing at remote cultivated land areas (Fig. 3).

Decreasing of average land use intensity indicates the decreasing of human occupancy in the study area. The increasing range of land use intensity indicates the diversifying the intensity of occupancy on land in 2016 as compared to it in 1996. However, decreasing standard deviation of land use intensity shows the overall shrinking the range of land use intensity in contrast to increasing range of maximum and minimum intensity. It indicates that some areas with higher intensity value in 2016 are different from general intensity. It means the higher intensity with increasing in urban area is abnormal than total intensity changes in the study area.

4.3 Explanatory variables of land use intensity change

Bivariate result of the GWR model of each explanatory variable for explaining land use intensity

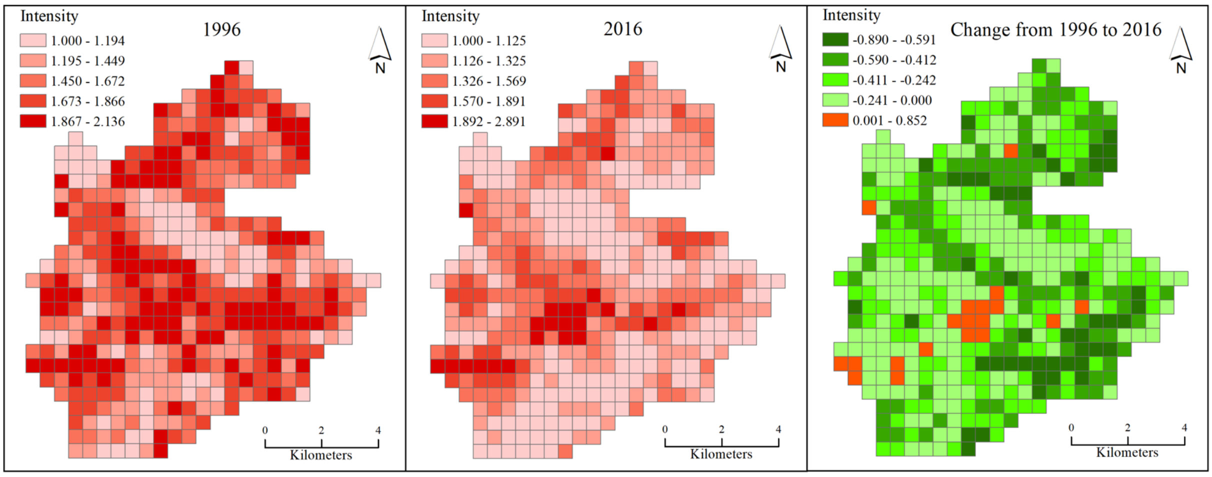


Fig. 3 Land use intensity in 1996 and 2016, and their changes during the period of 1996 to 2016.

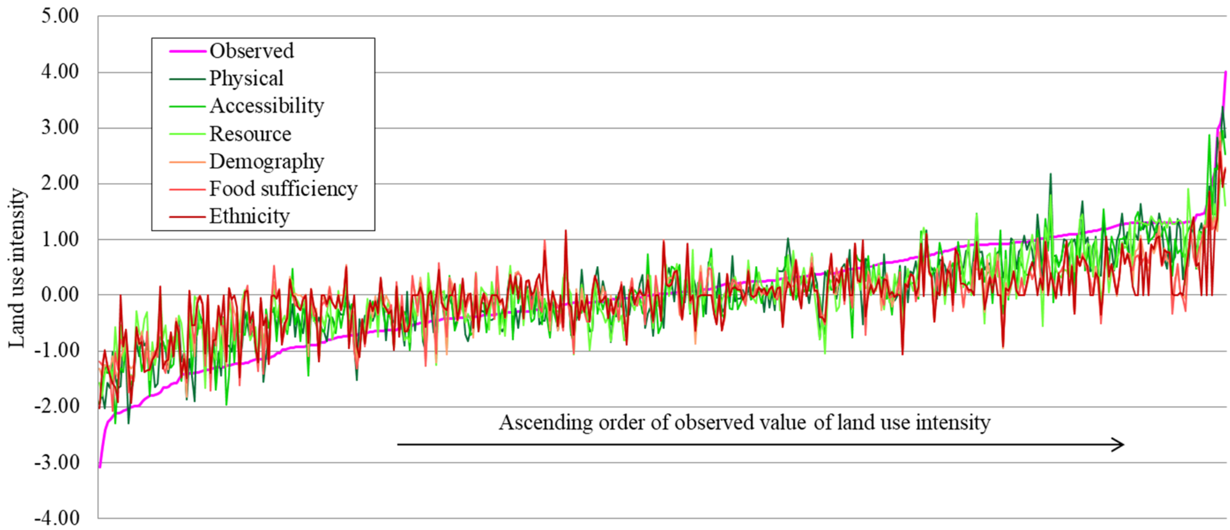


Fig. 4 Deviation of predicted land use intensity changes from observed land use intensity change during the period of 1996 to 2016.

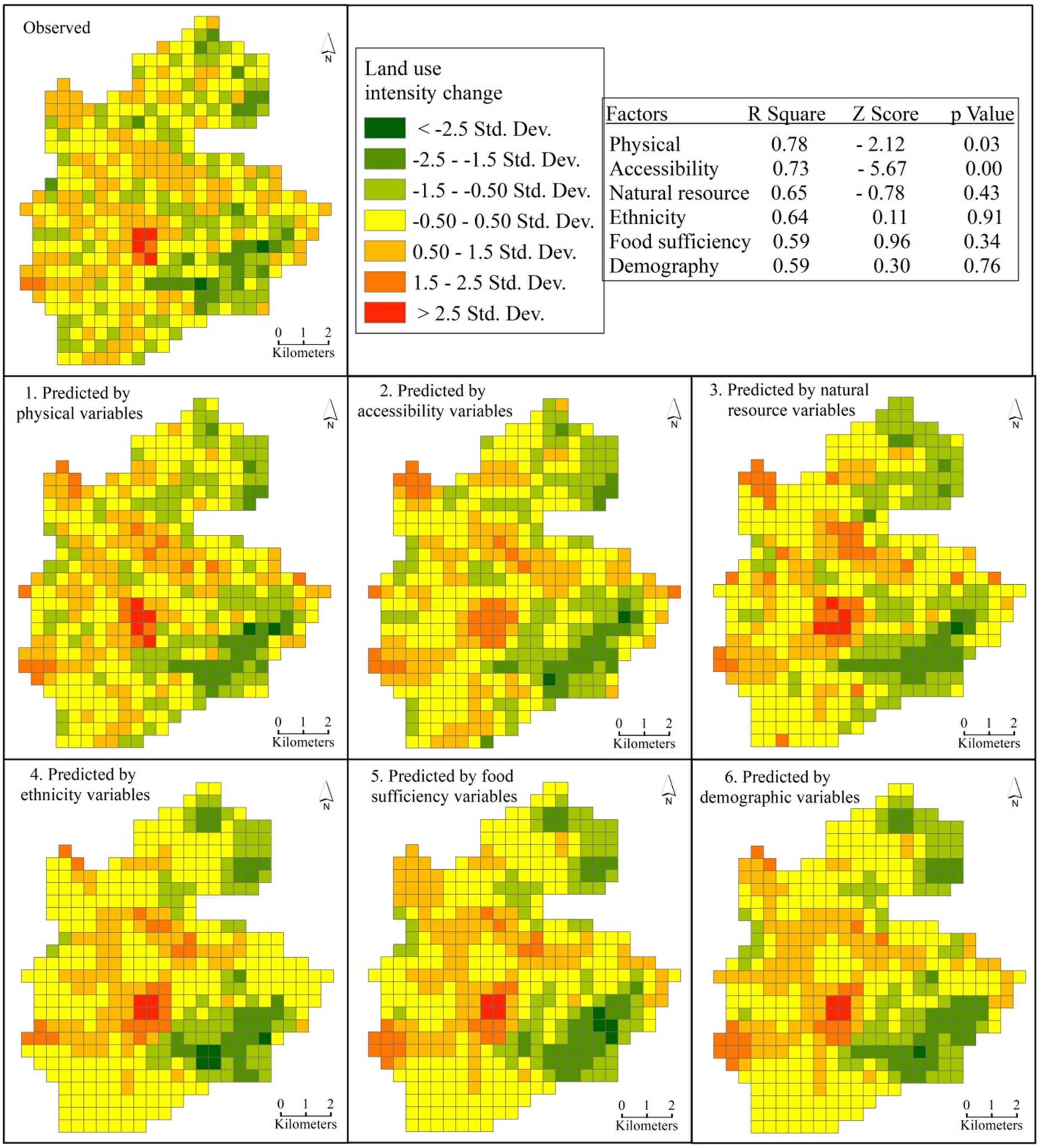
change shows that slope gradient and built-up have the highest strength of prediction, followed by land surface temperature, Solar radiation, irrigation facility and land capability follow them in terms of position of strength. Elevation and food sufficiency (for more than 9 months) variables have also higher s trength of prediction than other explanatory variables. Z-Score values less than 1.96 proves the validity of the prediction results of all variables except flow accumulation. However, p values do not prove their certainty of all variable at 95% confidence level (Table 2).

4.4 Prediction of land use intensity change

The multivariate GWR model was applied using the explanatory variables of six factors separately to identify the strength of different factors for predicting land use intensity change. Physical variables have the highest coefficient of determination (R^2) value of 0.78, followed by accessibility (0.73) and natural resources (0.65). The weakest strengths (0.59) belong to demography and food sufficiency variables. Z-Score of all six factors have less than 1.96 proves the validity of prediction in which the model validity of physical and accessibility variables have the certainty at 95% confidence level.

Dark green line of physical factor and light green line of accessibility factor are near to observed line. Inversely, red line of ethnicity seems the farthest due which is followed by food sufficiency (Fig. 4). The distribution pattern of predicted land use intensity change by physical variables is highly similar to the observed value. The predicted distribution pattern of land use intensity change tends to cluster according to the decreasing values of coefficient of determination (Fig. 5).

The GWR model gives local coefficient of determination (Local R^2) of each observation (square grid). Local coefficient of determination of physical variables is the highest (0.52), followed by accessibility (0.50). Next is the natural resource. Ethnicity has the lowest average value of local coefficient of determination. The hierarchical order of strength of coefficient of determination and average value of local coefficient of determination are similar in general. It represents that physical variables have the highest strength of prediction of the spatial distribution pattern of land use intensity change, followed by the accessibility and natural resource variables. Prediction capacities of grouping variables



Factors	R Square	Z Score	p Value
Physical	0.78	- 2.12	0.03
Accessibility	0.73	- 5.67	0.00
Natural resource	0.65	- 0.78	0.43
Ethnicity	0.64	0.11	0.91
Food sufficiency	0.59	0.96	0.34
Demography	0.59	0.30	0.76

Fig. 5 Comparison of land use intensity changes predicted by six determining factors with observed land use intensity change from 1996 to 2016.

of six different factors have also weaknesses in the perfect model validity. Condition number derived by the GWR model also determines the prediction validity of each observation by which none of the model has given perfect validity. It indicates the weaknesses in confidence limit of model validity. However, the physical and accessibility variables have given more valid prediction than others.

Frequent test of the model using various combination of the 24 explanatory variables shows that selected ten variables have the maximum strength of predicting land use intensity change. However, the condition numbers of 46% of observations were more than 30 which show the uncertainty of prediction validity of model. Thus, only six variables among ten were used as explanatory variables which gave 100% validity of the model but the strength of prediction has decreased. Fig. 6 shows that the predicted values of ten variables are nearer to observed value which indicates that the accuracy of prediction is higher by ten variables than six variables.

The distribution pattern of the predicted value of land use intensity change by 10 explanatory variables is more similar with observed value of land use intensity change as compared to the predicted value of land use intensity change by the six explanatory variables. It is also proved by value of coefficient of determination (R^2). The ten explanatory variables have defined 87% of total variance of land use intensity change, while the six explanatory variables have only 80%. Z-Score less than 1.96 and p value less than 0.05 proves the validity of both models (Fig. 7).

Standard deviation and maximum of predicted values have decreased in both models but the model by six explanatory variables has exceeded the ten variables. The average value of Local R^2 of the ten

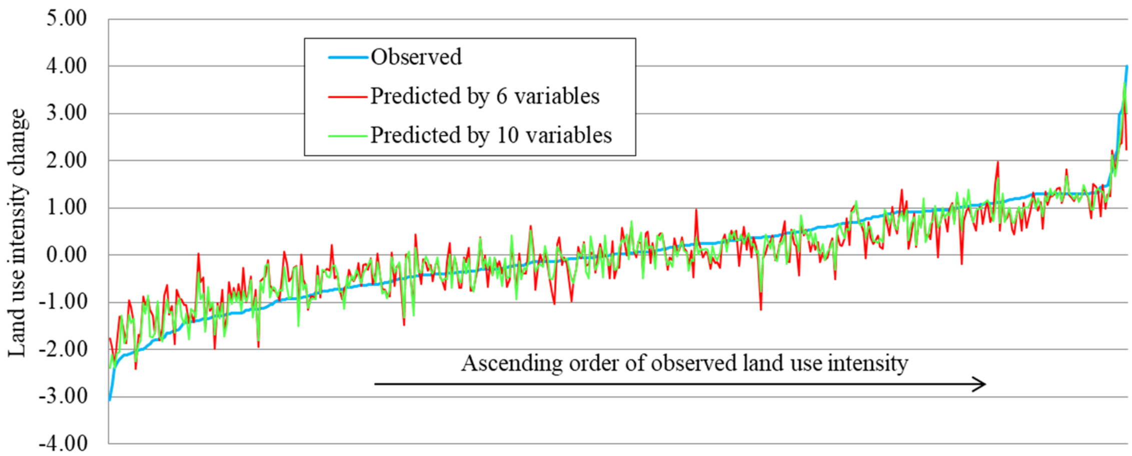


Fig. 6 Deviation of predicted change of land use intensity by 10 and 6 variables from observed land use intensity change during the period of 1996 to 2016.

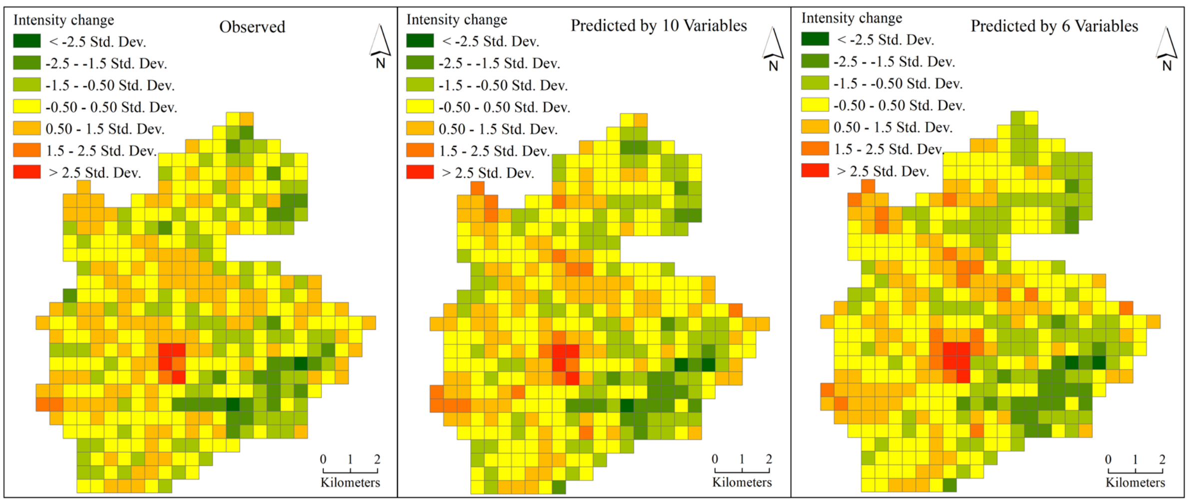


Fig. 7 Comparison of predicted change of land use intensity by 10 and 6 variables with observed land use intensity change from 1996 to 2016.

variables is higher (0.68) than that of six variables (0.54). It further proves the weak strength of the six variables as compared to the ten variables. Therefore, the ten selected variables have the greatest strength of prediction of land use intensity change.

5 Discussions

The result of this study is discussed with respect to land use intensity, relation between land use intensity and its suitability, driving factors of land use intensity change, nature of integrated agricultural system, implication of intensity change and evaluation of the study method. These aspects are described in detail below.

5.1 Land use intensity

This study has used unified approach to understand the integrated traditional subsistence farming system in the hills of Nepal. Each land use/land cover category is related to others and the change in one category affects other categories as well as in the whole farming system. Thus, individual land use/land cover category analysis is very difficult to understand the whole landscape pattern change in general. In recent years, land use intensity analysis is an emerging approach in various fields (Chaudhary and Brooks 2018; Yan et al. 2017). The intensity of land use differs across different parts within a country or a region because of different characteristics of land resource system and economic activities. It is the most difficult task to standardize common weighting of land use intensity even adopting the same land use/land cover category. Land-based production system encompasses all activities that convert some combination of inputs into output depending on properties of the system (Kuemmerle et al. 2013) in which land-based production system embedded within a territory should be at the center of the research (Erb et al. 2013). Weighting of land use/land cover category of this study differs from those used in the Yellow River basin, China and other parts of the world because of unique land-based production system (Aldwaik and Pontius 2012; Wang et al. 2010). This study has adopted its own weighting system of land use/land cover categories on the basis of local traditional agricultural system of Nepal and local situation of the study area. The result reveals that the method being used is found suitable to the areas of traditional agricultural areas in the hills of Nepal.

5.2 Land use intensity and land suitability

Quality of land is a complex attribute which acts in a distinct manner for its influence on the suitability for a specific use. Therefore, land quality is relevant to a certain type of use that influences either the level of input required or the magnitude of benefit obtained (FAO 1982). Land capability referring to the potentiality of land for agriculture is lower in highland and higher in low land areas of Nepal (KESL 1986). In the past, the land use intensity was increasing in the marginal area where the land capability is very low, but in recent decades land use intensity is decreasing in these areas due to the release of population pressure. Decreasing land use intensity in the hill slope and increasing in the lower part in the study area can be compared with the results across many parts of the highland areas of Europe and Asia (Corbelle-Rico and Maseda 2008; Zhang et al. 2014). Land use intensity is correlated with land capability (Mecella et al. 2008) although land capability is defined on the basis of physical factors mainly for agricultural suitability (Grose 1999; KESL 1986). Increasing general land use intensity in the low land area is not only because of physical suitability of land but also of accessibilily (Saghapour et al. 2017). Highway running through the low land area has promoted the development of market center and availability of basic service facilities that has accelerated the growth of urban areas and agricultural intensity resulting the increasing of general land use intensity. In general, carrying capacity of land determines the land use intensity change which is mostly related to physical factors (Yan et al. 2017) in which anthropogenic factors are also indirectly related to physical factors that is why balancing cost and benefit system works in natural process. The highest strength of solar radiation for predicting land use intensity change in the study area is also due to the crop growth which in turn is highly dependent on solar radiation (Duriyaprapan and Britten 1982). The intensity of solar radiation is highly dependent on the slope aspects in the study's hill area. The highest proportion of land abandonment was found in the northern slope aspect and the least in the south and southeast facing slopes in the Andhikhola watershed (Chidi 2017). Thus, land use intensity change is highly dependent on the solar radiation.

5.3 Driving factors

Over the decades, poverty in rural area of Nepal has been increasing despite the decline in the national poverty level and average monthly income of rural people is quite lower than that of urban people. Therefore, people in rural area are less interested in agricultural sector because it is less attractive in terms of cash income. Agriculture sector is deteriorating day by day because national policies of Nepal could not attract new generations toward. It is not surprising that younger generations are less interested in the agricultural sector nowadays in the world because of their perception of weakness of carrier and warranty in agricultural sector (Widiyanti et al. 2018), but it is far beyond the carrier rather than the economic in the study area as a whole. It is because the rural farmers are being unable to fulfill their basic needs or sustain their livelihood from their agricultural occupation. But carrier is not the exception for educated youngers ones. Agricultural sector has remained stagnant because plans and policies have failed to address agriculture problems and issues in Nepal (Chaudhary et al. 2018). Transformation of traditional farming to commercial agriculture through land pooling of fragmented and abandoned land will be one of the best ideas to solve the problems in the agriculture system of Nepal. It will help to attract younger generation into agriculture and thereby to increase food supply within the country. Government efforts on commercialization of agriculture and entrepreneurship development program are insufficient and not being so suitable particularly for the remote and hill areas, as they have various limitations and weaknesses over the plain areas (GoN 2013; Paudel et al. 2017). The situation is further worsening because of the frequent failure of government policies in Nepal. Policies and legislative provisions formulated by the government in Nepal were not implementable at the community level, because those provisions were top-down and supply driven mechanisms with focus on the relationship between technological inputs and outputs rather than the bottom-up approach with active participation of local communities and other key stakeholder. Although some improvement can be observed, but the growth rate remained very low as compared to that of the neighboring countries. The recent land use policy has repeated the same problems of overlapping of roles and responsibilities of the institutions at various levels and between the departments and lack of coordination among the government agencies (Khanal et al. 2020), leading to further failure of government efforts to solve land management problems and population mobility in Nepal. During the field survey, it was found that some commercial crop cultivation being practiced in the previously bandoned cultivated land in the higher hill slope areas, which was due to the farmers' self-initiation rather than the government effort. However, this encouraging effort was confined to very limited areas as compared to the scale of agricultural land abandonment area in the hill slope. The government efforts are however seen effective particularly along the highway as well as in the fertile lowland area. But if this situation remains the same, the abandonment trend of arable terraces land in the hill slope area will increase consistently even in the future. The watershed level analysis based on the ward level observation unit in the study area shows that there was high correlation between population change and agricultural land abandonment (Chidi 2016), which indicates that population changes was major driver of land use intensity change. However, the lower prediction strength of population change to land use intensity change in this study was because of incompatible spatial scale of demographic variables. The higher strength of built-up for predicting land use intensity has proven that compatible spatial scale is the first requirement for the spatial statistical analysis. Lack of agricultural labor in recent decades was not only because of decreasing number of farmers but also due to increasing school enrolment of the population of 10-25 years of age than before, because some of them were agricultural labor in the past. The trend is seen in other hill and mountain district of Nepal as well. The fact is that the proportion of agricultural occupation has sharply declined in the mountain and hills districts during the census decade of 2001 to 2011 (Suwal and Dahal 2014). Decreasing land use intensity in the mountain areas of China is mainly because of the policy intervention (Li et al. 2018), while this situation has never happened in Nepal because of the weak implication of the land use policy (Basnet 2016). However, the labor migration policy of Nepal for jobs in abroad is highly effective because of low carrying capacity of sloppy marginal land for cultivation. Therefore, the land use intensity existed in the marginal hill slopes has decreased in the recent decade. Higher strength of the physical determining factors is due to decreasing intensity of the marginal land is at the first than in the suitable area. Outflow of rural farmers to urban areas and the Tarai plain region has further accelerated the decreasing land use intensity in the marginal hill slopes.

5.4 Nature of integrated agricultural system

Traditional subsistence agricultural system is an integrated farming system that is interrelated with cultivated land, livestock and other natural resources (Waceke and Kimenju 2007). Decreasing number of farmers have multiple effects on the total farming system, that's why the general land use intensity in the hill slope is decreasing. Decreasing of the agricultural farmers has resulted in the lack of agricultural labor and livestock rearing at the household level, which ultimately resulted in the agricultural land abandonment and decreasing demand of forest product and grazing land. As a result, use of the forest resources has decreased. On the one hand, the process of human occupancy on abandoned agricultural land has decreased while on the other hand, decreasing demand for forest product has reduced the human intervention in the vegetated area (forest, shrubs and grass). In many parts of the study area, decreasing demand of public forest product has also helped successful implementation of community forest program. That is why the human occupancy of the hill slope has decreased. Built-up area has increased in the lower plain area due to accessible and suitable for human occupancy. Therefore, land use intensity is increasing in the lower plain area. Like in the study area successful implementation of the community forestry has also contributed to increasing forest area in the hills of Nepal (Gurung et al. 2011). However, in recent past greenery is increasing which is not only due to the community forests but also plantation of trees on the private land and naturally growth secondary plants in the abandoned cultivated land areas.

5.5 Implication of intensity change

Groundwater recharge is usually due to increasing natural vegetation (Mohan et al. 2018). Unlike this, there is drying up of water sources in the study area possibly due to climate change (CBS 2017; GoN 2014). Villagers in the hill slopes have shifted to plain area for living due to the scarcity of drinking water. It was also because of the increasing human population pressure on limited water resources. There is not visible impact of ground water recharge in the study area due to the increasing greenery at present. However, scientific research is required. Decreasing human occupancy in the hill slopes has increased intra species competition (Mackenzie et al. 2002) with wildlife which resulted difficulties to protect their crops from wildlife damage in the remote marginal areas of the study area. Similar result was also found in many abandoned cultivated lands in several parts of the world (Benayas et al. 2007; Hua et al. 2016). It is the indication of further pressure of wildlife to decrease the human occupancy in the marginal parts of the hill slope. Higher rate of decreasing land use intensity has several implications on food security, livelihood and environmental sustainability.

5.6 Tools and technique

Most land use intensity studies are concerned with the pattern and change relating with other aspects of environment and biodiversity (Ma et al. 2018; Pellissier et al. 2017; Stjernman et al. 2019), but detail spatial statistical analysis of determining factors of land use intensity is still limited. This study has made an effort analyze the spatial variability of determining factors of land use intensity dynamics in a complex hill topographical region. Quantification of land use/land cover on the basis of intensity has made possible for multivariate statistical analysis. The semi parametric GWR model is found very suitable in which most of the geographical data violate parametric statistical tools. The GWR model has been applied mostly for spatial analysis of health, climate and economics (Lewandowska-Gwarda 2018; Liu et al. 2018; Wang et al. 2012) rather than land use/land cover and allied research. This study is an example of explaining dependency analysis of land use intensity change. Thus, this study would be as a compliment work to contribute to the body of literature.

6 Conclusion

Increasing land abandonment due to decreasing population in the hills and shifting of population from the hill slope to lower plain area resulting urbanization are the major driver of land use intensity change in the study area. Economic poverty and weakness of the national agricultural policies are found playing significant role in decreasing population in the hill slope area, which is not only because of the land abandonment but also due to decreasing human occupancy of other resources like forest, shrubs and grassland. Land use intensity is a suitable concept for better understanding of integrated land use system of the traditional agricultural system in which separation of individual land use/land cover category is very difficult. Depopulation and decreasing involvement of people in the agricultural sector are the major drivers of decreasing average land use intensity in the study area. However, physical and accessibility factors have highly controlled the spatial variability of land use intensity change. Land use intensity change has multifaceted implications such as on food supply, soil erosion, vegetation, biodiversity and ground water recharge. Thus, further research should be carried out for more understanding of sustainable land management in the hill and mountain, so that suitable policy measures and implication modality can be formulated.

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