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Ecologically sensitive regions in Belgaum district, Karnataka, Central Western Ghats

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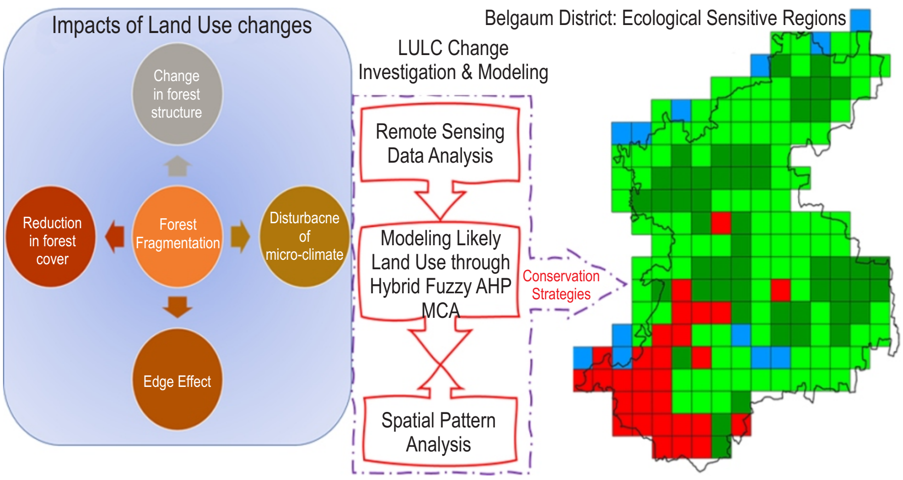
Abstract

Aim: Deforestation due to unplanned developmental activities leading to the loss of carbon sequestration capability and the release of stored carbon to the atmosphere has been a prime mover of global warming, with changes in the climate evident from the spatio-temporal changes in the rainfall, increase in temperature, and higher instances of vector-borne diseases. Unregulated land cover changes have necessitated prioritizing ecologically sensitive regions to develop location-specific management strategies. This entails estimating spatio temporal LULC changes using multi-resolution spatial data to understand landscape dynamics, which helps in the prudent management of natural resources.

Methodology: The current communication accounts for land use transitions in the Belgaum district, part of central Western Ghats, through classifying spatial data over a temporal scale using a supervised classifier. Ecologically sensitive regions are prioritized by integrating bo-geo-climatic, ecological, hydrologic, and social parameters.



Results: Temporal land use analyses reveal a loss of forest cover by 2.99% (90.29 sq km) with an increase in the built-up area during two decades (1989 to 2019 and a decline of contiguous interior forests from 16.26% to 6.77%. Geo-visualisation of likely land uses through a hybrid Fuzzy MCE AHP MCA modeling indicates a further decrease of forest cover of 5.6% by 2029. Hence, it necessitates the conservation of ecologically sensitive regions (ESR) at disaggregated levels.

Interpretation: Regions with exceptionally high sensitivity (ESR1) cover 15% of the spatial extent of the district, 27% (52 grids) cover higher sensitivity (ESR2), 52% (99 grids) are high to moderate sensitive (ESR3), and the rest 6% (12 grids) are minimal sensitive (ESR4). Prioritization of the region based on its ecological sensitiveness would facilitate decision-makers in the implementation of effective conservation policies focusing on maintaining the ecological integrity through prudent management of natural resources to support livelihood with the sustenance of natural resources.

Key words: Forest fragmentation, Hybrid modeling, Livelihood of people, Land use Land cover, Natural Resource Management

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Introduction

The landscape consists of a mosaic of ecosystems, driven by the natural and human interactions leading to changes in the physical, biological, and cognitive assets. Landscape dynamics can be understood by assessing land use and land cover (LULC) changes. Land cover (LC) characterizes physical features on the earth's surface (non-vegetation and vegetation). Land use (LU) indicates how a particular land is being transformed for human activities and other economic aspects. Ecosystems maintain dynamic equilibrium provided LULC transitions are within the threshold (Mensah *et al.,* 2019). Assessment of landscape dynamics helps to understand the Lu changes, fragmentation of forests, etc., which are essential for the sustainable management of natural resources (Ramachandra *et al.,* 2020a; 2018a). Detailed assessment of LULC patterns acts as a knowledge base, which aids in framing developmental plans and evaluates the magnitude of land conversion and the associated environmental degradations (Tiwari *et al.,* 2021).

The dominance of humans with unplanned developmental activities has converted biodiverse-rich landscapes into dense built-up environments that often lack basic amenities and infrastructure. The transition of native forests into exotic monoculture plantations, agriculture, built-up, open areas has altered hydrologic regime, evapotranspiration changes, land surface temperature, and variation in monsoon pattern (Devaraju *et al.,* 2015; Ramachandra *et al.,* 2018b; 2020b; Tran *et al.,* 2021), etc. Landscape health is governed by its structure (vegetation cover, quality, etc.) that decides the functional aspects. The current trends of declining forest cover across the globe through LULC changes are hampering the ability of ecosystems to adapt to changing conditions and thus resulting in the erosion of goods and services (Bellard *et al.,* 2012), which necessitates understanding LULC dynamics through assessment of spatial data acquired through space-borne sensors at regular intervals. The forest ecosystem provides a crucial source of food and other natural resources which sustain all life forms, including humans. The goods and services provided by forest ecosystems are vital for the social-economic development of regions.

The fragmentation of forests due to uncontrolled LULC changes modifies landscape structure affecting the food chain, which can cause an imbalance in the ecosystemwith alteration in the ecosystem processes such as carbon sequestration, hydrological regime, nutrient supply, loss of habitat, decline in biodiversity,etc. (Sharma *et al.,* 2017; Ramachandra and Bharath, 2019). Fragmentation processes involve alterations in the structure and composition of native forests through the division of contiguous forests into smaller non-contiguous fragments with a sharp increase in edges, induces loss of connectivity, impacts the structure and health by affecting the hydrological cycle, and results in biodiversity loss (Sharma *et al.,* 2011; Ramachandra *et al.,* 2016). Human activities are often non-compensatory compared with natural changes, involving deforestation and resource mismanagement, which have decreased the interior forest cover while enhancing the edge and perforated forests. The edge effect caused by LULC changes affects the species regeneration, genepool, increased instances of fire, etc. Understanding fragmentation processes would aid in framing policies to arrest further degradations and improve connectivity with the habitat quality through appropriate measures. LULC and fragmentation analyses depict landscape changes induced by anthropogenic pressure, and hence, a systematic understanding is crucial for framing policies toward prudent management. The advancement in geoinformatics with the availability of multi-resolution remote sensing (RS) data and Geographic Information Systems (GIS) during the past five decades has aided in understanding LULC changes with insights of underlying drivers, and integrating them to derive valuable outputs for planning a region.

Long-term space-based imaging and sophisticated image processing techniques assist in climate change studies, landscape status (forest loss, land use, etc), social studies, and natural resource evaluation and sustainable management (Roy *et al.,* 2016). LULC modeling has become a prime tool in recent decades for solving the problem that arises due to the modification and conversion of LULC (Lambin *et al.,* 2001; Singh *et al.,* 2015). Modeling LULC changes would lend an opportunity to review the current status and visualize likely impacts due to the sustained anthropogenic pressure in forested regions (Ramachandra *et al.,* 2017). Various models have originated during the past three decades, integrating mathematical functions to meet land management needs, predict the potential LULC change, ecological assessment, restoration planning and framing strategies for conservation (Scheller and Mladenoff, 2007; Xi *et al.,* 2009; Rama *et al.,* 2018; Bharath *et al.,* 2021). Integrating spatial models with a focus on resource usage and relating agents would lead the way into the future, which helps in future policy making (Shiftan, 2008) and control the exploitation of natural resources (van Meijl *et al.,* 2006).

Cellular Automata (CA) helps simulate spatial processes of complex systems with a small set of simple rules and states. CA works on what-if scenarios to help evaluate a set of scenarios for planning-related activities (Araya and Cabral, 2010). The Markov chain (MC) technique provides stochastic estimates of the likely change based on transitions quantified from two-time data. Integrating Markov with CA (MCA) provides a robust approach by capturing spatial and temporal dynamics through modeling LULC changes based on the spatial dynamics, with transition probabilities, and a set of local rules (Sang *et al.,* 2011). MCA modeling by combining biophysical and socioe-conomic data has emerged as an effective technique to simulate an accurate and plausible likely LULC of a region (Arsanjani *et al.,* 2013). Hybrid models are powerful to simulate spatial systems because they can capture essential neighborhood changes. MCA with Fuzzy Analytical Hierarchical Process (AHP) and Multi-Criteria Evaluation (MCE) hybrid technique helps to capture and simulate the growth dynamics with insights of agents (Bharath and Ramachandra, 2021). MCE technique assists in determining the best logical choice through evaluating several factors and analyzing the associations between these factors since every criterion is not equally important and does not equally contribute to suitability, which varies across different levels (Prakash, 2003; Mandal *et al.,* 2020). AHP approach ranks the relative importance of the criterion based on the AHP scale through the Pairwise Comparison Matrix (PCM), considering the strength of each factor (Tripathi *et al.,* 2021). Regions having diverse habitats, with an assemblage of species and prone to be threatened due to anthropogenic activity or natural disaster depicts very high sensitivity or is known as ecologically fragile or sensitive or vulnerable region. The ecological fragility can be accounted for by considering an ecosystem's distinct biological, geo-climatic, social, and LU qualities. Mapping and prioritizing these regions also aid in achieving sustainable development goals, which is crucial to sustaining direct and indirect services of ecosystems. Considering the varied characteristics at the disaggregated level helps prioritize based on ecological sensitivity, which aids in conservation planning as per the Biodiversity Act 2002.

Classifying regions based on the aggregate score of attributes with their weight requires an understanding of the ecosystem processes and the negative impacts due to the stressed condition with increasing human activities in the name of economy and growth. The weights are assigned to attributes based on expert advice and literature review. Conservation of ecosystems is challenging and needs to be based on a balanced plan considering multidiscipline inputs (Zhang *et al.,* 2013). This necessitates assessing the ecological integrity of a region based on biophysical, economic, and socio-culture attributes to evolve strategies to curtail all disastrous implications. The classification of a region at disaggregated levels based on the levels of ecological sensitivity would aid in formulating location-specific conservation measures with permissible activities in the corresponding zones. Prudent management of ESR/ESZ (Ecologically Sensitive Regions/Zones) aids in arresting deforestation, which regulates and minimizes anthropogenic changes, besides supporting the local community with the sustenance of natural resources (water, food, medicine, etc.) with the active participation of all stakeholders. Objectives of the current research are to (i) understand temporal LUchanges in Belgaum district, Karnataka State, India (Central Western Ghats) from 1989 to 2019; evaluate forest eco-system conditions through fragmentation metrics; modeling of likely changes through hybrid modeling technique to mitigate adverse LU transitions through appropriate policies and assessment of ecological sensitiveness at the disaggregated level through composite metrics based on bio-geo-climatic, ecological, hydrological and social attributes.

Materials and Methods

The protocol adopted in the current work is outlined in Fig. 1, which involves assessing temporal LU, estimation of forest fragmentation, modeling of likely LU and mapping ecologically sensitive regions at disaggregated levels.

Study area: Belgaum district is located at 15° 23'-16° 58' N and 74° 05'-75° 28' E with a spatial extent of 13,415 sq km and is divided into ten taluks for decentralized administration (Fig. 2). The district is administered at disaggregated levels through 10 taluks with 1270 villages,and has a population of 4.2 million with a growth rate of 13.41%. Belgaum has forest cover types ranging from dense evergreen forests stand at 450 to 900 m above mean sea level (amsl) in the west to the moist deciduous in the foothills of the Sahyadri (mountainous part of the Western Ghats), and dry deciduous thorn scrubs in the north and eastern portions. Dry deciduous hills define the central zone of the district to the west, and a succession of bare sandstone ranges to the east. The district is home to critically endangered and threatened species of flora such as *Syzygium travancoricum* Gamble, *Vateria indica* L., *Corypha umbraculifera* L, *Zornia gibbosa* Span., *Dimocarpus longan* Lour., *Garcinia gummi-gutta* (L.) Roxb., *Aspidopterys canarensis* Dalzell, *Calophyllum apetalum* Willd, *Chloroxylon swietenia* DC., *Dalbergia latifolia* Roxb, *Garcinia indica* (Thouars) Choisy, *Myristica dactyloides* Wall, *Myristica malabarica* Lam, *Saraca asoca* (Roxb.) Willd. The significant and vulnerable fauna includes birds (*Ardeotis nigriceps*, *Sarcogyps calvus*, *Vanellus gregarius*, *Gyps bengalensis*, *Gyps indicus*), Mammals (*Otomops wroughtoni*, *Bubalus bubalis*, *Cuon alpinus, Elephas maximus, Manis cradsicaudata, Panthera tigris, Hyaena hyaena, Panthera pardus, Equus asinus, Semnopithecus hypoleucos, Bos gaurus, Melursus ursinus, Platacanthomyslasiurus*), Reptiles (*Hemidactylus sataraensis, Ophiophagus hannah, Python molurus*).

The southern part of the district consists of the Bhimgad Wildlife Sanctuary (declared in 2011) and is part of the Western Ghats. Soil types in the district are black soil (46%), red (26%), sandy (12%), and sandy loam (5%). The agro-climatic region of the district is the northern transitional zone (KA-8) of the Western Ghats region. A large quantum of precipitation is received during the south-west monsoon period (71.6% of the annual, June to September), and the contribution by the north-east monsoon (October to December) is nearly 17.3%, the rest of 11.1% during the pre-monsoon period (January to May). Most of the water demand is met from Renuka Sagar reservoir of Malaprabha river, Ghataprabha river, and Krishna river. The average power demand of the industry sector is about 2732MU (2016-2017), met partly by renewable solar, hydroelectric, and gas-based projects. Agriculture, animal husbandry, forestry, and fishery generated around 3401crore rupees revenue in the district with cereal crops 42%, and pulses 2%. Land use and fragmentation assessment: LU dynamics are assessed using spatial data acquired through space-borne sensors at regular intervals and collateral data. Multi-temporal Landsat (remote sensing) data were acquired from the data archive portal (http://www.landsat.org; http://usgs.gov). Category-wise training data required for classifying remote sensing data were acquired from the field using a pre-calibrated global positioning system (GPS), and supplemented with information from online portals Bhuvan (bhuvan. nrsc. gov. in) and Google Earth (earth. google. com), collateral data for data interpretation from the Survey of India

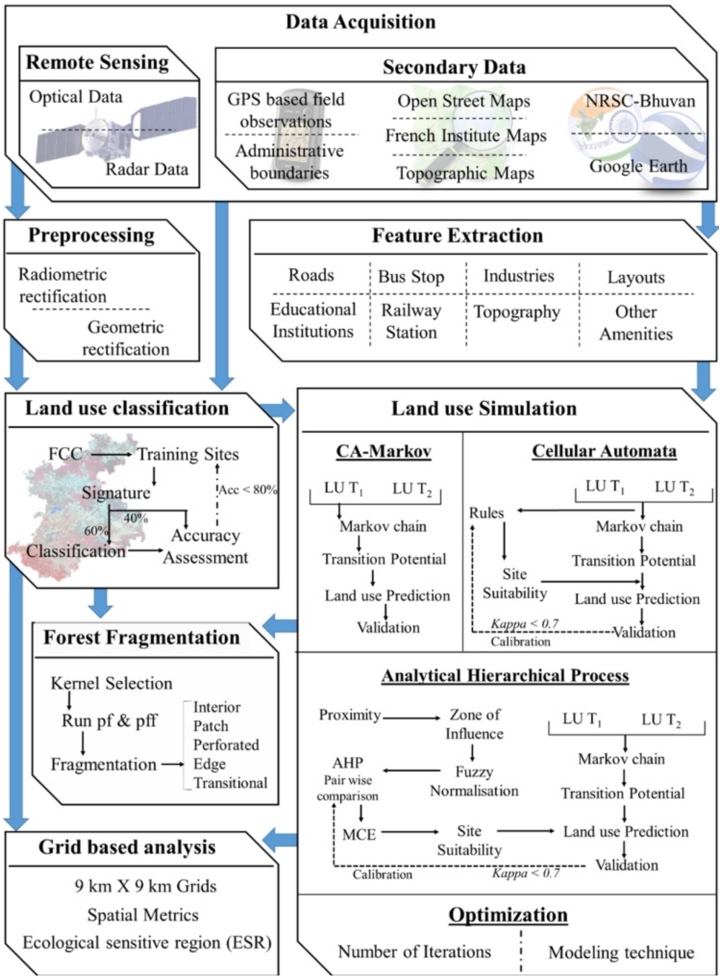

Fig. 1: The protocol for assessing the extent and condition of ecosystems.

(SOI) topographic sheets, SRTM data (for quantifying slope and elevation). The vegetation map (1985), prepared by the French Institute, aided in delineating various forest types and was also used as training data for pre-2000 RS data analysis. The acquired RS data was checked for geometric and radiometric integrity. The geometric correction was done by considering features such as roads junction, lake boundary corners, etc.

The study region was cropped from the preprocessed data using a vector layer of district boundary. False color composite (FCC) is generated using bands NIR, R, and G bands, which aided in distinguishing the heterogonous features in the study region. Training polygons corresponding to heterogeneous features were digitized so as to cover all LU features. Training polygons were digitized covering all visible heterogeneous LU types; 15% of the study area and uniformly distributed throughout the study region. 60 % of the training data were used for classification, and balance was used for accuracy assessment. LU classification was done using GRASS, an open source image processing software, through the Gaussian maximum likelihood (GML) algorithm. The algorithm calculates the mean and variance of each training polygon and classifies the unknown pixel accordingly. Accuracy of LU classification is assessed by computing Kappa statistics and overall accuracy. Fragmentation of forest ecosystem is estimated to understand the ecosystem condition through computation of P_f and P_{ff}, which indicates the amount and quality of forest types in the region. Temporal (1989, 1999, 2009, 2019) forest information is used for computing forest types as interior, patch, edge, perforated, and transitional. Interior forest indicates contiguous dense forests, while perforated forests are the opening within forests due to settlements, agricultural activities, etc. Patch forests were formed due to the division of forests by linear projects such as roads inside forests. Table 1 lists fragmentation types with P_f and P_{ff} metrics.

$$P_f = \frac{\text{Proportion of number of forest pixels}}{\text{Total number of non-water pixels in a window}} \quad (1)$$

$$P_{ff} = \frac{\text{Proportion of number of forest pixel pairs}}{\text{Total number of of adjacent pairs of at least one forest pixel}} \quad (2)$$

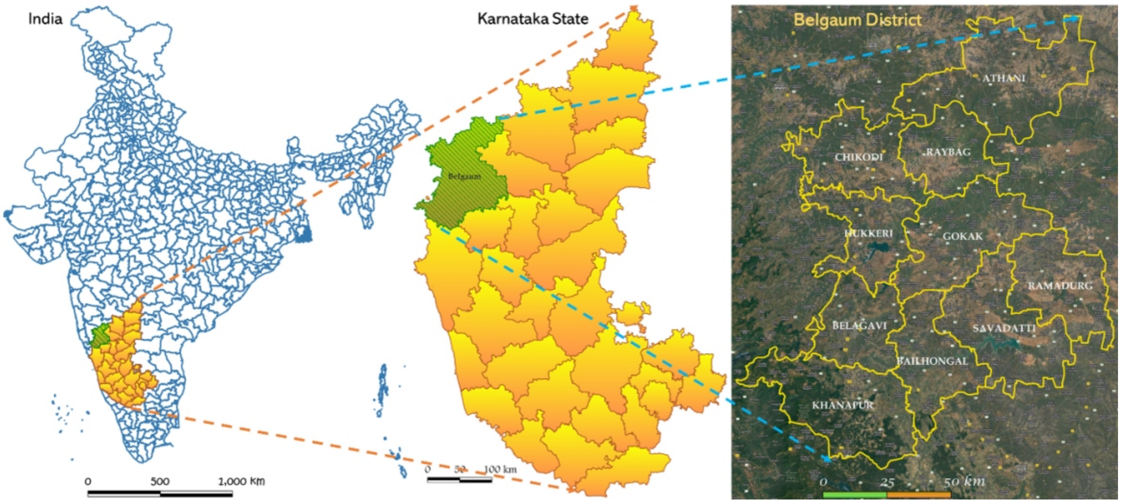

Fig. 2: Study area - Belgaum District, Karnataka State, India.

Modeling landscape dynamics through a hybrid model: The process of visualizing likely LU changes qualitatively and quantitatively is achieved through modeling. The LU of 2019 is used to predict the likely LU of 2029 using hybrid modeling (integrates-MCA, AHP-MCE, Boolean Algebra, Fuzzy logic, etc.). MC utilizes the probability of transitions from one state to another. MC simplifies the complex real-time process, considering the previous state, and will pay zero attention to neighborhood cell influence. MC generates a transitional probability, and transition areas between the two LU categories varied across the distinct timelines,and these probabilities aid in the prediction (Singh *et al.,* 2015; Mishra and Rai, 2016). In a landscape with multiple land uses, the transition probability Pij would be the probability that a LU type (pixels) i in time to changes to land cover type j in time t_1 (Schweitzer, 1968).

$$\sum_{l=1}^{m} Pij = 1 \quad i = 1,2\ldots m \qquad (3)$$

(Initial state vector)(transitional propability matrix)^m =(m state probability)*

$$x0 \;\; y0 * \begin{bmatrix} P11 & P11 \\ P21 & P22 \end{bmatrix} [= \;\; x1 \;\; y1] \qquad (4)$$

Here x0 , y0 are the base period of LU class pixel. x1, y1 are the next year LU class pixel. LU changes are multidirectional; change from one class to another class or any class may occur at any point. MC model uses matrices that represent the multidirectional change. The transition of a cell from one LU to another depends on the state of the neighborhood cells, which can be assessed through CA (Ramachandra *et al.,* 2017). CA model can be stated as,

$$S(t, t+1) = F(S(t),N) \qquad (5)$$

Here, S is the set of discrete cellular states, N is the cellular field, tand t+1 indicate the time interval, and F is the transformation function of cellular states in local space. A contiguity filter is utilized to evaluate the neighborhood, a standard, *i.e.,* each cellular center is surrounded by a matrix space which is composed of 5×5 cellular to impact the changes significantly. MCA model employed here run in two steps, *i.e.,* MC model evaluates series transitional probabilities, the transition areas, in step 2 CA analysis accounts neighbourhood and change quantity using MC output. MCA aids in prediction through spatial recognition with a certain rule-based filter under various scenarios as delineated through AHP and MCE. It is the decision-making process for a group of criteria, sub-criteria to line up in a hierarchical manner by assigning the weightage for individual criteria, sub-criteria weights to reflect the relative importance of one parameter with the others.

The simulation has accounted for the distance influence of factors/agents such as roads, social amenities, bus stations, city centre, industries, education institutions, new layouts, proposed layouts, etc. AHP weights are scaled from 1-9, depicting the relative importance of the range of scale as derived from MCE based on the distance influence of each factor with respect to the LU categories (Ji and Jiang *et al.,* 2003). Hence, assigning weights is a crucial step, and weights were assigned in consultation with the subject experts and resource persons. AHP is applied to have a pairwise comparison between the criteria and sub-criteria (Saaty, 1989). The assigned weights are compared, taking two pairs at a time to give the relative importance criteria of a parameter (Chaudhary and Uprety, 2015), and the final matrix is produced. The corresponding Eigen vector is developed for each criteria class whose total is the unity. AHP forms the crucial step in modeling (Ahmed and Kilic, 2019; Uzun Ozsahin *et al.,* 2021) aids in evaluating the consistency of weights derived from MCE through a pairwise comparison matrix. So, the inconsistencies in the decision-making can be significantly reviewed. The efficiency is measured by the consistency ratio (CR) as per equation 6.

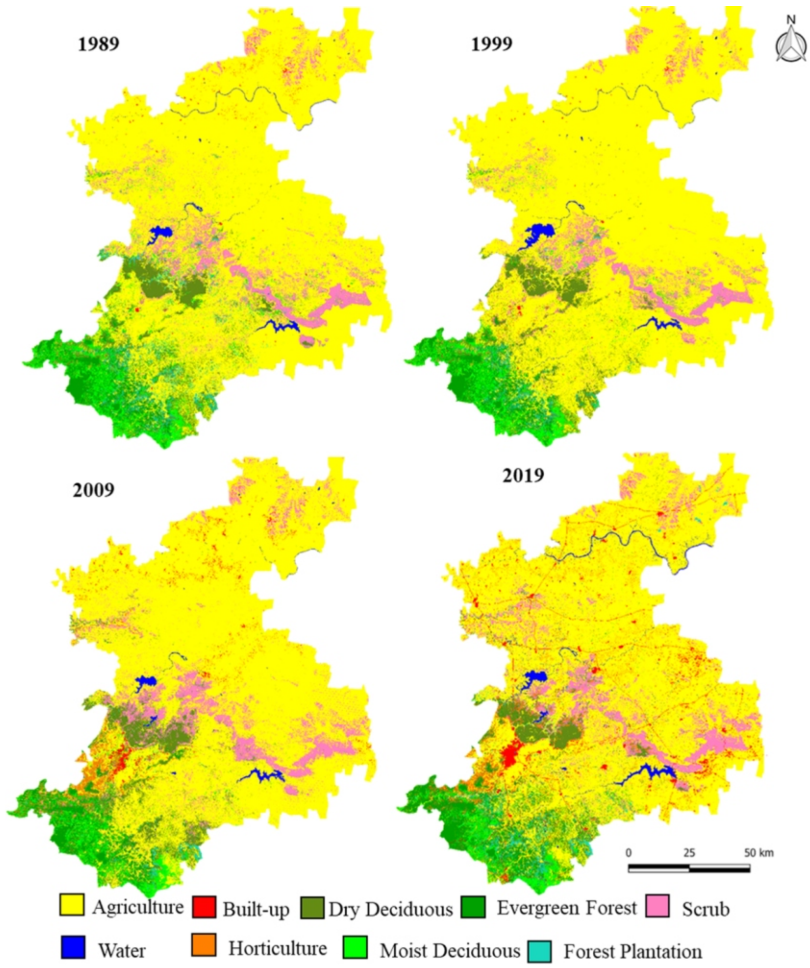

Fig. 3: LU in Belgaum from 1989 to 2019.

$$CR = \frac{CI}{RI} \tag{6}$$

where CI, RI indicates the consistency index, random index, respectively. RI tells the consistency of the randomly generated pairwise compared matrix with respect to the number of criteria present.

$$CI = \frac{(\lambda\ max- n)}{(n-1)} \tag{7}$$

λmax is the Eigen value which is always greater than or equal to the number of rows or columns. The value of CR should always be less than 0.10, so the pairwise comparison of the matrix value is considered consistent. If CR ≥ 0.10, the pairwise comparison is inconsistent with the weights assigned. Weights are calculated based on the relative importance assigned to various classes. Based on the simulated LU, validation was carried out by comparing the simulated LU map of 2019 against the actual LU map of 2019 through kappa statistics. The model was calibrated by varying the input variables to achieve higher accuracy. The calibrated model was used to predict and visualize the LU pattern for the year 2029.

Spatial Metrics: Landscape metrics (spatial metrics) characterize the landscape by quantifying spatial pattern variations and provide insights into LULC change's consequences (Ramachandra and Bharath, 2018). Various spatial metrics like the number of patches, patch edge density, etc., have been used to characterize the spatial pattern for multiple LU classes.The grid-wise changes in forest cover and built-up were estimated through select indices using the Fragstats (McGarigal, 1995; Aithal *et al.,* 2012; Kufer, 2012). The district was divided into grids, each of 9 km × 9 km (5'×5') corresponding to the 1:50000 scale of the India Topographic map grids. The output parameter is selected, *i.e.,* patch metrics and class metrics; both the metrics consist of decisive indices such as NLSI (Normalized Landscape Shape index), NP (Number of patches), AI (Aggregation index), and CA (cell/class area). CA notifies the area forthe number of cells present in a particular grid. NP is used to assess how compacted or dispersed the particular class category. The value of NP is low, indicating that

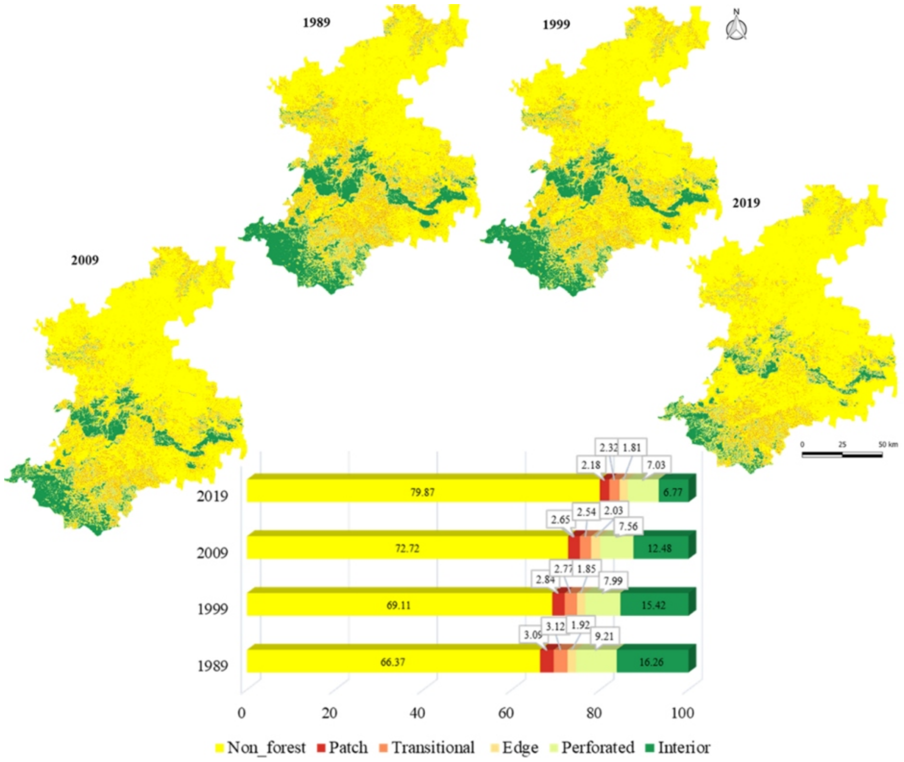

Fig. 4: Forest fragmentation- Temporal (1989 to 2019) pattern.

the class is more compacted. NP values are high, indicatings cattered class.

$$NP = n, \quad \text{where } NP > 0 \text{ without limit, } n \text{ is a number} \tag{8}$$

NLSI calculates the shape based on area and perimeter, whose value ranges between (0≤NLSI≤1) where 0 indicates the single, *i.e.,* without fragmentation and 1 indicates the dispersed class.

$$NLSI = \frac{\sum_{i=1}^{i=N} \frac{Pi}{si}}{N} \tag{9}$$

Where, *Si* and *Pi* are the area and perimeter of patch *i,* and N is the total number of patches

AI value ranges between 1 to 100, 1 indicates patches are maximally disaggregated or the landscape is fragmented and 100 indicates of aggregated patches.

$$\text{AI} = \sum_{i=1}^{m} \left(\frac{g_{ii}}{max \rightarrow g_{ii}} \right) * P_i * 100 \tag{10}$$

Ecologically Sensitive Regions: Regions consisting of unique landscape elements endowed with distinct bio-geo-ecological, hydrological, environmental, and social properties that help sustain natural resources are considered ecologically sensitive regions (ESR). Maintaining the landscape structure is vital for the sustenance of biological diversity, soil, water, or other natural resources in the local and regional context is often referred to as Ecological Sensitive regions (ESRs) or Ecologically Fragile regions (EFRs). The ecological sensitivity or fragility refers to unique ecosystems with the predominant natural ecological interactions affected by anthropogenic activities due to mismanagement. Mapping ESRs would aid in understanding the diversity of various parameters and their vital role in balancing the ecosystem by mitigating impacts of anthropogenic activities or providing stability by native species (Mingwu *et al.,* 2010; Haase *et al.,* 2018; Ramachandra *et al.,* 2018b). ESRs were delineated at a disaggregated level,considering bio-geo-ecological, hydrologic, and social factors. These variables were compiled from field-based standard protocol and supplemented with the information from published literature and data portals. Bio-geo-climatic, biological, hydrologic, and social aspects were assigned weights/ grades considering the ecosystem condition and extent, as listed in Table 2. Developing a composite metric by integrating diverse variables considered based on the comprehensive knowledge of the disciplines (and weights are assigned in consultation with the subject experts), and the composite weight per grid is as per equation 11.

$$Weighatge = \sum_{i=1}^{n} W_i S_i \tag{11}$$

where, n is the number of data sets (variables based on themes), Si is the value of variable i, and Wi is the weight based on

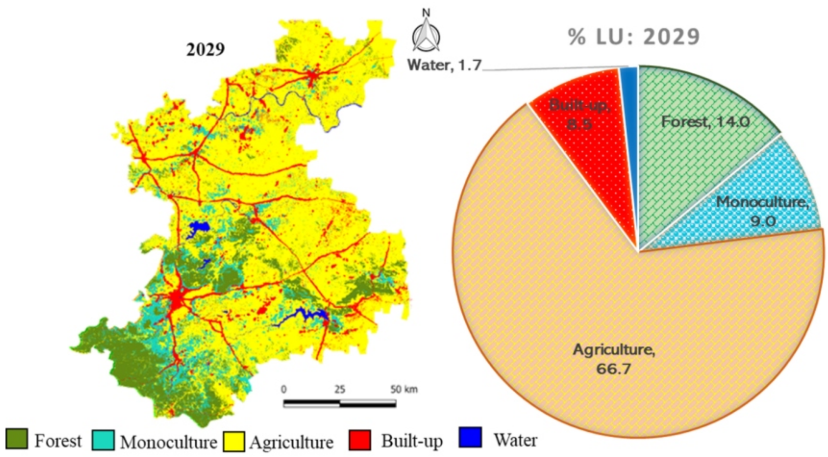

Fig. 5: Simulated LU (Hybrid Fuzzy AHP MCA).

the respective variable's contribution to ecosystem condition, which is normalized between 10 (high priority) to 2 (least). Values 8, 6, and 2 correspond to high, moderate, low levels of significance of a variable. Composite metric is computed for each grid by aggregating weights and is grouped into four categories as extremely high sensitive (ESR 1), high sensitive (ESR 2), medium sensitive (ESR 3), and low sensitive (ESR 4) based on the frequency distribution of aggregated scores considering mean (μ) and standard deviation (σ). Grids with the aggregated score > $\mu+2\sigma$ were assigned ESR1, grids with aggregated scores lying between $\mu+2\sigma$ and $\mu+\sigma$ are ESR 2, grids with scores between $\mu+\sigma$ and μ are ESR3,) and ESR 4 to grids with the aggregated score < μ.

Results and Discussion

The estimation of LU dynamics has been done using temporal RS data through a supervised GML classifier with the training data collected from the field using pre-calibrated GPS and other secondary datasets.

Spatio-temporal changes in LU and forest fragmentation: LU dynamics of the Belgaum district were analyzed for every decade from 1989 to 2019 and estimated the spatial extent of various classes such as agriculture, built-up, dry deciduous forest, evergreen forest, forest plantations, water, horticulture, moist deciduous, and scrublands, which are listed in Table 3 and LU trends are depicted in Fig. 3. The analysis reveals a decline of forest cover by 2.99% (9029.9 ha) due to anthropogenic activities involving an increase in agricultural land along the edges of forests. An increase in the agriculture area by 0.75% is due to cash crops with the availability of irrigation facilities. Urbanization and urban sprawl in and around the towns and cities led to conversation of agricultural lands to built-up. LU conversion is evident from the decline of large tracts of forests and grazing lands in Khanapur, Belagavi taluks. The inappropriate crops in the forested regions and water-intensive crops in the plateau region have caused imbalances in the water availability of the district (Vinod and Paresh, 2016). Large-scale land conversion is due to the implementation of infrastructure projects like the construction of Shirur Dam, and the peninsular region industrial development (PRIDE) corridor projects, etc. Tourism-related developmental activities near Malaprabha Dam, Hidakal, etc.,are responsible for inducing infrastructure developments..National Highway (NH)-4A expansion has caused a death trail of 22,000 trees to connect to Goa state through the Kali tiger reserve of Uttara Kannada district. The widening of NH-4A has a compounding impact on wildlife, endangers public health, and exacerbates natural disasters in an ecologically sensitive area.

Various unplanned developmental projects threaten the integrity of ecologically fragile regions, affecting the livelihood of indigenous forest-dwelling communities. Accuracy assessment of the classified image was evaluated by accounting overall accuracy and the kappa statistics using the training data compiled from the field, and from Google Earth for the latest time period, the pre-2000's data has been assessed using collateral data of published reports from the forest department, vegetation maps and the SOI toposheets (Table 4). The spatial changes of ecosystem structure assessed through fragmentation metrics aided in evaluating the condition of ecosystems over a temporal scale. Fig. 4 depicts spatial variations in the various forest fragmentation categories, *i.e.,* interior, perforated, edge, transitional, patch, and non-forest, and their dynamics in the Belgaum district. The interior forest cover has reduced from 16.26% to 6.77 % from 1989 and 2019, which includes a part of the wildlife sanctuary. Linear intrusions such as power transmission lines, and linear networks (rail and road) are causing a more significant impact on forest structure and accelerating fragmentation. Nearly 70% of protected areas in India have linear intrusions, penetrating through forest areas (Nayak *et al.,* 2020). Linear intrusion such as NH-4A has fragmented Kali Tiger Reserve in Karnataka, Bhagwan Mahaveer Sanctuary, and Mollem National Park in Goa, endangering wildlife and causing hydrological imbalances. Ensuring sustainable utilization of the

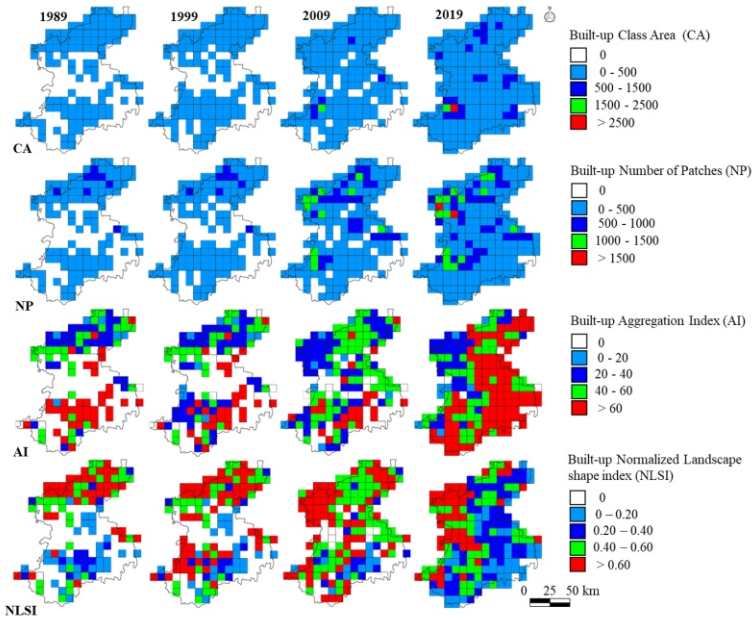

Fig. 6: Spatial pattern analysis of built-up class over time.

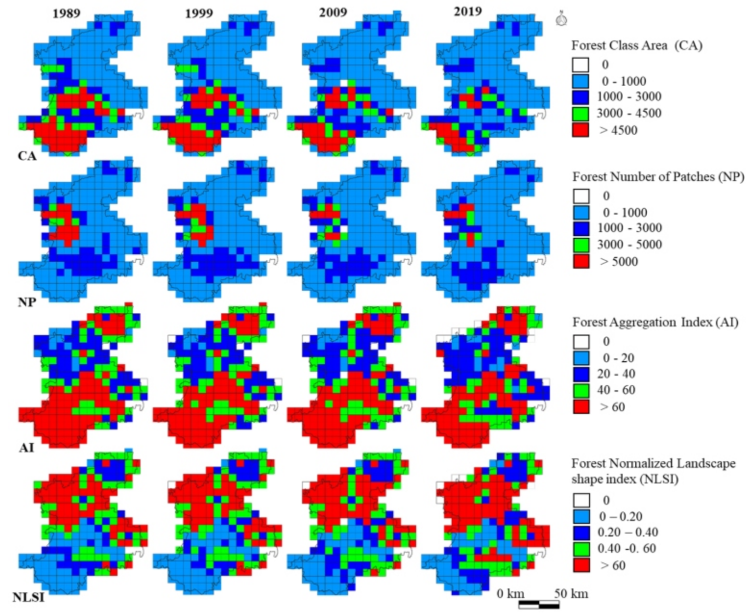

Fig. 7: Spatial pattern analysis for forest category.

natural diversity in the forest ecosystem is key to mitigating climate change impacts. There is a scope for enriching forests with native species, especially in forests of Khanapur and Bailhongal taluks. The teak monoculture plantations in the Khanapur need to be phased out with native species forests to enhance connectivity, minimize human-animal conflicts and support livelihood.

LU Modeling: Rule-based hybrid LU modeling was carried out to understand the likely changes in LU, by grouping the existing LU into five categories,namely Natural Vegetation/Forest (various forest types), monoculture plantation, agriculture, built-up, and water. Hybrid Fuzzy-AHP-MCA is the most efficient modeling technique for visualizing changes in forest landscapes (Bharath

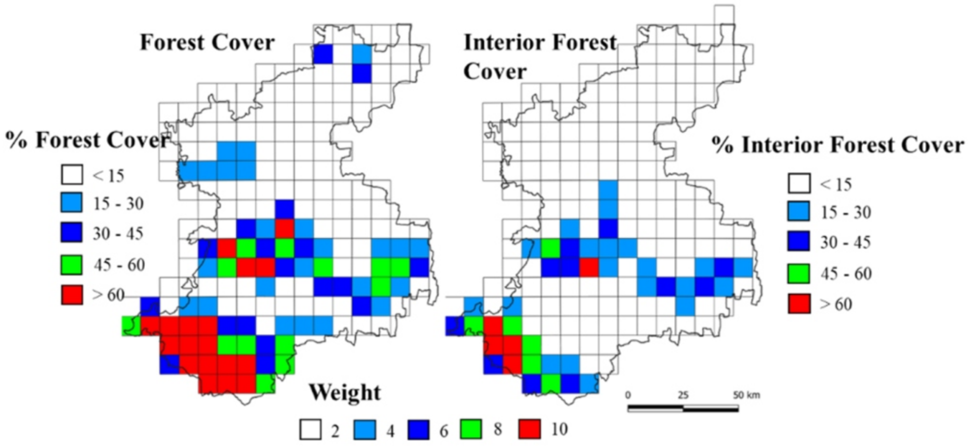

Fig. 8: Forest cover and interior forest variables and their weights.

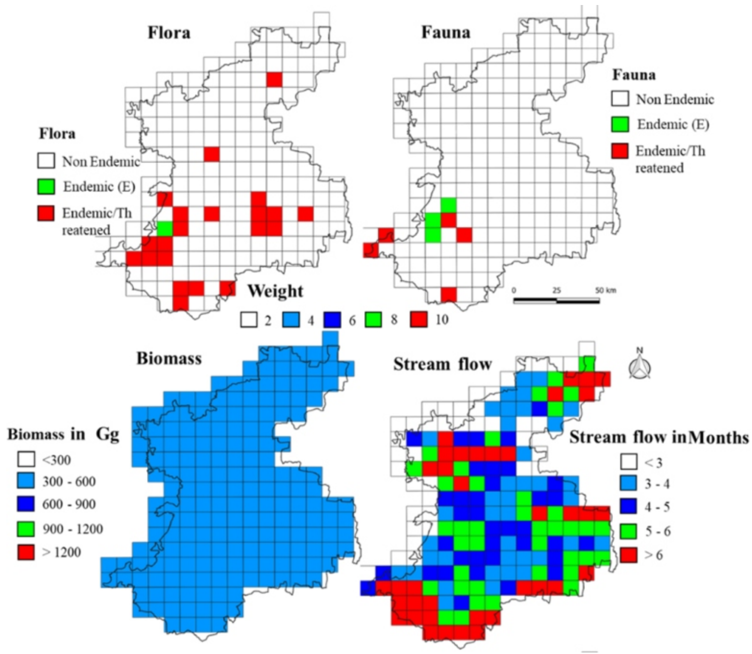

Fig. 9: Variables of ecology and hydrology themes and their weights.

et al., 2021). Agents of LU transitions considered are bus stops and railway stations, major towns and cities, industries, educational institutions, major roads, social-economic amenities and new and existing layouts. The agents were delineated based on field observations, published reports, and virtual earth portals. Proximity maps were created (Annexure-1) to understand the zone of agent's influence on LU features such as built-up, agriculture, monoculture, etc. The influence was normalized for the corresponding factor, and pairwise relative importance was calculated to obtain the site suitability maps. MCE integrates spatial analysis with statistics to address uncertainty, including criteria selection, input data accuracy, standardization, weight calculation, and aggregation method (Ristić *et al.,* 2018). In order to overcome this, the current approach evaluated the distance-based influence of individual agents on each LU type considered, and a probable relationship was derived. The minimum and maximum influences associated with each agent recorded were aided further in assigning weights. The influence of various factors on altering a particular LU is derived using the AHP and MCE, which evaluate the relative influence of factors on a particular LU type based on expert opinion (Table 5). MC analysis by

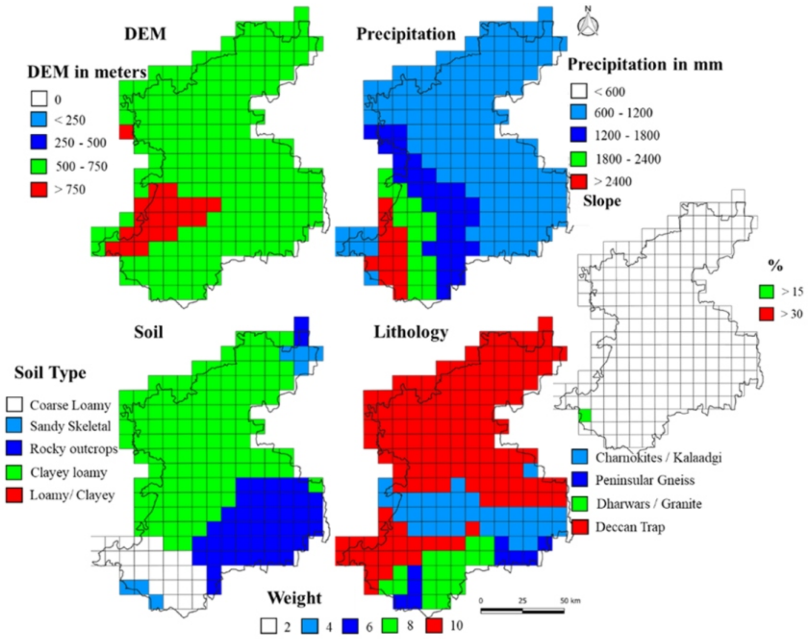

Fig. 10 : Geo-climatic variables and their weights.

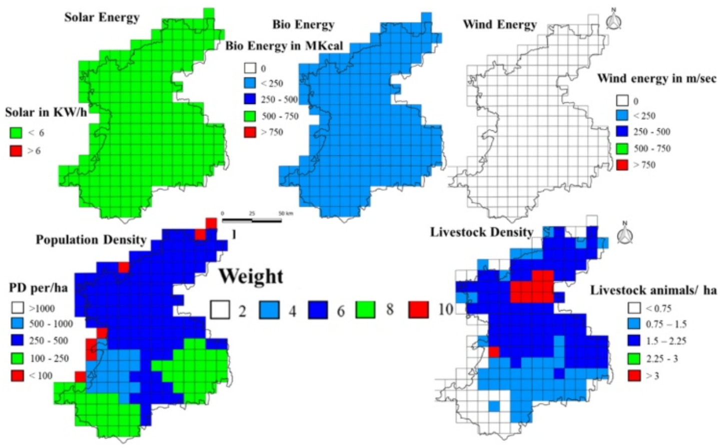

Fig. 11: Weights for variables of energy and social themes.

considering 2009 and 2019 LU information provided the likely transition areas for the year 2029.

CA is used to quantify the likely LU transition. MC has provided the probability of change, and CA has aided in forecasting spatially with constraints. The number of iterations is optimized while running the CA module. Annexure-1 provides the details of optimizing the number of iterations. Results indicate there is not much change in model accuracy post 10 iterations, and hence 10 iterations are considered to execute the model for other districts. MCA, along with the site suitability maps helped in generating the likely LU maps. Accuracy assessment of the model was done by comparing simulated LU of 2019 with actual LU, which showed an accuracy of 88% with high spatial consistency. The modeled LU showed an increase in built-up from 2.92 (2019) to 8.53 (in 2029)%. The growth in built-up areas could be attributed to the expansion of linear corridors, increase in urban areas, and other infrastructure projects. Athani, Chikkodi, Belagavi, Khanapur, and Nipani would experience significant transitions in their LU. Likely loss of 5.61% forest cover with an increase in built-up and monoculture LU. The forest cover in the district would be confined to the protected areas of the Western

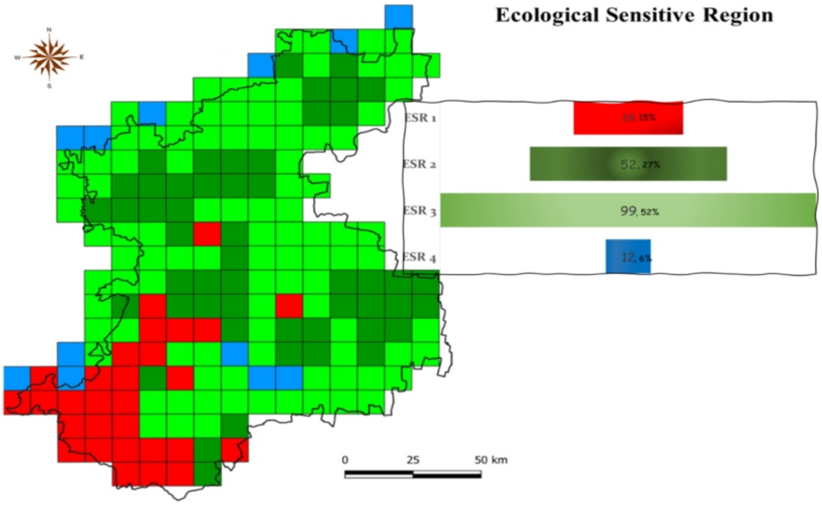

Fig. 12: Ecologically sensitive regions in Belgaum district.

Table 1: Fragmentation type and description

Fragmentation type	Value	Description
Transitional	0.4<Pf<0.6	Is intermediate of edge and no-forest
Edge	Pf> 0.6 &Pf - Pff< 0	The boundary between forest and non-forest LU.
Perforated	Pf>0.6 &Pf - Pff> 0	Small clearing and interior forest
Patch	Pf< 0.4	Small forest type to the non-forest area around
Interior	Pf = 1	Thicker forest area

Ghats, which emphasizes the necessity of effective management of forests (in the buffer regions of PA) through the conservation of ecologically sensitive regions at disaggregated levels in the district.

Landscape metrics: The spatial indices Normalized Landscape Shape Index (NLSI), Aggregation Index (AI), and Number of Patches (NP) were calculated grid-wise for built-up and forest class area (Fig. 6 and 7), for 1989, 1999, 2009, and 2019. Built-up has changed over time due to urban growth and other infrastructure development. Especially, Belgaum city and Athani town are experiencing major urbanization processes. The spatial extent of forests had decreased over time, particularly in Belagavi and Khanapurtaluks, depicting the response to anthropogenic pressures. NP metric highlights of the landscape's fragmentation status, *i.e.,* higher the number of patches, indicating fragmentation. The grids of Nipani, Belagavi city, are experiencing higher scattered growth rates due to increased NP values. The loss of forest patches around the Bailongal, Hukkeri, and Belagavi has been observed from 1989 to 2019. The higher fragmentation is noted due to the formation of new patches.

AI showed that the built-up area is confined to the grids of Belgaum, Gokak, and Bailongal in 1989, with a cluster growth due to urbanization and new infrastructure developments. The loss of forest cover in Khanapur, Belagavi, and Athanitaluks decreased AI values. Post-1999 Belagavi region has experienced urbanization, evident from a higher NLSI value, depicting complex shapes in the periphery. NLSI decreased in the areas indicating the compacted urban growth. NLSI values have increased in the Bailongal, Belagavi, and Saundatti grids, indicating the forest cover decline with higher shape complexity.

Ecologically Sensitive Regions: ESR were delineated at disaggregated levels considering environmental variables such as the biomass, fauna, flora, streamflow, population density, livestock, percent forest cover, percent interior forest, digital elevation model, precipitation, percent slope, soil type, lithology, bioenergy, wind energy, and solar energy. Fig. 8 provides an overview of forest cover, and interior forest variables based on the extent and conditions. The grids that are part of the Western Ghats have been assigned higher weight due to dense forest cover. Fig. 9 shows the geo-climatic and hydrology theme parameters and their corresponding weights. The region has endemic flora and fauna species in the western region, and high weights were assigned based on endemism with IUCN status. The stream flow of the region highlights the role of forests in sustaining water in the landscape as the Western Ghats region, with relatively higher forest cover, is endowed with perennial streams. In contrast, towards the eastern portions, the transition and plane regions dominated by monoculture plantations and agriculture have

Table 2: Range and weights for various parameters assessed

Theme	Variable	Weight				
		2	4	6	8	10
	Forest cover	< 15%	15 - 30%	30 - 45%	45 - 60%	> 60%
Land	Interior forest cover	< 15%	15 – 30%	30 – 45%	45 – 60%	>60%
	Altitude	NA	< 250 m	250 -500m	500-750	>750
	Slope	NA	NA	NA	>15%	>30%
	Rainfall	<600mm	600-1200	1200-1800	1800-2400	>2400mm
Geo climate	Soil	Coarse Loamy	Sandy or Sandy skeleton	Fragmented or Rocky outcrops	Clayey loamy or Clayey Skeleton	Loamy or Clayey
	Lithology	-	Charnokites or Kalaadgi	Peninsular Gneiss	Dharwars or granite	Deccan trap
	Flora	Non- Endemic			Endemic	Endemic / Threatened.
	Fauna	Non-Endemic			Endemic	Endemic / Threatened
Ecology	Biomass (Gg)	<300	300-600	600-900	900-1200	>1200
Hydrology	Stream Flow	< 3 months		4	5	> 6
	Solar				<6KW/h	> 6KW/h
	Wind	1.5	1.5 – 2	2 – 2.5	2.5 - 4	> 4m/sec
Energy	Bio	-	230k	230-360k	360-660k	> 660k
	Population density	>1000	500-1000	250-500	100-250	< 100 person/ha
Social	Livestock density	<0.75	0.75-1.5	1.5-2.25	2.25-3	> 3 animals per ha

Table 3: LU dynamics in Belgaum

Year	1989		1999		2009		2019	
Category	Ha	%	Ha	%	Ha	%	Ha	%
Agriculture	999709	74.69	1009765	75.44	1002205	74.94	948953	74.72
Built-up	3747	0.28	12246	0.91	17408	1.3	39016	2.92
Deciduous	84996	6.35	83121	6.21	67223	5.02	69882	5.23
Evergreen	50037	3.74	49662	3.71	49994	3.36	44361	3.32
Forest Plantation	23407	1.75	12246	0.91	12855	0.96	18973	1.42
Water	9542	0.71	1070	0.89	24639	1.84	20942	1.57
Horticulture	103	0.01	1028	0.08	16203	1.21	46711	3.5
Moist Deciduous	64402	4.81	57421	4.29	53698	4.01	50908	3.81
Scrub	102570	7.66	101190	7.56	98559	7.36	96338	7.21
Sensor	Thematic Mapper (TM)		Thematic Mapper (TM)		Enhanced TM plus (ETM+)		Operational Land Imager (OLI)	
Path & Row			146/48; 146/49;					
Date of Acquisition	1989/02/07;		1999/03/04;		2009/03/07;		2019/03/11;	
Spatial	1989/02/07		1999/03/04		2009/03/23		2019/03/11	
Resolution	30		30		30		30	

intermittent and seasonal streams with water availability of 6 to 8 months. Streams in the Khanapur forest range, parts of Ghataprabha and Malaprabha catchment areas covered with the natural forest cover have water for over six months. The digital elevation model (DEM) shows the range of 500-750 m all over the district, and greater than 750 m is seen only in the south-western region grids. Precipitation is clearly in the descending order from southwest to northeast of the district, *i.e.,* greater than 2400 mm in the regions of Khanapur, followed by Saundatti, and least in the northern part of Raybag and Athani. Raybag taluk experiences the least rainfall (average 491.7 mm) compared to other taluks. Soil and lithology of various types are found in the area. Bio-energy, wind energy, and solar energy potential estimation depict higher potential across the district (Fig. 11). Social variables assessment

Table 4: Accuracy assessment of LU classification of temporal data- Belgaum

Year	1999		2009		2019	
Category	PA	UA	PA	UA	PA	UA
Agriculture	97.62	93.29	97.99	99.25	95.84	57.08
Built-up	87.35	99.96	94.57	98.07	73.04	98.68
Dry Deciduous	78.53	14.57	14.74	30.50	98.34	98.54
Evergreen	80.03	99.02	81.11	98.45	99.50	99.96
Forest Plantation	79.95	99.89	95.24	92.72	90.88	99.44
Water	77.35	7.36	78.16	9.220	82.25	99.367
Horticulture	99.62	98.42	99.99	100	83.66	90.8
Moist Deciduous	95.20	99.83	98.40	99.21	98.85	99.99
Scrub	92.59	95.85	94.29	95.68	94.21	99.87
	OA	91.88	OA	94.11	OA	87.750
	Kappa	0.883	Kappa	0.914	Kappa	0.8777

Table 5: Weights assigned based on distance influence of each factor

Features	Built-up	Weights Monoculture	Agriculture
Road	0.2935	0.3239	0.3367
Bus, Railway	0.1551	0.2353	0.2908
Institution	0.1336	0.1813	0.0897
Factory	0.0827	0.1201	0.1807
Social	0.0329	0.0826	0.0716
City Centre	0.3022	0.0568	0.0305

provides a thorough understanding of human-environment interactions in developing consistent evidence for evaluating conservation actions (Ban *et al.,* 2013). Population density (PD) is computedbased on the population data of 2011. The northern region of the district indicates a higher PD of 250-500 per hectare. Livestock density (LD) computed grid-wise indicates that Raybag taluk had the most LD in the district. Aggregation of weights of all variables in a grid aided in computing the composite metric.

Grids are grouped based on the statistical analyses by computing mean (μ) and standard deviation (σ). Grids are grouped -based on overall sensitivity into four categories (Fig. 12) as ESR 1 (for grids having composite metric ESR 1: aggregated scores > $\mu+2\sigma$, ESR 2 (for grids within $\mu+2\sigma$ and $\mu+\sigma$), ESR 3 (for grids with $\mu+\sigma$ and μ) and ESR 4 (grids with values < μ). Integrating various parameters of biological, geo-climatic, and social variables at disaggregated levels aided in delineating regions based on ecological sensitivity at disaggregated levels, which would be helpful in developing and implementing location-specific sustainable development and management plans. ESR1 depicts the extremely high sensitive areas that cover 15% of the southwest portion in the Khanapur range with a wildlife sanctuary, and a part of the Ghataprabha catchment region of Belgavi taluk. Most Khanapur taluk falls under the Western Ghats, the principal catchment area of the Ghataprabha and Malaprabha rivers. ESR 2 (27%) covers taluks such as Athani, Ramdurg, and Saundatti. ESR1 and ESR 2 signify that they are susceptible zones and must be conserved without any land use changes; hence, no large-scale development activities are permitted. A medium-sensitive region such as ESR3 covers 29% of the district, where regulated development activities such as small-scale industries like agro-processing, and IT sectors may be encouraged. ESR 4 represents the least diverse areas, and the developments are allowed as per the requirement of local people with a strict vigilance of regulatory mechanism. ESR 1, and 2 regions have scope for further enrichment to sustain water in the Ghataprabha River catchment through afforestation of degraded forest patches with the location-specific native species and management by involving all local stakeholders. ESR1 and ESR 2 signify highly susceptible regions where no alteration in the ecological integrity be permitted.

Developmental activities such as dams, mining, etc., should not be allowed. ESR-3 is the region of moderate sensitivity, and developmental activities may be allowed with the stringent environmental norms. Developmental activities need to be regulated with a strict environmental impact assessment (EIA) and implementation of environmental management plans (EMP) to mitigate the environmental impacts. Un-authorised and conversionis to be regulated, while promoting location-specific and mitigation rules. Small-scale industries like agro-based, garments, IT, etc. can be encouraged. Belagavi, Bailhongal, Gokak taluks are growing in the food processing industry, which would boost the rural economy. Hence rural youth and women self-help groups should be provided incentives/subsidies for setting up new agro-processing sectors based on the locally available natural resources. These activities must be strictly regulated and subject to social audits. Monoculture plantations should be discouraged, and existing exotic plantations need to be replaced by planting native endemic species. Controlled activities are permitted based on socioeconomic importance. Activities such as reclaiming and depriving wetlands and transferring areas under natural forests or activities leading to introducing alien invasive species are restricted through appropriate conservation and management measures. The burgeoning population and the pressure on natural resources need the formulation of community-based conservation programmes. The enactment of the Forest Rights Act 2006, echoes this philosophy and made instrumental, but the implementation is not fruitful due to the exclusive approaches followed on the ground. The success of the ESR also would depend on how effectively it lightens the fear of exclusion from developmental opportunities to the dwellers, which nature provides.

Assessment of land-use dynamics using temporal remote sensing data of 1989 to 2019 provided vital insights for prudent management of natural resources toward sustainable development. A decline inforest cover by 2% from1989 to 2019 is due to unplanned developmental activities including infrastructural projects, industrialization, natural resource mining, urbanization, etc.Spatial patterns assessed through landscape matrices aided in understanding the LU change patterns at a temporal scale.The hybrid Fuzzy AHP model used here evaluated a complex decision problem by constructing the hierarchy framework, which considered different criteria and factors responsible for the change. Prediction of likely LU changes reveals a reduction of 5.62% of forest cover, with an increase inbuilt-up by 5.61%, and a decline of the area under agriculture by 7.98% during 2019-2029. The mapping of ESR was done using geo-climatic and ecological parameters at disaggregated levels, which depicts 15% (29 grids) under extremely high sensitive (ESR 1), 27 % (52 grids) under high sensitive (ESR 2), 52% (99 grids)under medium sensitive (ESR 3), and the rest 6% (12 grids)are under low sensitive (ESR 4) categories. Delineation of regions based on ecological sensitiveness aids in evolving prudent management policies to ensure the sustenance of natural resources (water, food, fodder, etc.) to support the livelihood of ecosystem-dependent people.

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Authors' contribution: Ramachandra T. V: Concept Design, field data collection, data analysis and interpretation of data; revising the article critically for important intellectual content; final editing; **K Naik:** Field data collection, data analysis and interpretation of data, manuscript writing; **B. Setturu:** Design of the experiment, review of data analysis and manuscript.

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