







Impact of anthropogenic activities on landslide occurrences in southwest India: An investigation using spatial models

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Landslides are global natural hazards with significant social and economic impact. The study is conducted in the wake of landslide occurrences in Kerala state, India, during 2018–2019. This study aims to demarcate landslide hotspots in the study area, identify anthropogenic activities, and critically examine their role in landslide occurrences. The identified landslide hotspots are utilized to comprehend spatial patterns of landslide distribution throughout the state. The landslide hotspots are concentrated in Idukki, Ernakulam, Kottayam, Wayanad, Kozhikode and Malappuram districts. Anthropogenic conditioning factors stimulating landslide occurrences are identified from land-use activities and the results obtained manifest that about 59.38% of total landslides have occurred in the plantation area. Human-induced parameters accelerating landslides are examined along with other natural parameters using various regression methods in the latter part of the study. The modelling techniques used in the study are the ordinary least square (OLS), spatial autoregressive model (SAR), and geographically weighted regression (GWR). All models point to the fact that anthropogenic activities such as plantation, quarry, road density, and cropland influence landslide occurrences. Results of both spatial models give excellent predictive capability compared to the OLS model. SAR analyzes the spatial interaction of parameters globally, whereas GWR considers the local aspect. The study encapsulates the importance of global and local spatial models in landslide studies based on their applicability.

Keywords. Human-modified landscapes; hotspot analysis; spatial lag model; geographically weighted regression.

1. Introduction

A landslide is a geological mass shedding process of rock debris or earth down natural and engineered slopes. It also includes events such as the mass movement of rock, failures of slopes, topples slides and flows such as debris flows and mudflows (Novotný 1978; Cruden and Varnes 1996; Hungr *et al.* 2013; Gariano and Guzzetti 2016; Subramani

et al. 2017). Landslides cause serious peril to human life, habitats, and socio-economical activities such as industrial establishments and lifelines, including transportation networks and communication systems (Martha *et al.* 2015). The prediction of hazardous landslide areas and their causative factors has become a growing concern due to the pressure of urbanization (Aleotti and Chowdhury 1999; Sajinkumar *et al.* 2011). Increasing

population exerts pressure on land resources causing human activities to extend over hilly regions. This has resulted in increased socio-economic losses because of unstable slope failures during landslides (Das *et al.* 2011; Subramani *et al.* 2017; Hong *et al.* 2017).

According to the Geological Survey of India, about 0.42 million km² (12.6%) of land area, excluding snow-covered regions, falls under the landslide hazard zone in India (NLRMS 2019). This 0.09 million km² is in the Western Ghats and Konkan hills, which pass through Tamil Nadu, Kerala, Karnataka, Goa and Maharashtra (NDMA Annual Report 2018–2019; Deepu *et al.* 2019; Thennavan and Ganapathy 2020). The Western Ghats is the second-most vulnerable region for landslide in India after the Himalayas according to the National Disaster Management Authority, Government of India (Kuriakose *et al.* 2009; Anbazhagan and Sajinkumar 2011; Sajinkumar and Anbazhagan 2015; Pradhan *et al.* 2019). Landslide is a severe hazard that causes substantial human and financial losses in the country. On average, landslide claims about 500 lives and causes approximately Rs. 300 crore damage annually (Parkash 2015).

Historically, landslide susceptibility modelling is widely explored and has attracted widespread research interest. The methods used for susceptibility modelling are classified as qualitative and quantitative in the literature (Chalkias *et al.* 2014). Qualitative methods are knowledge-driven (Aleotti and Chowdhury 1999; Westen 2000), whereas quantitative methods are based on the relationships between controlling factors and landslides (Guzzetti *et al.* 1999). These quantitative methods can be again classified as: (i) data-driven methods, which include bivariate statistics, multivariate statistics, artificial neural networks, etc., and (ii) physically-based methods include deterministic methods and probabilistic methods (Niyogi *et al.* 2010; Tsai *et al.* 2015; Chae *et al.* 2017). Geographic Information System (GIS) has played a significant role in landslide research as it has combined functions of collection, storage, manipulation, display and analysis of spatially referenced data. The combination of GIS and multivariate statistical analysis is considered as a beneficial approach in landslide mapping (Van Westen 1994; Chung *et al.* 1995; Guzzetti *et al.* 1999; Chen and Wang 2007). Even though these statistical models are considered as an important method in landslide studies, they lack efficiency in explaining spatial

variations in the study area while modelling (Pourghasemi *et al.* 2020). Especially in landslide susceptibility studies, which are area-specific, it is essential to understand the spatial interactions between landslide location and conditioning factors (Erener and Düzgün 2010). So the combination of spatial elements and the statistical model could be a more robust method for landslide modelling than the standard statistical landslide prediction methods (Pourghasemi *et al.* 2020).

Spatial econometrics is an evolving stream of econometrics that manages spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data (Anselin 2003). These methods are applied in an extensive range of studies such as demand analysis, labour economics, agricultural economics, environmental economics, etc. Spatial autoregressive model (SAR) and geographically weighted regression (GWR) are widely used global and local regression techniques. The study explores spatial models and the possibility of identifying and measuring the human influencing parameters of landslide occurrences in Kerala.

This investigation was spurred by landslides in Kerala during the years 2018 and 2019. According to Kerala State Disaster Management Authority (KSDMA), 1426 landslides are reported in 2018 and 711 in 2019 (Martha *et al.* 2019). This study emphasizes land-use alterations made by human interventions and their association with landslide occurrences along with other natural parameters. The study is classified into three sections: section 1 identifies the landslide hotspots in Kerala, section 2 deals with the identification of human influencing parameters that accelerate landslide occurrences and section 3 deals with landslide modelling and comparative performance of various methods.

2. Study area

2.1 Geographical and geological setting

Kerala is a relatively small state of 38,863 km² area and is located in the southwestern tip of peninsular India between latitudes 8°17'30"–12°47'40"N and longitudes 74°51'57"–77°24'47"E (figure 1) (SoE Report 2007; Vinod 2017). The state is topographically diverse with physiographic divisions starting from low lands on the west to the midlands (7.5–75.0 m) and further on to the highlands

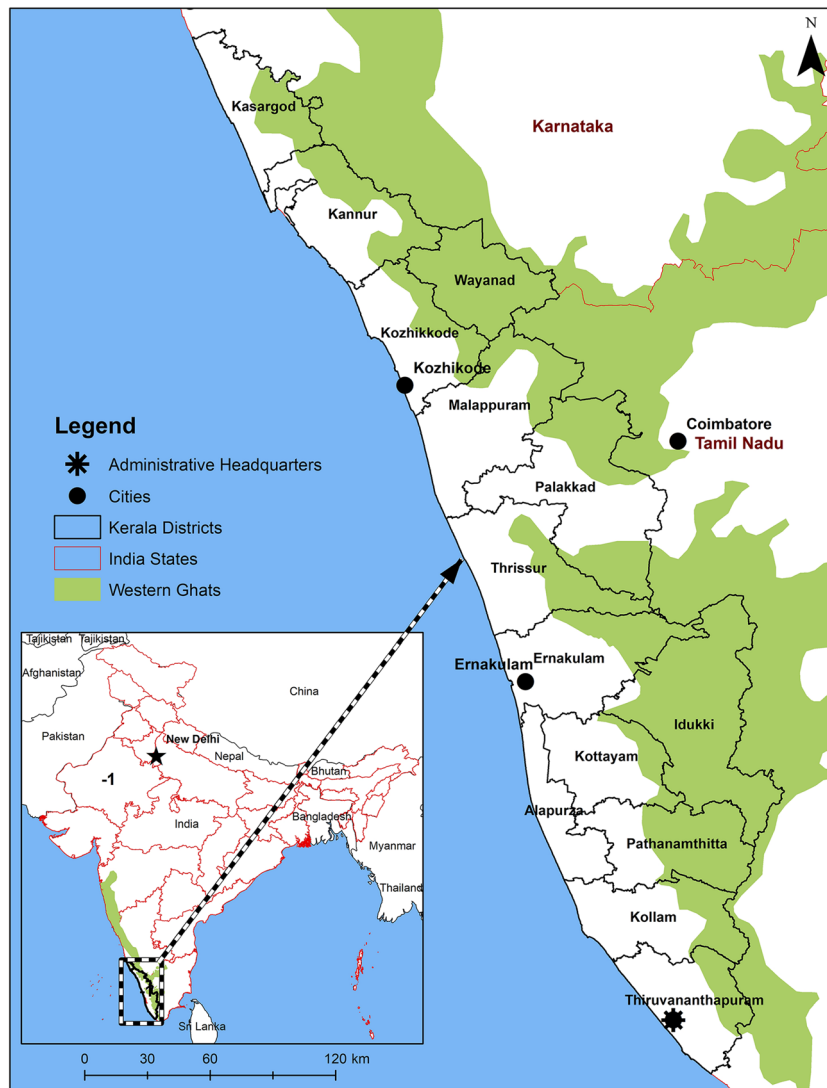


Figure 1. The study area.

(> 75.0 m) in the east (SoE Report 2007). There is a gradual sloping from the eastern Western Ghats to the western Arabian Sea (Das 2020). Kerala's distinct geomorphic features include the tallest mountain peak of Western Ghats, Anamudi (2695 m), 44 rivers and a coastal plain studded with several lagoons and barrier systems (Kumar 1994). The state is geologically a portion of the south Indian shield, preponderance with the crystalline rock formation (Singh *et al.* 2016). The state is a treasure trove of natural resources such as biodiversity, forest, water and mineral resources. Temperature and humidity are high throughout the year and the state is blessed with copious rainfall for nearly 10 months. Kerala is highly vulnerable to various natural disasters, along with changing climatic conditions. The state's topographic position with the steep slope gradient on

one side and sea on the other increases disaster complexity.

2.2 Landslides of 2018 and 2019

According to KSDMA, 14.43% of the state is prone to landslide, especially during the monsoon season. Among landslides, debris flows are the most common in Kerala, named as *Urul Pottal* in the local vernacular (Vineetha *et al.* 2019). During 2018 and 2019, the state experienced the worst disaster in its history since 1924 (KPDNA 2018). 2018 disaster resulted in the death of 483 persons and large-scale loss of property and massive floods, which affected around 5.4 million people (PDNA 2018; Abraham *et al.* 2019; Martha *et al.* 2019). Several landslides, mainly debris flows, occurred in various parts of the state along with floods. According to KSDMA,

in 2018, 1426 landslides were reported from 10 districts of the state. It is evident from figure 2 that, Idukki district witnessed the maximum number of landslides in 2018. The combination of high-intensity rainfall and steep slopes with highly dissected hills and thick topsoil accelerates the probability of landslide (Martha *et al.* 2019). The sudden release of excess water from dams due to increased water levels resulted in toe cutting of rivers and accelerated occurrences of landslides and damages (Abraham *et al.* 2019).

Following 2018, the state faced severe landslides in 2019. A total of 711 landslides and extensive flooding were reported from various parts of the state, causing the death of 121 people (KDSMA 2019 data). Even though the number of landslides reduced, the intensity was observed to be larger than the previous year causing more casualties. Figure 2 clearly shows that the northern districts of Kerala, Wayanad, Malappuram and Kozhikode are

the worst affected region in 2019. In 2019, two hamlets in the state, one at Kavalappara in Malappuram district and the other at Puthumala in Wayanad district were completely washed away by landslides (<https://indianexpress.com/article/explained/how-a-hill-in-the-western-ghats-buried-a-part-of-a-village-in-kerala-kavalapparalandslide-5903013>). The village-wise landslide distribution for the years 2018 and 2019 are represented in figure 3.

3. Data and methods

The data sources used in the study are landslide location, topography, rainfall, geology and land-use. This study's landslide inventory comprises of 2137 landslides from 2018 and 2019 and was obtained from KSDMA. The landslide locations are spatially analyzed and intersected with land-use to identify their respective land-uses. The land-use for

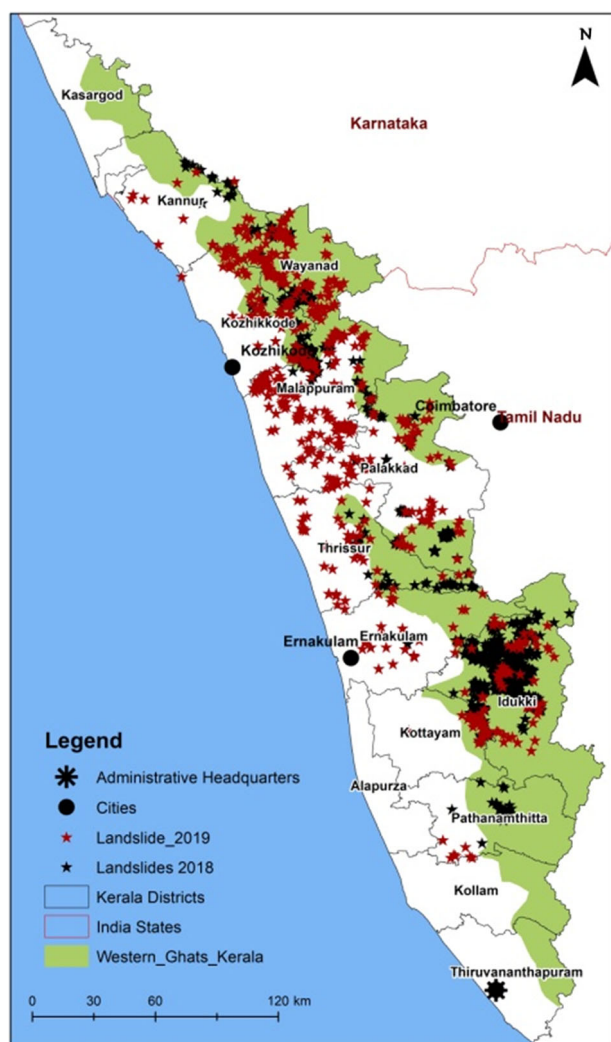


Figure 2. Landslide location (2018 and 2019).

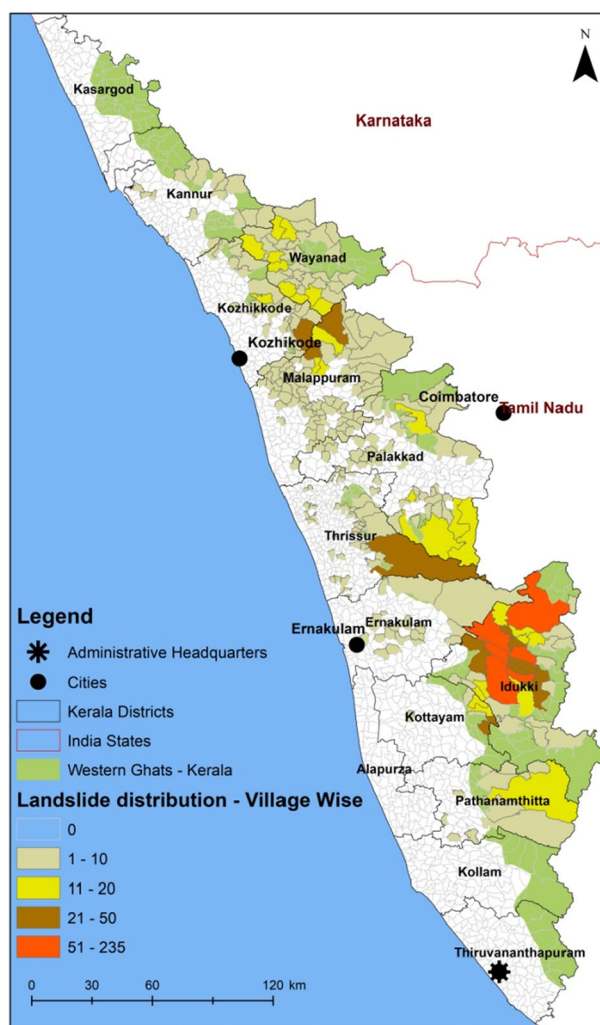


Figure 3. Village-wise landslide distribution.

the study is prepared from sentinel-2 images for the year 2018 downloaded from United States Geological Survey (USGS) website. The image is classified using unsupervised classification algorithm K-means clustering and verified with government data. The quarry data for the whole state was collected from a study conducted by Forest Health Division, Kerala Forest Research Institute Peechi (Alex and Sajeev 2017). Freely available road network data from Open Street Map (OSM) is used for road density calculation. Elevation is obtained from $30 \times 30 \text{ m}^2$ Digital Elevation Model (DEM) collected from USGS. ASTER GDEM of 30-m resolution is downloaded from the USGS website and used for slope generation in GIS. Rainfall location data obtained from the India Metrological Department (IMD) is averaged and interpolated to generate the rainfall map for Kerala. Lithology and lineament were acquired from Kerala State Land Use Board, Department of Planning and Economic Affairs, Government of Kerala.

The methodology flowchart for the study is represented in figure 4. The initial part of the study identifies anthropogenic conditioning factors influencing landslides through the spatial intersection of landslide location and land-use data. Based on the results obtained, anthropogenic conditioning factors such as plantation area, built-up area, cropland, forest plantation, and quarries (figure 5) were selected for statistical evaluation along with natural condition factors (figure 6). The study is carried out at an aggregated unit level, village boundary with landslide density as the dependent variable (figure 7). The landslide hotspots were identified throughout the Kerala state. Hotspot analysis identifies statistically significant clusters of high (hotspots) and low values (coldspots) in the dataset. These clusters are a set of neighbouring spatial units with similar values. In other words, hotspots group locations with positive spatial autocorrelation (Getis and Aldstadt 2004).

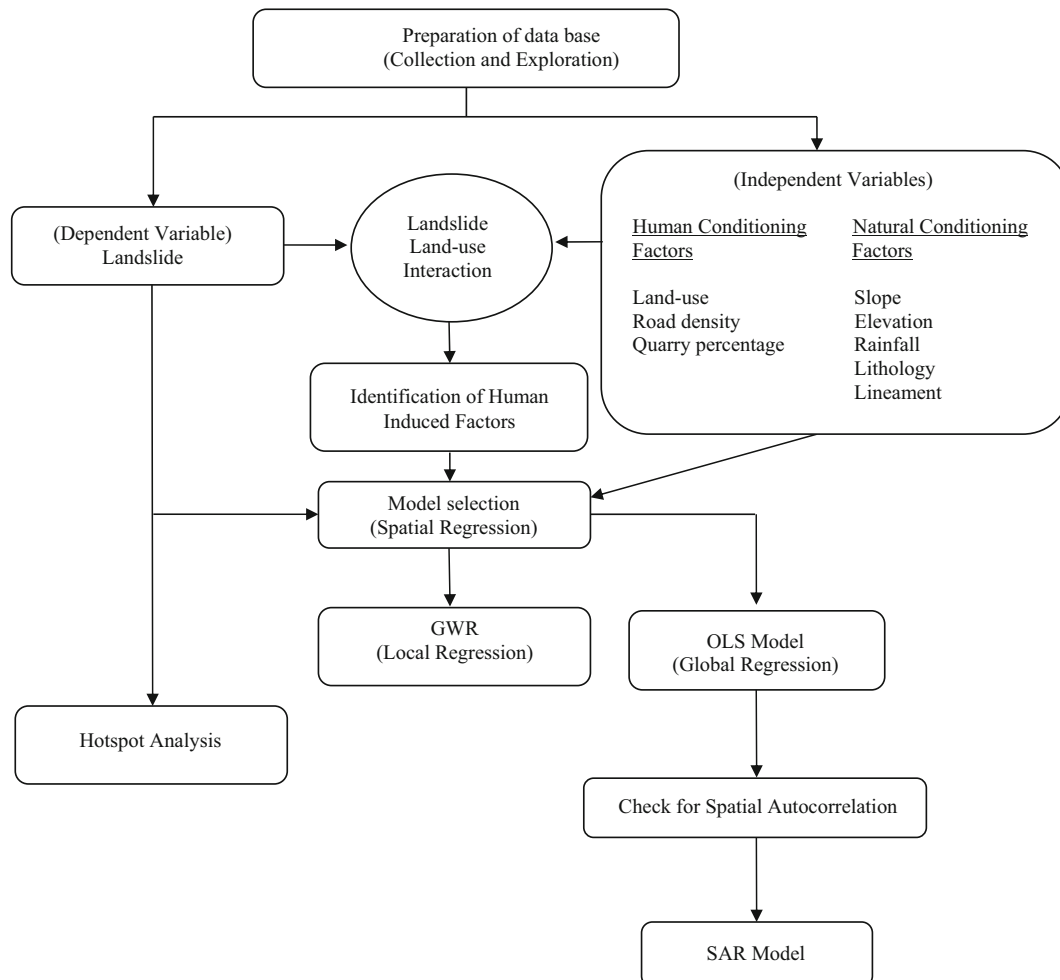


Figure 4. Methodology.

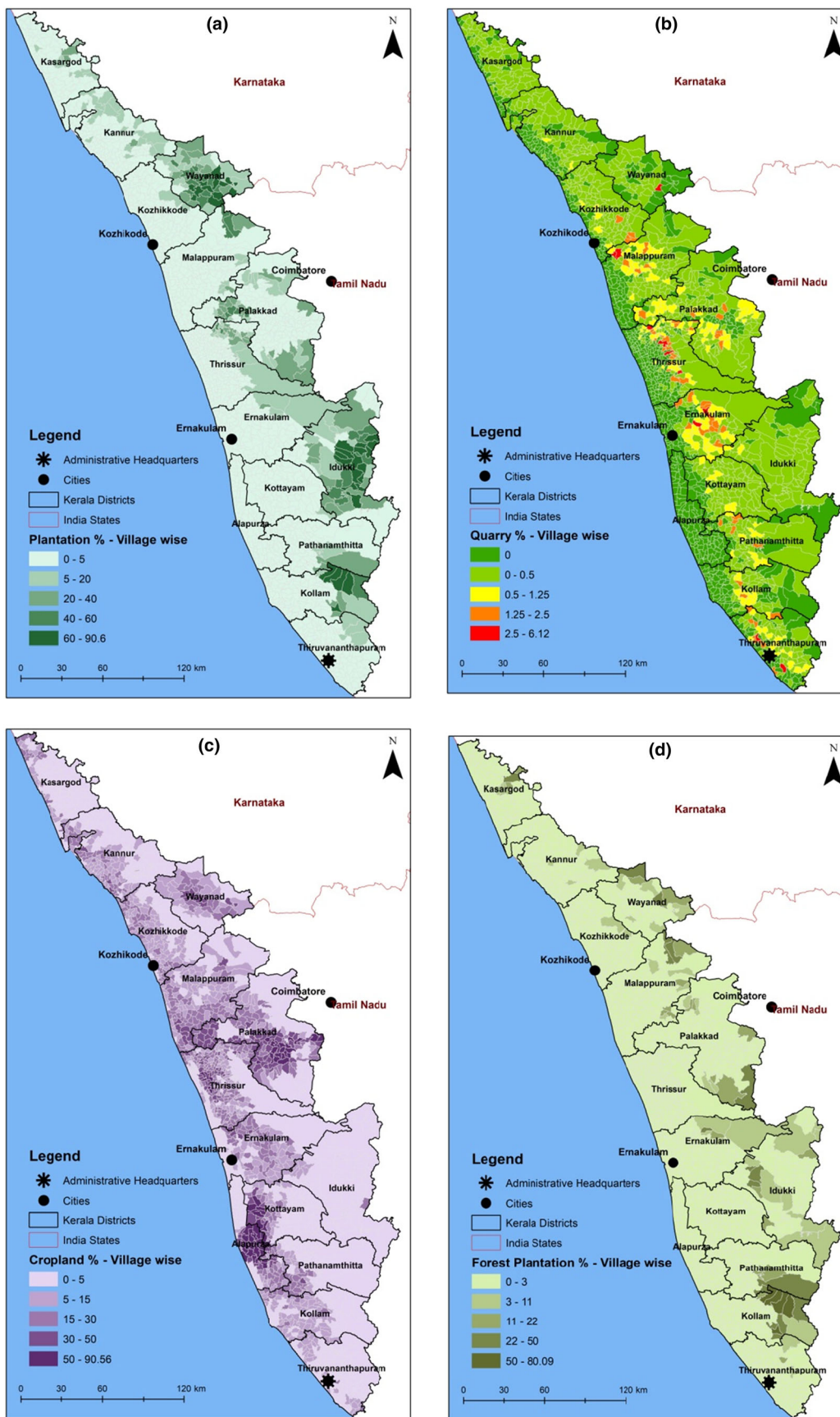


Figure 5. Spatial distribution of human conditioning factors (independent variables): percentage distribution of (a) plantation area; (b) quarry area; (c) cropland; (d) forest plantation area; (e) built-up area; and (f) road density.

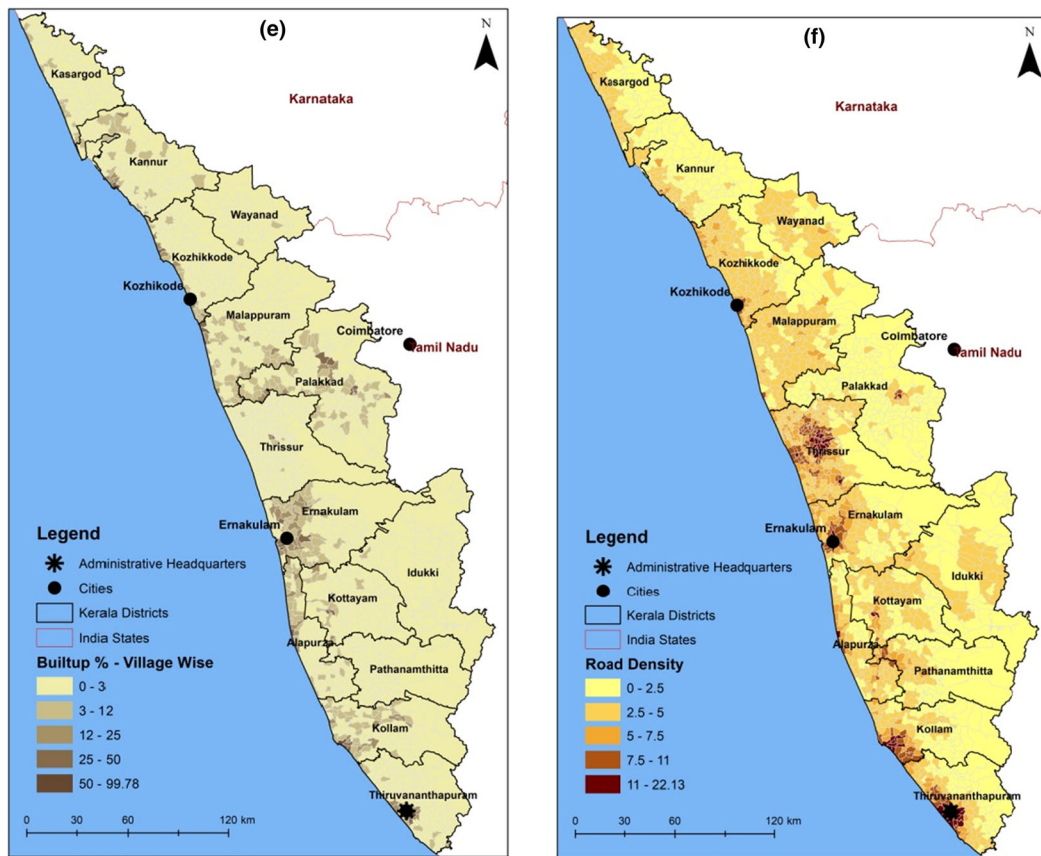


Figure 5. (Continued.)

The regressors used in the study include anthropogenic conditioning factors such as the plantation area, built-up area, cropland area, forest plantation area, quarry area represented as a percentage along with road density and the natural condition factors such as slope, elevation, rainfall, lithology and lineament density, aggregated at the macro-level village boundary and all these are used as independent variables. Based on the results of ordinary least square (OLS) regression, it was decided to check for spatial models. Moran's I test on the OLS residuals indicates the presence of spatial autocorrelation in the data. Lagrange multiplier test is used to identify the suitable spatial regression model. The results of LM test found that both the spatial autoregressive model and spatial error model are significant. Since both models were found significant, the robust LM statistics is used for model selection. SAR model is selected for the study based on its lower p value as per Robust LM test. As spatial phenomena have variability across space, the local spatial analysis could endow more accurate and realistic depictions of situations, especially in landslide studies. Geographically weighted regression (GWR), a local regression

method, is used to analyze the local variability of landslides. The study used Geoda software for OLS and SAR modelling and R programming for GWR.

3.1 Spatial autoregressive model (SAR)

Spatial regression is a standard linear regression model formed by incorporating spatial effects into the model (Saputro *et al.* 2019). SAR model considers the dependency of the spatial unit and the corresponding neighbouring units (external effects or spatial interaction) of the dependent variable. The spatial lag term ρWy is added into the regression equation to incorporate the neighbourhood effects. This is expressed as (Saputro *et al.* 2019):

$$Y = \rho Wy + X\beta + \varepsilon,$$

where ρ is a spatial autoregressive coefficient and Wy is the weight matrix.

3.2 Geographically weighted regression (GWR)

GWR is a spatial regression technique used to study the local variations in the process and

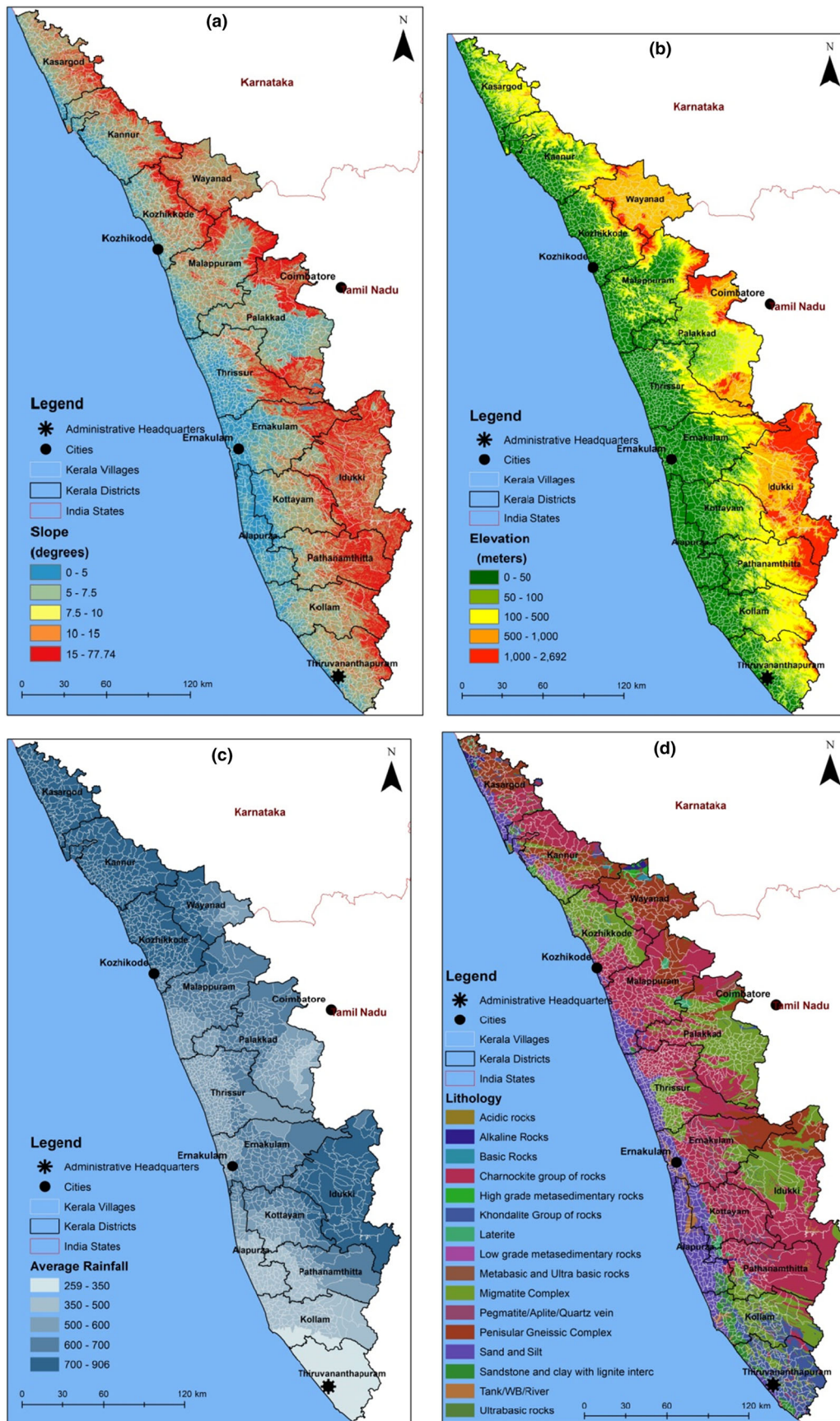


Figure 6. Spatial distribution of natural conditioning factors (independent variables) (a) slope, (b) elevation, (c) rainfall, (d) lithology, and (e) lineament density.

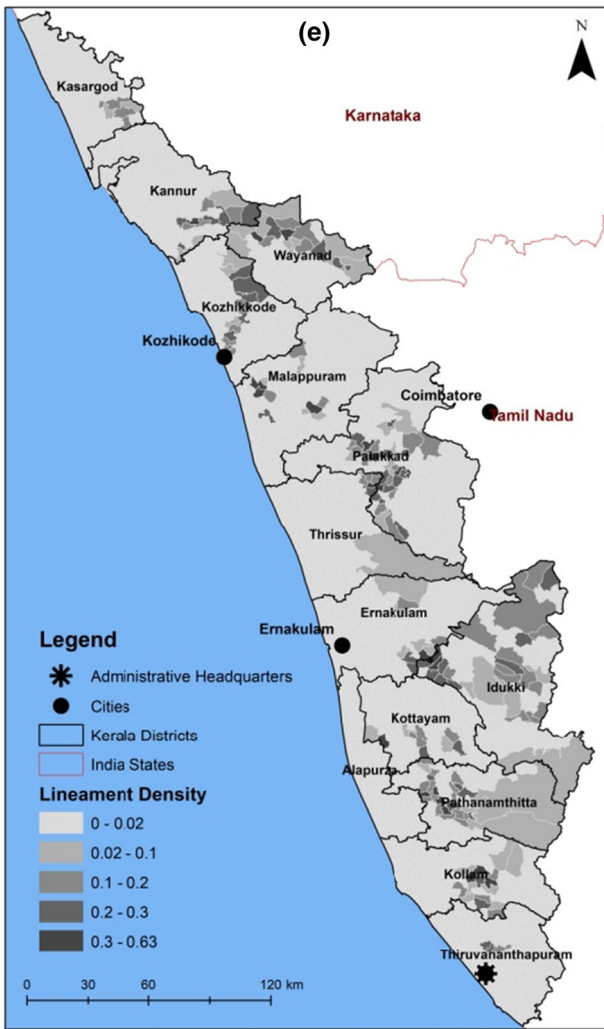


Figure 6. (Continued.)

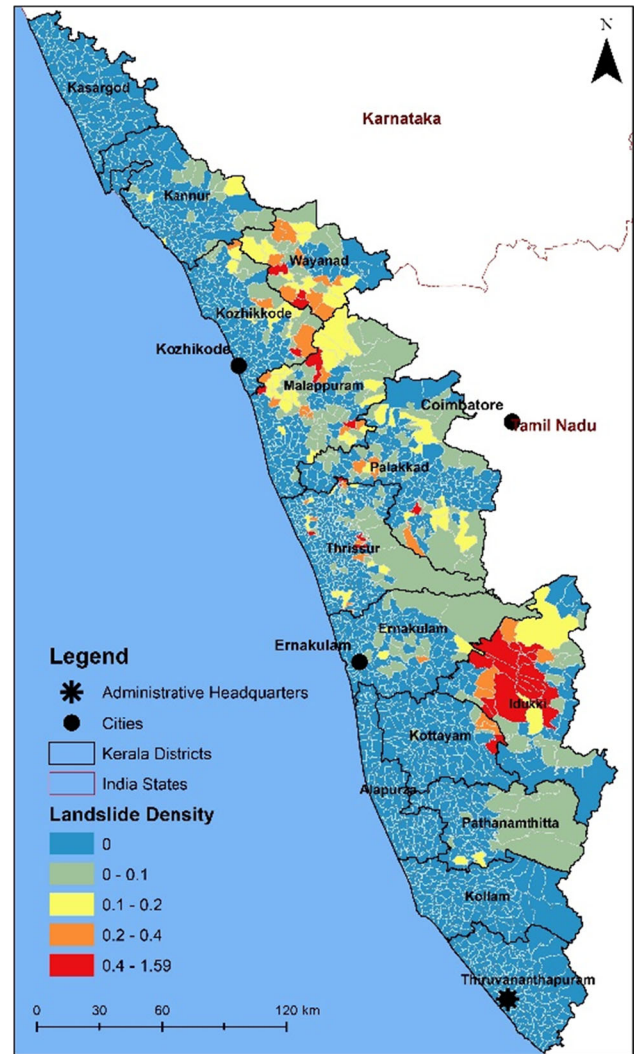


Figure 7. Village-wise landslide density (dependent variable).

variables (Brunsdon *et al.* 1996, 1999). GWR calculates the local variation of the parameter based on geographical location, incorporating real-world spatial variations (Hong *et al.* 2017). In simple linear regression, a model developed as a linear function of a set of independent variable is as follows:

$$y_i = a_0 + \sum_{k=1,m} a_k x_{ik} + \varepsilon_i, \quad i = 1, 2, \dots, n,$$

where y_i is the i th observation of the dependent variable, x_{ik} is the i th observation of the k th independent variable, the ε_i is error terms with zero means, and each a_k is the beta coefficient of the k variables and a_0 is the intercept. The coefficients in the GWR are unique to each location i rather than being global estimates. This is estimated as (Hong *et al.* 2017):

$$y_i = a_{i0} + \sum_{k=1,m} a_{ik} x_{ik} + \varepsilon_i, \quad i = 1, 2, \dots, n,$$

where a_{ik} is the coefficient value of the k th parameter at location i (Brunsdon *et al.* 1996; Hong *et al.* 2017). The GWR output provides a localized estimate of parameters including R^2 and provides the local variation of beta coefficients (Hong *et al.* 2017).

As mentioned above, this study utilizes the global regression models OLS and SAR and local regression model GWR for identifying human conditioning factors influencing landslide occurrence and the results are interpreted and analyzed.

4. Results

4.1 Landslide and anthropogenic conditioning factors

Earth’s surface is continuously changing due to unsustainable practices that occur without

considering the terrain conditions. Improper land-use management is a major determinant for natural disasters such as landslides (Aleotti and Chowdhury 1999; Ercanoglu and Gokceoglu 2004; Lee and Talib Jasmi Abdul 2005; Madhu and Vijith 2008; Vasantha Kumar and Bhagavanulu 2008). Large areas of forest land is cleared for agriculture, plantation, and other activities in Kerala (Jha *et al.* 1995; Kumar 2005). The consequences of all these are evident by the recurrent disasters occurring in the state, such as frequent flash floods and landslides, soil erosion and silting of reservoirs, resulting in ecological and environmental problems (Kumar 2005).

Table 1 consolidates the distribution of the number of landslides in each district of Kerala and its corresponding land-use. The highest percentage of landslides occurred in the Idukki district with 49.04%, followed by Malappuram (12.82%) and Wayanad (11.04%) districts. District-wise percentage distribution of land-use activities in landslide spots are represented in figure 8. While analyzing the landslides, landuse-wise, the maximum number of landslides have occurred in plantation area with 59.38% (tea, coffee, rubber, cardamom etc.) located in plantations. Forest comes second with 21.85% of the total landslides falling in forest land (includes all types of forests such as evergreen forest, deciduous forest, fragmented forest, etc.). Other human-modified land-use practices such as built-up, cropland, forest plantation (teak, pine, etc., planted forest by the government) and quarry have landslide occurrences of 0.37%, 2.20%, 2.39%, and 0.42%, respectively. From table 1, we could also infer that the landslides in the forest plantation are

maximum in the Malappuram district mainly due to large government teak plantations. Ernakulam and Palakkad have more number of landslides in the built-up area. About 64.76% of total landslides have occurred in the human-modified land-uses, which could elucidate that land-use could significantly impact landslide occurrences. Therefore human conditioning factors such as plantation area, built-up area, cropland, forest plantation, and quarries were selected for statistical evaluation along with other natural conditioning factors such as slope, elevation, rainfall, lithology and lineament in the latter part of the study. Figure 9 gives the correlation of selected landslide conditioning factors and the result indicates that elevation and plantation area and elevation and slope are correlated.

4.2 Hotspot analysis

The spatial pattern of landslide distribution is analyzed using hotspot analysis in the study area and depicted in figure 10. The result indicates that the landslide hotspots are concentrated in Idukki, Ernakulam, Kottayam, Wayanad, Kozhikode and Malappuram districts of Kerala. Table 2 shows that no cold spots were identified in the study area. These identified hotspots could be grouped into two clusters. The primary cluster is located in the southeast portion of the state, including areas of Idukki, Ernakulam and Kottayam districts. At the same time, the secondary cluster located in the northeast portion of the state includes parts of Wayanad, Kozhikode and Malappuram districts. Among the 14 districts in the state, six districts are part of landslide hotspots and all these hotspots are

Table 1. District-wise landslide distribution and land-use.

District/total % of landslide	Plantation	Built-up	Cropland	Forest	Forest plantation	Others	Quarry	Total
Ernakulam (1.92)	23	3	1	3	0	10	1	41
Idukki (49.04)	674	1	0	209	18	146	0	1048
Kannur (2.01)	17	0	0	19	0	7	0	43
Kottayam (2.99)	45	0	0	10	0	8	1	64
Kozhikkode (5.05)	58	0	1	42	0	7	0	108
Malappuram (12.82)	153	1	11	33	23	48	5	274
Palakkad (7.58)	88	3	4	37	8	21	1	162
Pathanamthitta (1.82)	27	0	2	8	0	1	1	39
Thrissur (5.71)	78	0	14	7	0	23	0	122
Wayanad (11.04)	106	0	14	99	2	15	0	236
Total (in numbers)	1269	8	47	467	51	286	9	2137
Total % of landslide	59.38	0.37	2.20	21.85	2.39	13.38	0.42	

Note: Others include land use such as rock, water bodies, grassland, sandy area, land with and without scrub, etc.

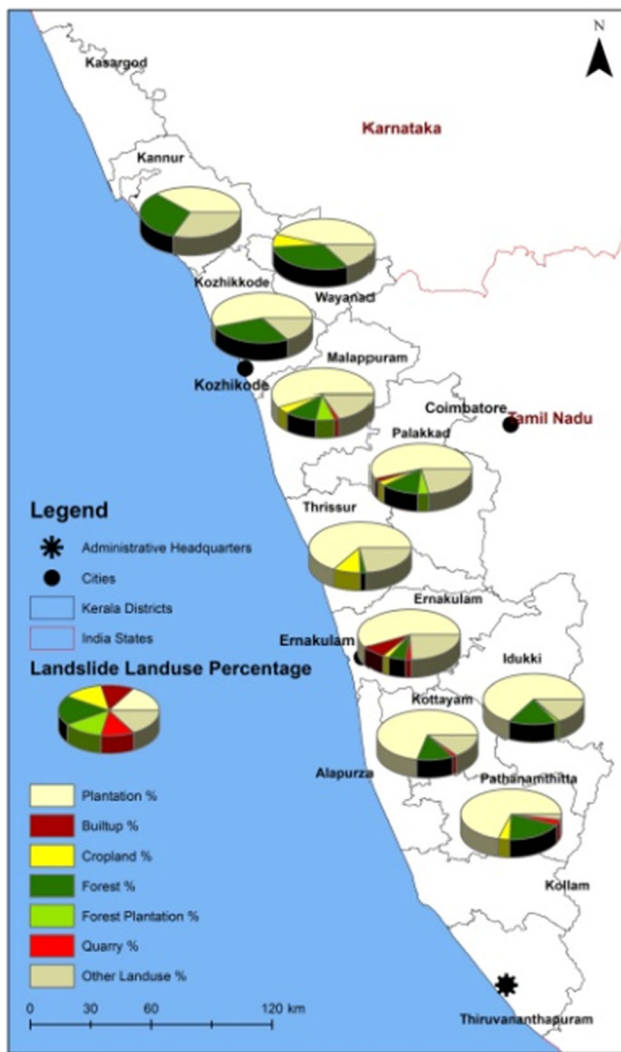


Figure 8. Landslide and land-use percentage.

located in the Western Ghats. Hotspots in the Idukki district include 41 villages with 99% confidence and two villages with 95% confidence. In the case of Ernakulam district, one village each with 99% confidence and 90% confidence is present. While considering the Kottayam district, five villages have 99% hotspot confidence. In the case of Wayanad district, four villages are within 90% and one village in 99% confidence of landslide hotspots. For the Kozhikode district, three villages fall within 95% and one village with 99% hotspot confidence is present. In the case of Malappuram district, one village, each with confidence percentage of 95 and 99 is present. The Idukki district included in primary cluster of landslide hotspot, has plantation as its predominant land-use. The plantation is a major land-use in Wayanad and Malappuram districts too.

4.3 OLS model

Human influencing parameters identified based on results from table 1 were regressed with landslide density aggregated to village boundaries along with natural conditioning factors. The results of OLS regression give less explanatory power as the R^2 value obtained is 21.7%. Since Moran's I value of the residuals is statistically significant, spatial autocorrelation is established, rejecting the null hypothesis. The result of the Lagrange Multiplier test (LM) indicates that both LM-Lag and LM-Error are significant, but the Robust LM-Lag statistic is highly significant, comparing to Robust LM-Error statistics. The result provides a perfect platform for the selection and estimation of the SAR model. Most of the anthropogenic conditioning factors along with the natural parameter slope and rainfall, gave statistically significant results. Details of the OLS model are provided in tables 3 and 4.

4.4 SAR and GWR models

The coefficients of the six human influencing parameters and five natural condition parameters regressed on landslide density using the SAR model are presented in table 5. The results indicate that human-modified land-use activities such as plantation, quarry, cropland and road were found to be significant in the study area. Also, natural parameters slope and rainfall are influential to the landslide. Based on the coefficients of SAR results, it is clearly understood that quarry has a vital role in landslide occurrences among the anthropogenic conditioning parameters. The increase in the log-likelihood from 1315.54 (OLS) to 1590.34 for SAR indicates the improved fit of the model and its better explainability. The Akaike information criterion value reduced to -3124.68 indicates lower information loss in SAR models compared to OLS. The spatial autoregressive coefficient is estimated as 0.669. The predictive performance of the model is 50% indicating better performance than OLS.

On the other hand, GWR allows examining the relationship between the dependent and independent variables in aggregated spatial units, as if each cell has a unique local regression parameter expressing their relationship. The range and average values of coefficients along with the model performance indicators are given in table 6. The AICc value obtained is -2977.968 and R^2 is 47%. The ranges of the local coefficients of the

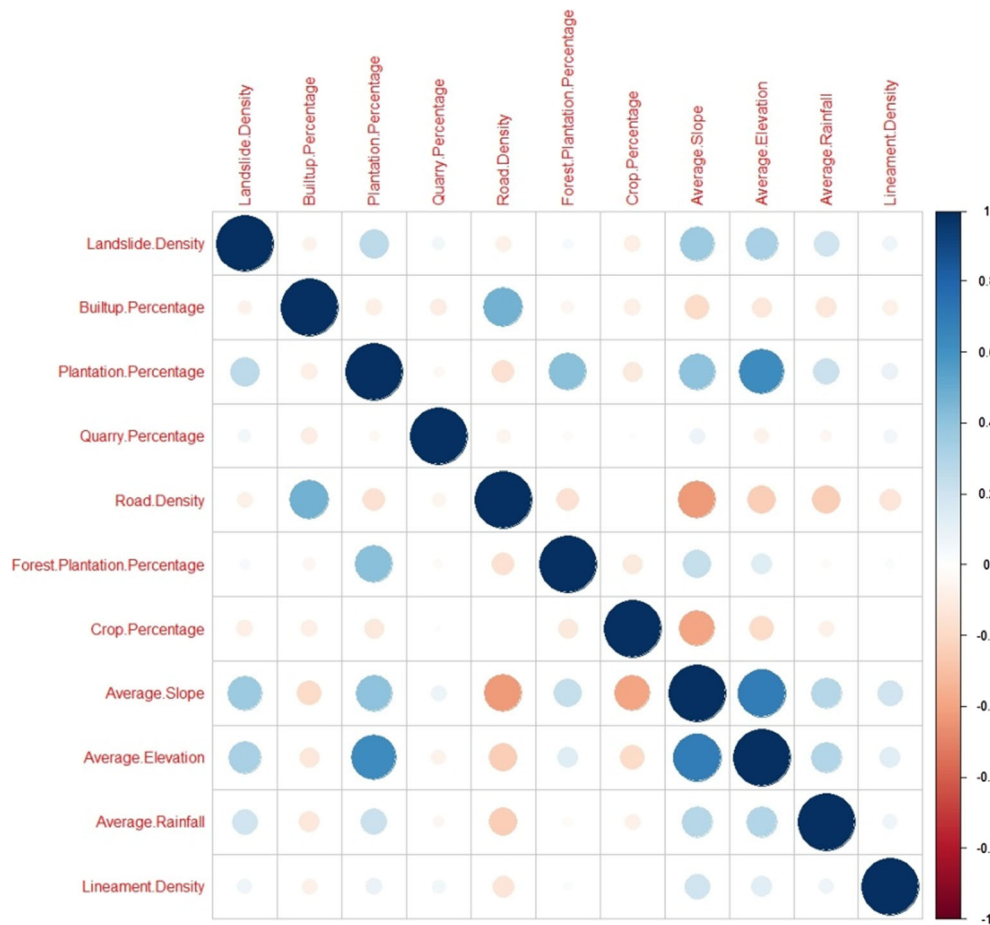


Figure 9. Correlation of independent variables.

independent variables obtained in GWR are -0.0032700 to 0.10691 with a mean of -0.00026869 (percentage area of built-up), -0.0024609 to 0.0025813 with a mean of 0.00020947 (percentage area of the plantation), -0.0077835 to 0.043267 with a mean of 0.0093223 (percentage area of the quarry), -0.0043979 to 0.013156 a mean of 0.0015400 (road density), -0.0076673 to 0.0092037 with a mean of -0.000045277 (percentage of forest plantation), -0.00040918 to 0.00099887 with a mean of 0.00017659 (percentage area of cropland), -0.0027095 to 0.032236 with a mean of 0.0094472 (average slope), -0.0011853 to 0.00055598 with a mean of 0.0000071149 (elevation), -0.00020374 to 0.00055299 with a mean of 0.000077782 (average rainfall) and -0.23077 to 0.18941 with a mean of (-0.021993) (coefficients of lithology is given in table 6). These local coefficients indicate that the relationships between the landslide density and independent variables are not stationary and they vary throughout the space. The predicted values of all three regression values are plotted in GIS and

represented in figure 11. The maximum range of landslide predictions obtained in OLS is 0.344 , SAR is 0.33 and GWR is 0.66 .

5. Discussion

The study analyzes the relationship between landslide occurrence and land-use activity using spatial overlay and statistical modelling. The results indicate that 64.76% of the total landslides fall in the category human-modified landscapes and majority of them are in plantation. According to the results of hotspot analysis, two clusters of landslide hotspots are identified in Kerala. The primary cluster includes most of the area under Idukki district and small regions of Ernakulam and Kottayam districts. The secondary cluster is located in the boundaries of Kozhikode, Malappuram and Wayanad districts. All regression results indicate that the percentage area under the categories quarry and plantation along with road

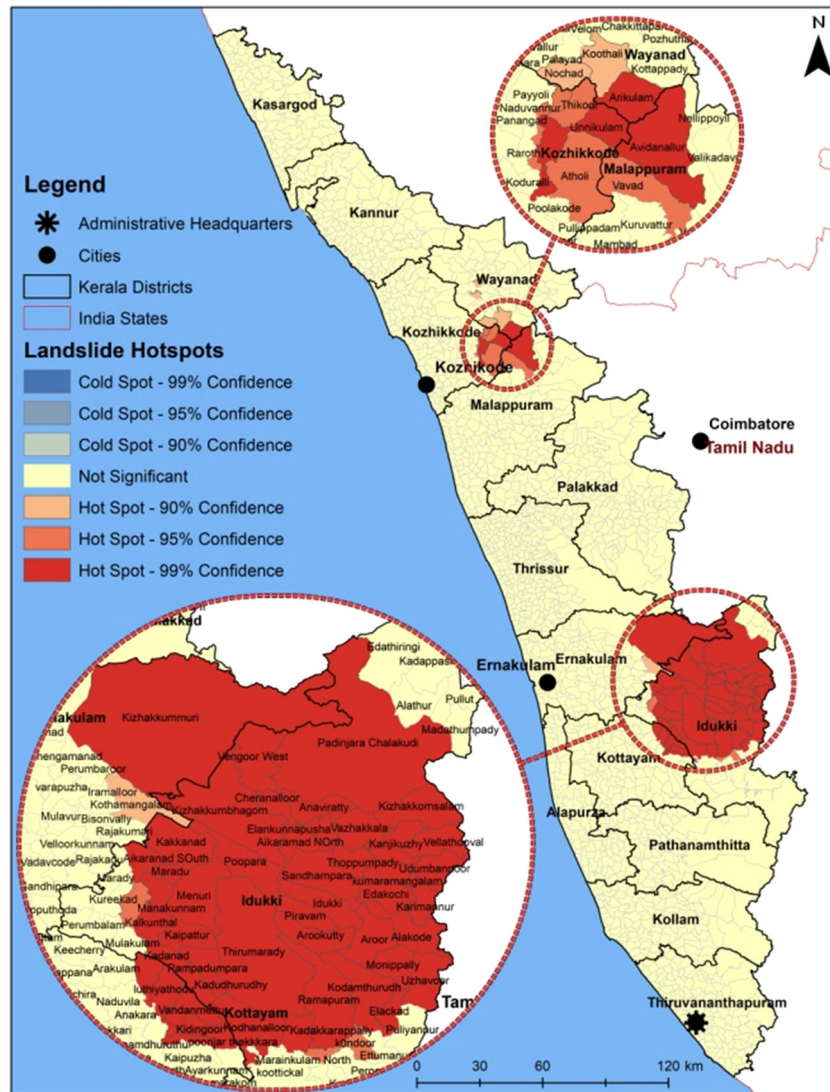


Figure 10. Landslide hotspots.

Table 2. Coefficients of hotspot analysis.

Sl. no.	District	No. of hotspot villages with confidence percentage		
		90	95	99
1	Idukki	0	2	41
2	Ernakulam	1	0	1
3	Kottayam	0	0	5
4	Wayanad	4	0	1
5	Kozhikode	0	3	1
6	Malappuram	0	1	1

density has a major role in landslide occurrences. Among the natural conditioning factors, slope and rainfall indicate major role in landslide occurrences.

The model performance indicators like AICc and R^2 show that spatial regression models are better

than OLS in understanding the dynamics of landslides. Comparison of the predicted plots of the three models with landslide density map indicates that the spatial pattern of prediction is better in GWR. The two clusters identified by hotspot analysis are predicted correctly as high landslide

Table 3. Summary statistics for OLS model.

	OLS model	
	Coefficients	S.E.
<i>Constant</i>		
Land-use	-0.123276	0.10855
% Built-up	-0.000347321	0.000380427
% Plantation	0.00166645***	0.000293741
% Forest plantation	-0.00242101***	0.000569772
% Cropland	0.000609236***	0.000217402
% Quarry	0.015613***	0.00597379
Road density	0.00524347***	0.00121239
Average slope	0.0142567***	0.00132331
Average elevation	-0.0000152904	0.0000214212
Average rainfall	0.00007.96059***	0.0000297648
<i>Lithology</i>		
Acidic	-0.0016068	0.00133981
Alkaline	-0.000668365	0.00124239
Basic	-0.00125535	0.0013845
Charnock	-0.000492354	0.00106653
High	0.00006.82937	0.00152819
Khondali	-0.000624364	0.00108061
Laterite	-0.000327828	0.00112961
Low	-0.00042983	0.00111763
Metabas	-0.00409258*	0.00241829
Migmatit	0.000000182795	0.0010664
Pegmatit	-0.0129998	0.0139928
Peninsula	-0.000731259	0.00107265
Sand	0.0000139258	0.00106692
Sandstone	-0.000210738	0.00108621
Tank	0.000670708	0.00113471
Ultrabas	-0.000945106	0.00153144
Lineament density	-0.0208097	0.0383929
R^2	0.217434	
Adjusted R^2	0.204374	
S.E.	0.106422	
Log likelihood	1315.54	
AICc	-2577.09	

Note: Confidence intervals are represented as ***99%, **95%, and *90%.

Table 4. Summary statistics of test for spatial autocorrelation.

	Coefficients	Probability
Moran's I	27.7258***	0.00000
LM (lag)	711.1075***	0.00000
Robust LM (lag)	16.7260***	0.00004
LM (error)	706.4949***	0.00000
Robust LM (error)	12.1134***	0.00050

density areas by GWR. The other two models identify one more cluster in northern Kerala as high landslide density region in Kannur,

Table 5. Summary statistics for SAR.

	Coefficients	S.E.
<i>Constant</i>		
% Built-up	-0.000155707	0.000301331
% Plantation	0.000627547***	0.000233564
% Quarry	0.00970834**	0.00473157
Road density	0.00270531***	0.000964878
% Forest plantation	-0.0012458***	0.000452028
% Cropland	0.000374571**	0.00017265
Average slope	0.00867506***	0.00108594
Average elevation	-0.00004.33585**	1.69721e-005
Average rainfall	0.000022464	2.37116e-005
<i>Lithology</i>		
Acidic	-0.000868792	0.0010612
Alkaline	-0.000482987	0.000984003
Basic	-0.000745578	0.00109657
Charnock	-0.000396252	0.000844671
High	0.000440126	0.0012103
Khondali	-0.000466239	0.000855822
Laterite	-0.000461586	0.000894633
Low	-0.000255734	0.000885172
Metabas	-0.00226617	0.00191528
Migmatit	-0.000133172	0.000844608
Pegmatit	-0.00440099	0.011082
Peninsula	-0.000507707	0.000849577
Sand	-0.0000682734	0.000845
Sandstone	-0.000231192	0.000860276
Tank	0.000386219	0.000898843
Ultrabas	-0.000442404	0.00121291
Lineament density	-0.0214545	0.0304065
Spatial lag coeff.	0.669209	0.0231462
S.E.	0.0842844	
Log likelihood	1590.34	
AICc	-3124.68	
R^2	0.500640	

Note: Confidence intervals are represented as ***99%, **95%, and *90%.

Kasaragod region. The real landslide density shown in figure 7 is spatially similar in pattern with the GWR prediction compared to the other models. GWR models have a better prediction range at higher landslide densities.

6. Conclusion

This study aims to identify the landslide hotspots in Kerala, India, based on 2018 and 2019 landslides and apply spatial modelling techniques to identify human influencing parameters that accelerate landslide occurrences. Results of hotspot analysis indicate that the landslide hotspots are concentrated in two clusters, the primary cluster includes

Table 6. Summary statistics for GWR.

	Coefficients		
	Minimum	Mean	Maximum
<i>Constant</i>	-0.43440078890	-0.03971027755	1.20945392960
% Built-up	-0.00327004139	-0.00026869212	0.00106906591
% Plantation	-0.00246089502	0.00020946705	0.00258129508
% Quarry	-0.00778345054	0.00932229497	0.04326688228
Road density	-0.00439792404	0.00154000167	0.01315613334
% Forest plantation	-0.00766734869	-0.00004527715	0.00920365504
% Cropland	-0.00040917841	0.00017659152	0.00099886677
Average slope	-0.00270948819	0.00944718005	0.03223580436
Average elevation	-0.00118529875	-0.00000071149	0.00055598339
Average rainfall	-0.00020374345	0.00007778241	0.00055299121
<i>Lithology</i>			
Acidic	-0.03575002507	-0.00229032322	0.05915805280
Alkaline	-0.02750424521	-0.00039186203	0.05561432204
Basic	-0.01585203551	-0.00159442327	0.00857059042
Charnock	-0.01274530605	-0.00034471409	0.00002173021
High	-0.02129346428	-0.00494270095	0.04817696106
Khondali	-0.03582334502	-0.00288855466	0.00053723923
Laterite	-0.01252208745	-0.00039585926	0.00024838456
Low	-0.01305986437	-0.00131954712	0.00036623629
Metabas	-0.02574379000	-0.00160814638	0.01883694697
Migmatit	-0.01315917872	-0.00005032233	0.00063286082
Pegmatit	-0.42192543250	-0.05294983521	0.00127384646
Peninsula	-0.01378770758	-0.00048409538	0.00619102251
Sand	-0.01284323368	-0.00010479237	0.00055432961
Sandstone	-0.01298608481	-0.00021762037	0.00059833764
Tank	-0.01438324990	0.00008025897	0.00236974214
Ultrabas	-0.01395324460	-0.00213839335	0.00011059000
Lineament density	-0.23077447569	-0.02199267982	0.18940580604
AICc	-2977.968		
R ²	0.4672624		

Idukki, Ernakulam and Kottayam districts and the secondary cluster includes Wayanad, Kozhikode and Malappuram districts. All these hotspots recline in the Western Ghats mountain region, which indicates the necessity of detailed regional study on landslides in the Western Ghats area. While examining the landslide locations and their corresponding land-use, the maximum number of landslides have occurred in the plantation area (59.38%), with the maximum in the Idukki district. 64.76% of the state’s total landslides have happened in the human-modified land-use such as plantation, built-up, cropland, forest plantation, and quarries.

OLS, SAR and GWR models were used in the study to analyze the role of anthropogenic conditioning parameters triggering landslides. The result

indicates that the human-modified landscapes also have an imperative role in landslide occurrences along with natural parameters. The study indicates that even though landslide occurring in the quarry is less in number, quarry also has a significant role in landslide occurrences comparing with other anthropogenic conditioning factors. All models clarify that human-modified land-use practices such as quarry, plantation, cropland indicate a positive correlation with landslide occurrences. Slope and rainfall are found to be positively influencing landslides.

SAR and GWR models used in the study incorporate the spatial correlations of the independent variables. Therefore, the results of the analyses illustrate that the conventional susceptibility assessment method can produce better results by

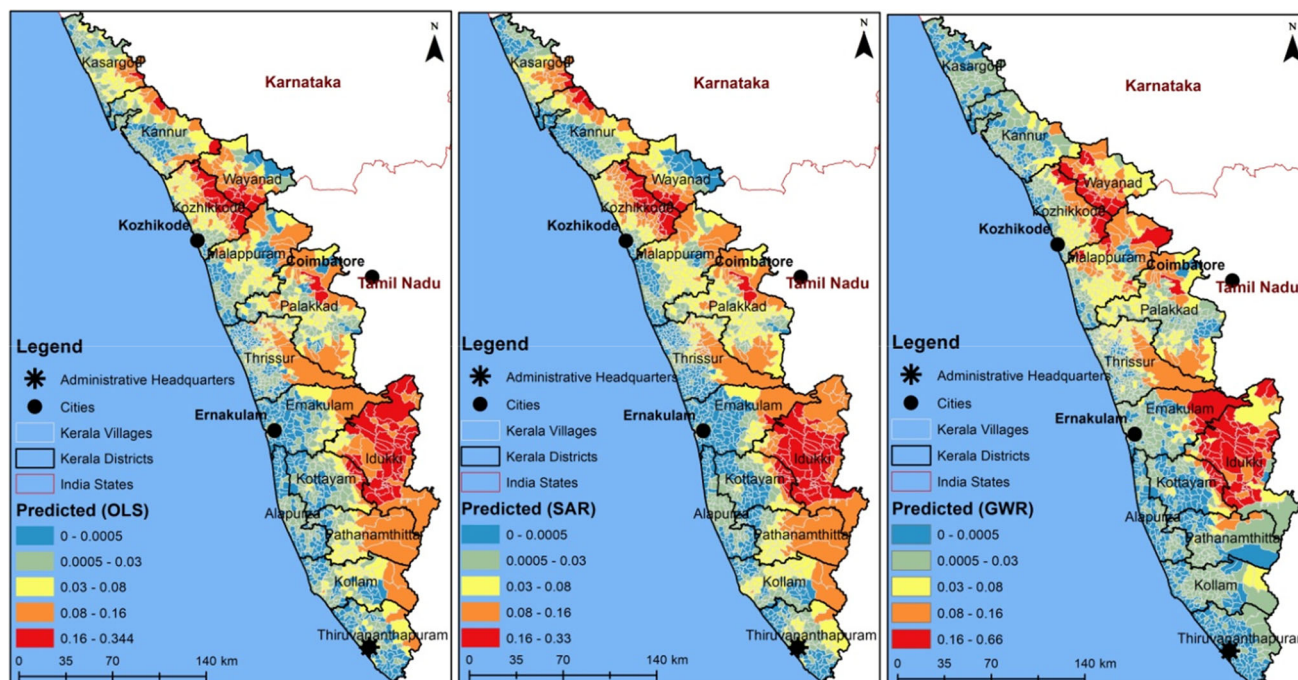


Figure 11. Landslide model comparison of predicted values of OLS, SAR and GWR.

applying spatial regression models. Even though the statistical evaluation of the models show that the performance of SAR model is superior, spatial examination of the predicted values prove that GWR is the better model. Since the regional variation in each variable is considered in GWR models, this is more useful to understand the behavioural pattern of independent variables. The study surmises that both global and local models can be used for landslide studies based on their applicability. SAR model could be used if the spatial effects are to be incorporated in a global aspect, while GWR can be applied if the local effects of spatial variations are to be analyzed.

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Author statement

Sheelu Jones: Data collection, analyses, interpretation, conceptualization, writing-reviewing-editing of the manuscript. Kasthurba A K: conceptualization, methodology and reviewing. Anjana Bhagyanathan: conceptualization, methodology and reviewing. Binoy B V: data interpretation, analyses, conceptualization of manuscript, visualization and reviewing.

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