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Geoinformatics-based prioritisation of natural resources rich regions at disaggregated levels for sustainable management

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Abstract

Natural Resource Rich Regions (NRRRs) are ecologically and economically vital regions that support the livelihood of people through the sustained ecosystem process involving interaction among biotic and abiotic elements. Identifying NRRRs, considering spatially ecological, geo-climatic, biological, and social dimensions, would help in conservation planning and prudent management of natural resources as per the Biodiversity Act 2002, Government of India. Changes in the landscape structure would lead to alterations in the composition and health of these regions with irreversible changes in the ecosystem process, impacting the sustenance of natural resources. Landscape dynamics is assessed by classifying temporal remote sensing data using the supervised machine learning (ML) technique based on the Random Forest (RF) algorithm. Additionally, predicting likely land use changes in ecologically fragile areas would help formulate appropriate location-specific mitigation measures. Modeling likely land uses through the simulation of long-term spatial variations of complex patterns has been done through the CA–Markov model. Prioritization of NRRRs at disaggregated levels highlights that 12% of the total geographical area of the district is under NRRR 1 and NRRR 2, 54% of the total geographical area under NRRR 3, and the rest of the region under NRRR 4. The current study emphasizes the need for robust decision support systems to aid in effective policy formulation for conserving and restoring natural resources. *Clinical trial number*: Not applicable.

Keywords LULC change · Supervised learning · Machine learning · Random Forest · CA-Markov · Natural Resource Rich Regions (NRRRs)

Abbreviations

LU	Land use
LC	Land cover
NDVI	Normalized difference vegetation index
LULC	Land use land cover
ML	Machine learning
RF	Random Forest
SVM	Support Vector Machine
MLC	Maximum Likelihood Classifier

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CA	Cellular Automata
NRRRs	Natural Resource Rich Regions
kWh	Kilowatt hour
Gg	Giga gram
M kcal	Million kilo calorie
ST	Schedule tribes
Km	Kilometer
m	Meter
mm	Millimeter
sq. km	Square kilometer
m/sec	Meter per second
ha	Hectare

1 Introduction

A landscape consists of the physical arrangement of interconnected biotic components such as flora and fauna, along with abiotic factors such as rainfall, climate, temperature, etc., influenced by natural processes and human actions. Landscape dynamics are reflected through the changes in land use (LU), and land cover (LC) operating on a temporal scale in physical and biological properties [1, 2]. Anthropogenic activities and natural processes are responsible for changes in the landscape structure, which can be assessed through LU and LC dynamics [3, 4].

LC refers to the physical and biological cover of the land surface, vegetation, and non-vegetation (water bodies, bare soil, paved surfaces, etc.). Compared to LC, land use is the activity that is practiced on the piece of land, for example, agriculture, wildlife habitat, and recreation [5]. The burgeoning human population amplifies land use changes, expansion of settlements, changes in food production and consumption, energy demand, deforestation, agriculture intensification, alteration of natural landscapes, and overexploitation of natural resources [6–9]. Detailed information about land use land cover (LULC) change would aid in framing policies and initiating action plans to protect the environment and maintain ecological integrity [10]. Monitoring spatial patterns of changing LULC provides crucial information for effective decisions to achieve the objective of sustainable development [11]. Changes in land use due to unplanned developmental activities (anthropogenic activities) have contributed to land degradation with the fragmentation of contiguous (intact) native forests into fragments, which have been affecting the ecology and sustainability of natural resources [12, 13].

Fragmentation of forests refers to the process involving the division of contiguous intact (interior) forests into isolated small forest patches, leading to drastic changes in the structure (patch shape and sizes, connectivity) and composition (internal heterogeneity) of forests [12, 14–17]. Loss of contiguous native forests and fragmentation pose significant risks to biodiversity and endanger the long-term viability of ecological resources and services [18, 19]. LULC changes lead to land degradation, and deforestation alters the landscape structure [20, 21], impacting the ecosystem functions with an altered microclimate (elevated temperature, decreased humidity, etc.), which has hindered natural recovery processes, and affected the sustenance of natural resources exacerbating poverty of communities reliant on natural resources [22–24].

Ecological sensitivity or fragility refers to the ecological integrity of a region that is vulnerable to even small changes leading to permanent and irreversible erosion in ecosystem services, affecting the livelihood of local people. Unplanned developmental activities leading to large-scale changes in the LU are responsible for the erosion of natural resources and disturbances in the ecosystem. Natural Resource Rich Regions (NRRRs) are ecologically and economically vital regions that support the livelihood of people through the sustained ecosystem process involving interaction among biotic and abiotic elements. These are vulnerable to any disturbance by external anthropogenic or natural influences and pose serious restoration challenges to sustain ecosystem services [25]. NRRRs are biologically and ecologically rich, valuable, and distinct ecosystems with high potential value to human societies. Identifying NRRRs, considering spatially ecological, geo-climatic, biological, and social dimensions, would help in conservation planning and prudent management of natural resources as per the Biodiversity Act 2002, Government of India. The unregulated exploitation of natural resources gained impetus with industrial development, which also accentuated the deterioration of ecosystems. Quantification of the landscape dynamics through LULC provides valuable insights into the factors influencing LU transitions. Conservation of NRRRs at disaggregated levels would help maintain ecological stability and preserve biological diversity. Prioritization of NRRRs requires integrating factors contributing to ecological vulnerability to address the adverse effects or mitigate the negative consequences of unregulated development.

Recent advancements in geoinformatics with the availability of multi-resolution spatial data, and improvements in data analytics (ensemble classifiers with machine learning, and deep learning algorithms) have empowered the assessment of LU dynamics [26, 27]. In this regard, non-parametric ensemble algorithms provide consistent and accurate prediction due to reduced variance and bias compared to non-parametric approaches and hold advantages over traditional parametric classifiers (e.g., maximum likelihood classifiers) [28–31]. Among the machine learning algorithms, the Random Forest (R.F.) classifier has been found optimal for land use classification based on the earlier work [32] as it minimizes the correlation among decision trees, maintains multi-variance and is less sensitive to noise, overtraining, and reduction in training samples [30]. Ensemble learning methods use the same base classifier for iteratively classifying a similar dataset [33] or combine multiple base classifiers for multiple classifications of the same dataset or target distinct subsets within the data [34].

The Cellular Automata (CA) consider spatial transitions in the neighbourhood for modelling and visualization of likely land use scenarios [35, 36]. According to the transition probability matrix, the ability to monitor changes in an object's State depends on the relationship between its current state, the previous state, and the states of its neighbouring objects. It is incorporated into LULC models, which can simulate many types of land uses [37–42]. Cellular Automata Markov (CA-Markov) model has performed relatively better than regression-based models in predicting spatial transitions in complex land use systems, as evident from earlier studies [35]. CA–Markov model can integrate geospatial, remote sensing, biophysical, and socio-economic data to create more comprehensive simulations of LULC changes. Accurately predicting LU changes with their associated spatial and functional alterations is crucial for land-use planners and decision-makers. This predictive capability informs the development of sustainable management practices and mitigation strategies to minimize negative environmental impacts [43–45]. Predicting and modelling land use would help to understand the future State of natural resource-rich regions.

The current study investigates LULC changes in the rapidly urbanizing district of Kalyana Karnataka (Bidar). The district is witnessing drastic growth in built-up areas and the National Investment & Manufacturing Zone [NIMZ] expansions in response to the industrial policy of the Government of Karnataka 2014–19 for industrial development. During the past decade, the mining activities, mainly non-metallic (Bauxite, Kaolin, Red ochre) have increased in Alwal, Sirsi, Aurad, Kamthana villages, and south of Basavakalyan in the district. The study area, being in a semiarid climate, has been undergoing severe land degradation, leading to degradation of soil quality, water scarcity, frequent occurrences of drought, and floods, which resulted in the large-scale migration of youth and hindering economic progress and social mobility due to inadequate access to infrastructure and basic amenities, etc. The economy of the region is reliant on agriculture, making it susceptible to changes in the climate with frequent occurrences of droughts, which necessitates understanding landscape dynamics to evolve appropriate land use strategies to restore degraded landscapes and develop drought-resilient systems. In this regard, the current study focuses on assessing landscape dynamics, including the extent, condition, and likely changes in land use as the region has faced historical neglect due to the absence of studies and developmental activities. This has necessitated long-term ecological monitoring considering local factors like socio-economic conditions, community dependence on natural resources to prioritise natural resources regions at disaggregated levels for prudent management through innovative solutions for water conservation, sustainable agriculture, and rural development.

The objectives of the study are to (i) analyse the spatio-temporal patterns in a landscape through the assessment of LC, LU, and fragmentation of forest ecosystems. LU assessment has been done through supervised non-parametric machine learning technique Random Forest (R.F.), (ii) simulation of likely LU changes for 2030 and 2038, and (iii) prioritize NRRRs at disaggregated levels based on the geo-climatic, biological, ecological, environmental, and social considerations.

2 Material and methods

2.1 Study area

Bidar is the northernmost district of Karnataka state, with a spatial extent of 5448 sq. km, has a geographical extent of 98 km from north to south, and is located between 17°35′ N and 18°29′ E to 76°41′ N and 77°40′ E (Fig. 1). The district consists of five taluks (administrative unit for implementation of development plans/policies, decentralised governance): Aurad, Basavakalyan, Bhalki, Bidar, and Humnabad, for decentralized governance (https://bidar.nic.in). The district is bounded by Kalaburagi district in the south, Sangareddy and Kamareddy (in Telangana) in the east, and Maharashtra in the North and West. Bidar, with a total population of 1,703,300 is at the 16th position in terms of population in the State. The district ranks 13th and 15th in Karnataka, India in terms of rural and urban population

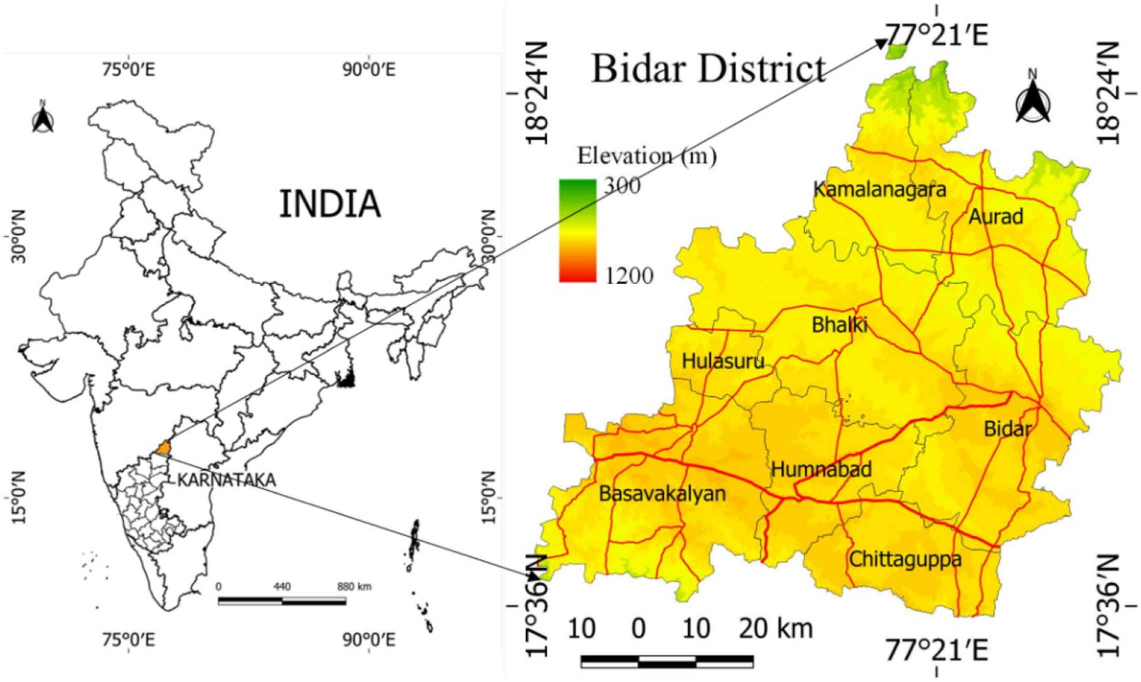


Fig. 1 Study area—Bidar district, Karnataka State, India

respectively. The district has registered the lowest work participation rate of 41.2% in the State. As per provisional reports of the census of India, the average literacy rate of Bidar district in 2011 was 70.51%.

The Bidar district exhibits distinct physiography. The northern portion comprises low-lying plains (420–640 m ASL), while the south is dominated by the elevated Bidar Plateau (laterite, 640–684 m ASL). This plateau features a gentle southward slope with broad valleys and mesas. The entire district, part of the Deccan Plateau (solidified lava), displays expanses of level plains in the north with black soils and basaltic rocks. Alluvial deposits are found along the Manjra River and its tributaries. The district is located in the Godavari and Krishna basins, and the main river of the district is Manjira, which is a tributary of Godavari. The main occupation in rural parts of Bidar is agriculture (Bengal gram, Green gram, wheat, sugarcane, paddy, red gram, black gram, groundnut, and chilies).

The climate is generally dry throughout the year, except during the southwest monsoon, which lasts till the end of September. The months of October and November constitute the post-monsoon or retreating monsoon season. The average rainfall ranges between 600 and 900 mm. The district has a maximum temperature above 40 °C in summer and a minimum of 3 °C in winter. The forest vegetation cover in the district is about 4.22% [46] and consists of dry deciduous and scrub-type [47]. The region has monoculture plantations of *Eucalyptus, Acacia auriculiformis, and Glyricidia.*. Native species include *Hardwickia, Albizia, Azadirachta,* and *Pterocarpus*. The fauna consists of Blackbucks, Jackals, Spotted Deer, Wild boars, Langurs, and various birds like peacocks and Partridges.

Landscape of Bidar district is a blend of agriculture, and small scale industries (traditional crafts and modern engineering). Traditional crafts like Bidriware metalwork coexist with agriculture-based industries and an emerging modern manufacturing sector. Bidar, known as the "pulse bowl of Karnataka," boasts a strong agricultural base focused on pulses, sugarcane, and oilseeds. This presents significant potential for agro-processing unit development. While a nascent manufacturing sector exists, large and medium-scale industries remain relatively few. However, a textile-focused Special Economic Zone offers promise for future growth. The district has been classified as one of India's most backward districts. Farmers in the region struggles with drought-prone agriculture, limited industry, and low per capita income. While boasting a diverse social fabric with minority populations, these communities often experience social and economic marginalization. Furthermore, low literacy rates hinder social mobility and economic development, particularly among rural women.

2.2 Data source

Evaluation of landscape dynamics involved spatial analysis of temporal remote sensing data with a spatial resolution of 30 m and cloud cover less than 15%, collected from the U.S. Geological Survey from Landsat Multi-spectral scanner (Landsat 1, 2, 3), Landsat Thematic Mapper (Landsat 5), Landsat Operational Land Imager (Landsat 8 OLI), and Landsat Operational Land Imager (Landsat 9, OLI-2) from 1973 to 2022 and details are provided in Table 1.

Secondary data used for classification and validation included ancillary data such as topographic maps of 1:50,000 and 1:250,000 from the Survey of India (SOI), non-spatial data from the District National Information Center portal, virtual earth data from Google Earth (http://earth.google.com) and Bhuvan http://bhuvan.nrsc.gov.in), thematic maps and district and taluks administrative boundaries from Karnataka Geographic Information Science (K-GIS, https://kgis.ksrsac.in).

2.3 Methodology

Figure 2 outlines the protocol adopted for prioritizing natural resource-rich regions a, which entails (i) LC analyses through NDVI (normalized difference vegetation index) using temporal remote sensing data, (ii) LU analyses through supervised non-parametric classifier using temporal remote sensing data, (iii) prediction of likely LU, and (iv) prioritizing NRRR by (a) dividing the study region into 5′ × 5′ (9 km × 9 km) grids comparable to a grid in the Survey of India topographic map of 1:50,000, (b) compiling data pertaining to bio-geo-climatic, ecological, environmental and social variables at grid level and assigning weight based on the relative significance of the variable, (c) aggregation of weights (of variables) for each grid, and (d) grouping of grids into 4 groups based on the frequency distribution of aggregated scores.

2.3.1 Land cover analyses

LC was assessed through the Normalized Difference Vegetation Index (Eq. 1), which identifies areas under non-vegetation and vegetation (5, 6, 13, 20, 25, 32, 35, 40, 61).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

where, NIR represents the near infrared red band and RED to the red band. Areas under vegetation and non-vegetation (soil, water) are based on NDVI values considering the training data collected from the field (corresponding to soil, water, and vegetation) and higher spatial resolution data (google earth). Thresholds considered for delineating vegetation and non -vegetation, are listed in Annexure (Table 7).

Table 1 Remote sensing data used for the landscape dynamics study

Satellite	Sensor	Year	Path/Row	Date
Landsat	Multi-spectral scanner	1973	155/47	5/1/1973
			155/48	5/1/1973
			156/47	6/1/1973
			156/48	6/1/1973
	Thematic Mapper (TM)	1999	145/47	9/2/1999
			145/48	9/2/1999
		2007	144/48	8/2/2007
			145/47	15/2/2007
			145/48	29/12/2006
	Operational Land Imager (OLI-1)	2014	145/47	18/2/2014
			145/48	18/2/2014
	Operational Land Imager (OLI-2)	2022	145/47	31/1/2022
			145/48	31/1/2022

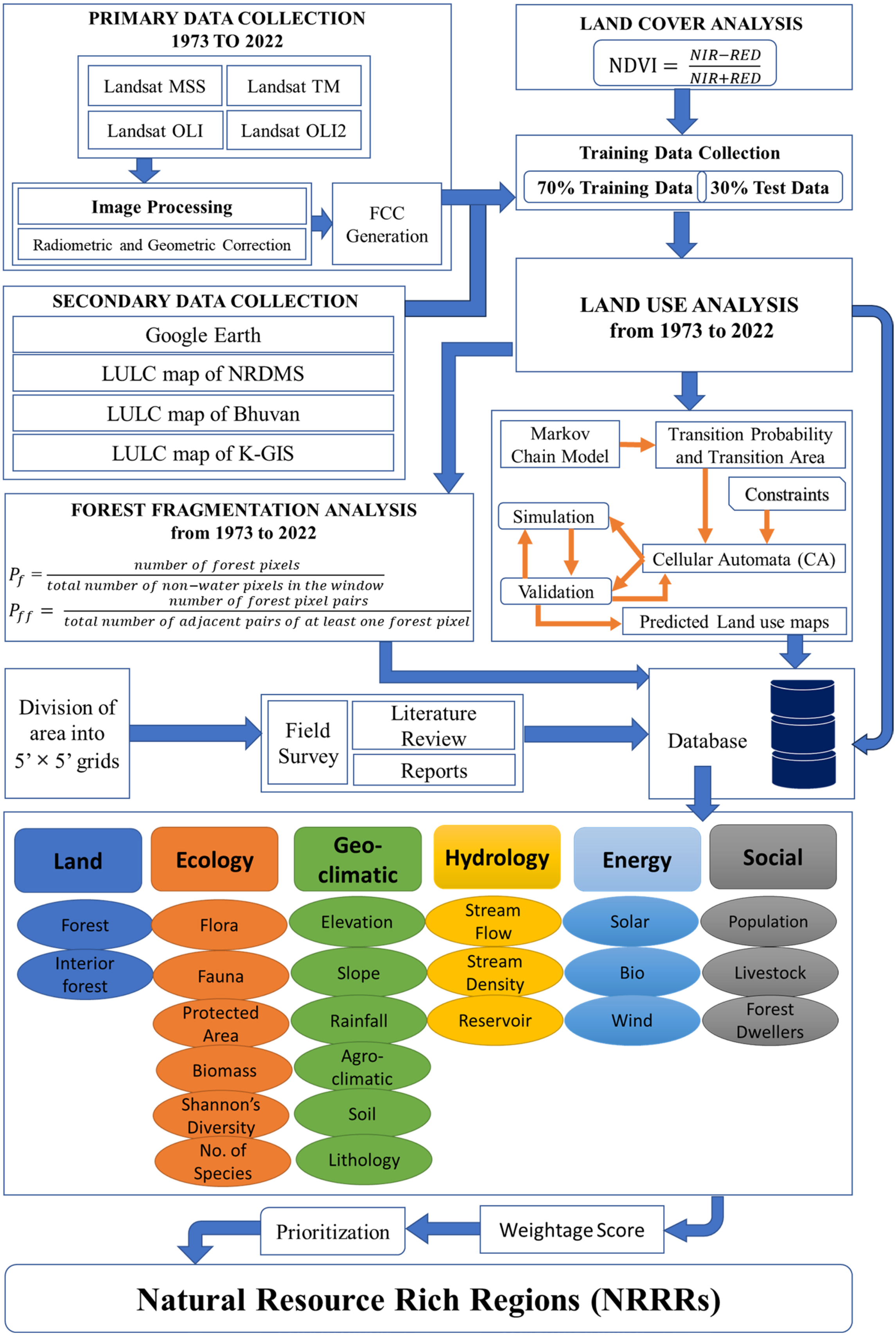


Fig. 2 Method for prioritising natural resources rich regions at disaggregated levels

2.3.2 Land use analyses

Temporal remote sensing data from 1973, 1999, 2007, 2014 and 2022 were collected from a public archive (http://landsat.org). The LULC analysis was done in Google Earth Engine for each period. The study used the surface reflectance (SR) product, which is already radiometrically, geometrically, and atmospherically corrected. The study has also done pre-processing such as cloud masking despite using cloud cover image less than 10% in the Google Earth Engine platform. LU analyses involved the generation of False Color Composite (FCC) using visible bands (Red and Green bands) with near-infrared bands (NIR), and FCC facilitated the identification of heterogeneous landscape features. Training polygons were digitized to correspond to heterogeneous patches, which are distributed uniformly across the region and account for a minimum of 15% of the study region. The attribute data for these training polygons was collected in the field using a pre-calibrated handheld Global Positioning System (GPS) and a virtual data portal (Google Earth, https://earth.google.com). 70% of these training polygons were allocated for LU classification purposes, while 30% was used for validation (accuracy assessment). The classification of LUs in temporal remote sensing data was accomplished using a supervised non-parametric classifier known as Random Forest, which is a machine-learning (ML) algorithm.

Random Forest (RF): RF classifier is an ensemble of classifiers, illustrated in Fig. 3. The classification accuracy of RF is increased by bagging using multiple decision trees [48, 49]. RF is based on the bagging principle, which samples a random subset (with replacement) from the training data and constructs a tree [50, 51]. Each subset was chosen to create trees encompassing around 2/3 of the sampled data, and the remaining 1/3 part is considered the out-of-bag (OOB) subset. Each classifier contributes a single vote towards assigning the most prevalent class, and is based on the majority of voting [52–55].

RF is popular among the non-parametric algorithms because it is robust compared to individual decision trees, avoids overfitting, and can handle big and unbalanced data. RF classifier minimizes the correlation among decision trees, maintains multi-variance, and shows less sensitivity towards noise and reduction of training. Primarily, two parameters are chosen for implementing RF: the number of trees (*ntree*) and the number of features in each split (*mtry*). Previous studies reported significant results and accuracy using default parameters. The performance of a Random Forest (RF) model is optimised by fine-tuning number of trees (*ntree*), starting with 50 trees, and evaluated the model's accuracy with progressively larger forests (100, 150, 200, 250, 300, 350, 400, 450, 500 trees). The analyses revealed that a forest with 300 trees achieved the highest accuracy. The number of features considered at each split within the trees (*mtry*) was default value of square root of number of features as per the earlier reports [56–58]. LU classification was validated with the ground truth data through computation of the confusion matrix (including overall accuracy, and Kappa coefficient), which are provided in Annexure as Table 8.

2.3.3 Forest fragmentation analysis

Forest fragmentation analysis was done based on the LU of the study region to quantify total forest cover (P_f) and the occurrence of forest in adjacent pixels (P_{ff}). This process involves utilizing a fixed-area window (3×3) centered on the specific pixel and its neighboring pixels [32]. The value is assigned to the central pixel, representing pixel fragmentation in relation to the associated forest location [35]. Comparative assessment of varied kernel sizes done across the fragmented

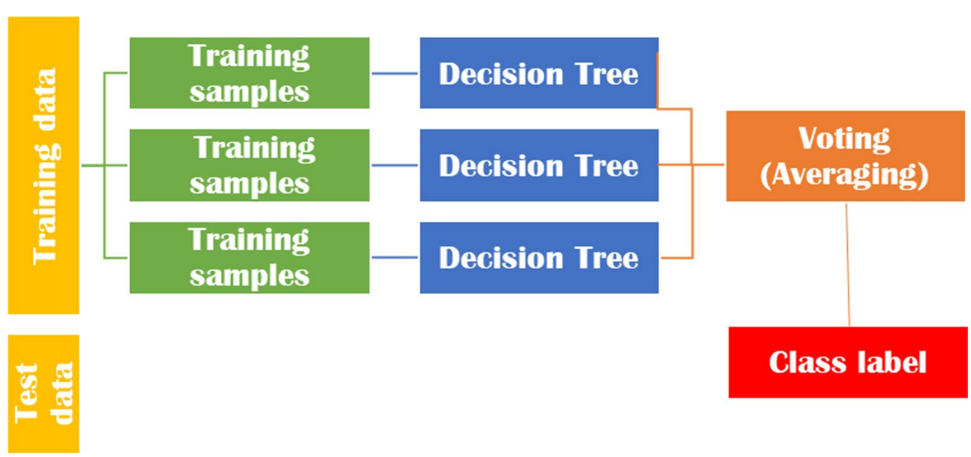


Fig. 3 Random Forest Classifier

forest in the Western Ghats illustrates that a kernel of 5 × 5 is apt for intact forest patches considering 30 × 30 m spatial resolution remote sensing data [12, 13, 17, 20]. While a 3 × 3 kernel is appropriate for sparse or fragmented forests [32]. As forests in Bidar are degraded, 3 × 3 kernel was adopted for computing fragmentation metrics [12, 13, 17, 21, 25, 59–61], and the outcome of fragmentation analyses is validated through field data and higher spatial resolution remote sensing data (of the latest time). The examination of forest fragmentation occurs at the pixel level, involving the computation of two measures within the window: firstly, the ratio of forested pixels to the total number of non-water pixels (P_f). Additionally, the proportion of adjacent pixel pairs in cardinal directions was calculated, where at least one pixel in the pair is forested (P_{ff}). The analysis helped evaluate the forest type in the study area as interior, patch, edge, perforated, and transitional forest. Forest pixel is classified according to the values of P_f and P_{ff} in the landscape surrounding that pixel, for each of the five landscape sizes. The interior forest includes all forest pixels for which the surrounding landscape was completely forested ($P_f = P_{ff} = 1$). In landscapes for which $0.6 < P_f < 1.0$, the value of P_{ff} determines whether the fragmentation component is perforated or edge. The difference is characterized by ($P_f – P_{ff}$), when P_{ff} is larger than P_f, the implication is that the forest exists in compact clusters or perforated forest; Conversely, when P_{ff} is smaller than P_f, the implication is that the forest exists in clusters that are not compact or edge forest. The perforated forest is the boundary area between interior forest and patch forest with small perforations with $P_f > 0.6$ and ($P_f – P_{ff}$) < 0. Transitional forest ($0.4 < P_f < 0.6$) forest pixels between forested and non-forested pixels. The patch forest includes all forest pixels ($P_f < 0.4$) within landscape surrounded by non-forested pixels [12, 13, 25, 61–64].

2.3.4 Prediction of likely land uses through cellular automata-Markov (CA-Markov)

CA-Markov predicts LULC through a combination of Multi-objective land allocation (MOLA), multi-criteria, Markov chain, and cellular automata by considering the spatial distribution of each LU category, the spatial direction of growth, and information on the distribution of LU added to the Markov chain analysis. There are numerous agents-based and non-agent-based modelling techniques for visualization of LU change. Among these, the CA–Markov model [61] is prioritised for the current analyses compared to the regression-based models for predicting likely spatial transitions in complex LU systems. CA–Markov model can integrate geospatial, remote sensing, biophysical, and socio-economic data to create more comprehensive simulations of LULC changes. Based on the concept of spatial proximity, the CA–Markov model predicts the likely changes of LULC. Land use dynamics were assessed through CA-Markov using IDRISI Selva 17.02. Historical land use data was used to simulate land use patterns for the year 2022. The accuracy of this simulation was assessed by comparing it to actual 2022 land use data. Validation assessment reveals higher conformity of predicted LU with the actual. The model was then used to predict likely land use scenarios for 2030 and 2038. The study used a conventional 5 × 5 contiguity filter (Fig. 4) as the neighborhood characterization with the 5 × 5 pixels matrix impacts the subtle variations in the cellular center surrounded by a matrix space.

Key limitations of models are (i) unable to account complex variability within the LC categories, (ii) use of only two LC maps for calibration, and (iii) are only affected spatial distribution (MCE, MOLA, and CA), and not temporal distribution, of simulated scores. CA configuration was refined to mitigate limitations by prioritizing neighborhood filters that capture broader spatial dependencies. The iteration process and the statistical indices used for validation were carefully

Fig. 4 Contiguity filter (5 × 5)

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

calibrated. This ensured a more robust comparison between the simulated map and reference maps representing the current landscape.

2.3.5 Prioritizing natural resource rich regions (NRRRs)

Natural Resource Rich Regions (NRRRs) were identified and delineated at disaggregated levels based on weighted averages of biological, ecological, hydrological, geo-climatic, energy, and social themes. The protocol adopted for mapping NRRRs at disaggregated levels is based on the protocol developed and implemented successfully earlier in the Western Ghats of India [13, 14, 17, 20, 59]. Then, based on the resource richness and sensitivity to the environmental factors, regions at disaggregated levels are divided into four levels. The study area was divided into 5′ × 5′ equal area grids (covering approximately 9 km × 9 km) comparable to grids of 1:50,000 topographic maps of the Survey of India, Government of India (https://onlinemaps.surveyofindia.gov.in). Weights are assigned considering the relative significance of themes and variables (listed in Table 2 and the source of the data variable-wise are listed in Annexure A3) and this approach provides a transparent mechanism for combining multiple data sets to know their relative significance and impact on the landscape.

$$Weightage = \sum_{i=1}^{n} W_i V_i \tag{2}$$

where, W_i represents that weight associated with particular variables *i*.

V_i is the associated value with variables.

n represents the number of variables.

Cumulative weights for each grid were computed, and the aggregated values were grouped into four groups as four zones (NRRR 1-4) based on the frequency distribution. NRRR 1 represents ecologically highly sensitive, requiring stringent protection and conservation measures, NRRR 2 is slightly less sensitive than NRRR 1, and has a very high probability to become NRRR 1. NRRR 3 represents a region of moderate protection region, and NRRR 4 characterizes less sensitive regions. The aggregate weights (of all variables) were computed for each grid, and grids were grouped into four categories based on the aggregated scores [NRRR 1 is highly sensitive with aggregate score > (μ (mean) + σ (standard deviation)], NRRR 2 (high sensitive, grids with aggregate scores within between [(μ + σ) and μ)], NRRR 3 (moderately sensitive, for grids with values between [(μ–σ) and μ)]) and NRRR 4 [less sensitive, for grids with values less than (μ–σ)]).

3 Results and discussion

3.1 LC analyses

The LC of Bidar district is depicted in Fig. 5, and details listed in Table 3 highlight that the area under vegetation has increased from 33.27% (1973) to 52.23% (2022), with a decrease in non-vegetation (66.73 to 47.77%).

3.2 Land use analyses

Figure 6 depicts temporal LUs, highlighting that the Bidar district landscape is urbanizing rapidly. The spatio-temporal analyses illustrate that built-up has increased from 18.53 km^2 in 1973 to 162.30 km^2 in 2022 by 2.63%, as represented in Table 4. Urban growth in Bidar City, with sprawl in the peri-urban area, is noticed due to the good interconnectivity of the vast road network. The expansion of the Indian Air Force training center in the core area aided as the catalyst for the expansion of Bidar City. The rural built-up makes up the major part of the total built-up in the district, which is increasing tremendously. Agriculture has marginally increased from 91.96% (1973) to 93.02% (2022). The area under water bodies has increased from 6.76 km^2 (0.12%) to 100.82 km^2 (1.85%) from 1973 to 2022 due to the construction of reservoirs and the increase in water spread area in tanks with the good monsoon rainfall. The Godavari River basin, which covers the major part of the district, and the Krishna River basin, meets the water demand. The district showed a shift from a dry cropping pattern due to the increased water security by the Karanja Dam Karanja Irrigation Project in the district. The forest ecosystem declined from 128.59 km^2 (2.36%) to 58.95 km^2 (1.08%) from 1973 to 2022 due to the expansion of the area under agriculture. Mining of non-metallic

Table 2 Ecological, bio-geo-climate, and environmental factors and their relative importance

Sl. No	Variables	Weightage/Ranking					
		0	2	4	6	8	10
LAND							
1	Forest Cover	0	< 15%	15–30%	30–45%	45–60%	> 60%
2	Interior forest	0	< 15%	15–30%	30–45%	45–60%	> 60%
ECOLOGY							
3	Biomass (total Carbon)	0	< 300	300–600	600–900	900–1200	> 1200
4	Shannon's Diversity	0	< 1	1–1.5	1.5–2	2–2.5	> 2.5
5	No. of species	0	< 50	50–100	100–150	150–200	> 200
6	Flora	Not Present	–	–	–	Endemic	–
7	Fauna	Not Present	–	–	–	Endemic	–
GEO-CLIMATIC							
8	Elevation (m)	–	–	< 250	250–500	500–750	> 750
9	Rainfall (mm)	–	< 600	600–1200	1200–1800	1800–2400	> 2400
10	Agro-Climatic Zone	–	Hot Dry Arid	Arid	Hot Dry Semiarid	Hot Dry Sub Humid	Hot Moist Sub-Humid/ Sahyadris
11	Lithology	–	–	Charnokites or Kalaadgi	Peninsular Gneiss	Dharwars or Granite	Deccan Trap
12	Soil	–	Coarse loamy	Sandy or sandy skeletal	Fragmental or Rocky outcrops	Clayey loamy or Clayey Skeletal	Loamy or Clayey
HYDROLOGY							
13	Stream density	< 0.5	0.5–1	1–1.5	1.5–2	2–2.5	> 2.5
14	Stream flow	–	< 3 months	3 months	4 months	5 months	> 6 months
15	Reservoir	Not present	–	–	–	Present	–
ENERGY							
16	Solar energy (kWh)	–	-	–	–	< 6	> 6
17	Wind (m/s)	–	< 1.5	1.5–2	2–3.5	3.5–4	> 4
18	Bio (Mkcal)	–	< 100	100–200	200–400	400–600	> 600
SOCIAL							
19	Pop. Density (persons per sq. km)	–	> 1000	1000–500	500–250	250–100	< 100
20	Livestock Density (animals/ha)	–	< 0.75	0.75–1.5	1.5–2.25	2.25–3	> 3
21	Forest dwellers	Not present	–	–	–	–	S.T. population

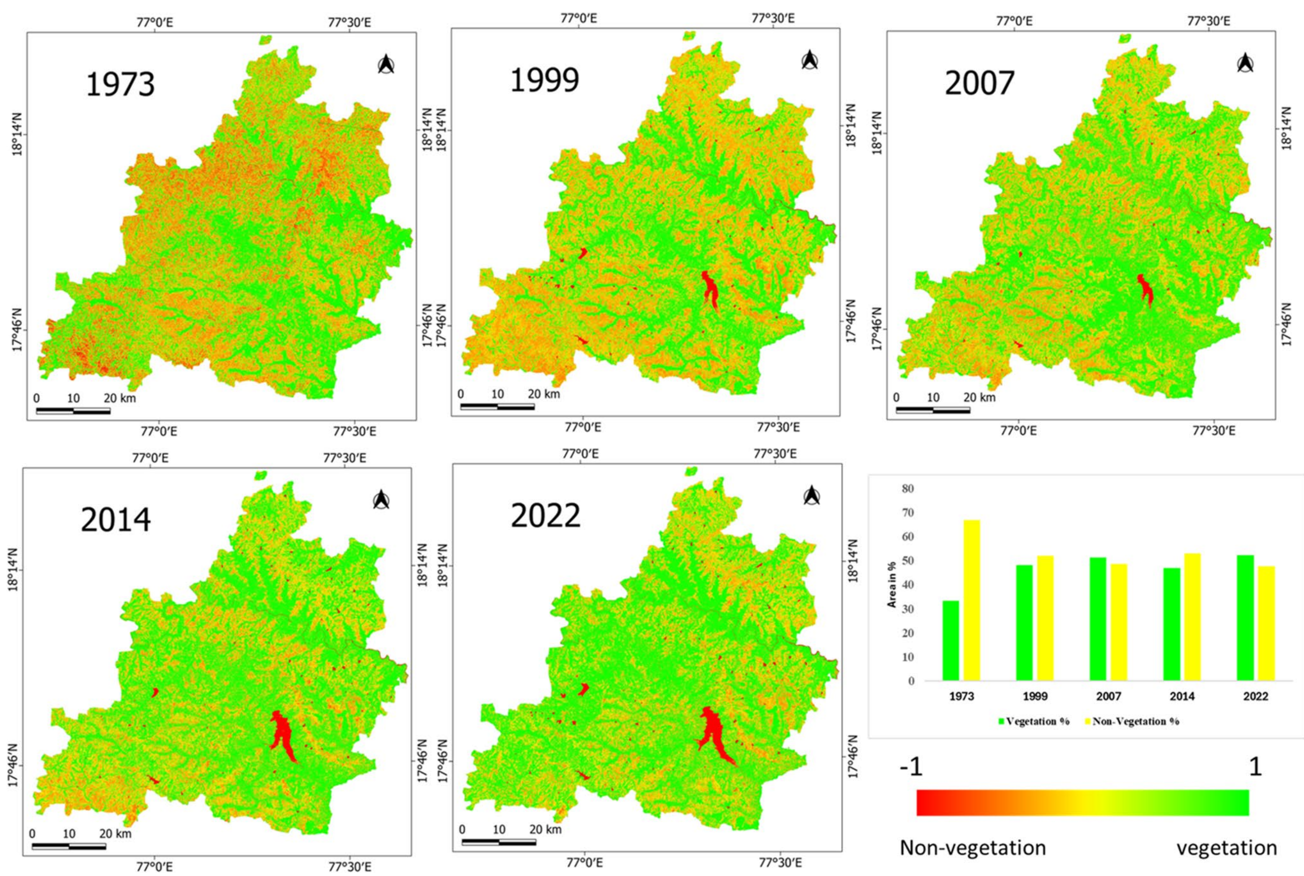


Fig. 5 Changes in the LC in Bidar district from 1973 to 2022

Table 3 LC analyses of Bidar district from 1973 to 2022

NDVI	Vegetation		Non-vegetation	
	Sq. km	%	Sq. km	%
1973	1817.58	33.27	3645.7	66.73
1999	2625.31	48.05	2838	51.95
2007	2807.08	51.36	2658.6	48.64
2014	2563.61	46.92	2899.8	53.08
2022	2852.48	52.23	2608.9	47.77

minerals (Bauxite, Kaolin, and red ochre) has increased post-2005 in the district, mainly in the south of Basavakalyan taluk, Bidar, and Aurad taluks. The scrubland is converted into built-up lands and agriculture. The scrubland sharply declined from 274.47 km^2 (5.03%) to 51.55 km^2 (0.94%) from 1973 to 2022.

The accuracy assessment details are provided in the Annexure as Table 8.

3.3 Forest fragmentation analyses

Forest ecosystems in the Bidar district are undergoing degradation and depletion due to anthropogenic pressures involving the transition to agricultural land. The district has degraded forest patches, and the results of fragmentation metrics depicted in Fig. 7 reveal that the interior forest has declined from 39.66 km^2 (in 1973) to 13.77 km^2 (in 2022), and details are listed in Table 5 show that area under non-forest has continuously increased from 5047 km^2 (92.49%) in 1973 to 5245.7 km^2 (96.13%) in 2022. Based on the forest fragmentation analysis, the study identified some regions such as Changler forests (depicted below, Fig. 7), Shantabad Protected Forest, and Shahapur Reserved Forest. These forests show fragmentation on the edges, leading to the shrinking of interior forest patches. Anthropogenic activities leading to the

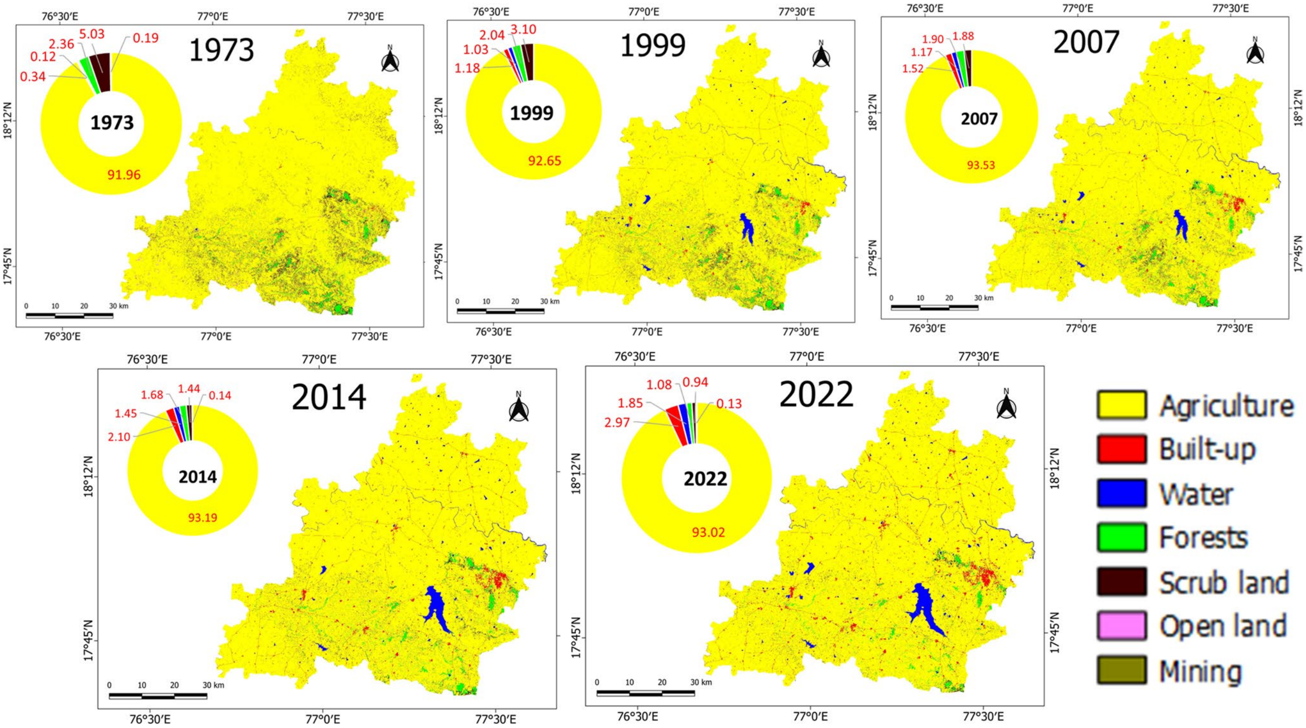


Fig. 6 Changes in LU of Bidar district from 1973 to 2022

Table 4 Changes in LUs of Bidar district from 1973 to 2022

Land use	1973	1999	2007	2014	2022
Agriculture					
sq. km	5018.11	5055.81	5103.71	5085.48	5076.29
%	91.96	92.65	93.53	93.19	93.02
Built-up					
sq. km	18.53	64.46	82.95	114.34	162.3
%	0.34	1.18	1.52	2.1	2.97
Water					
sq. km	6.76	56.33	63.73	79.07	100.82
%	0.12	1.03	1.17	1.45	1.85
Forests					
sq. km	128.59	111.38	103.87	91.9	58.95
%	2.36	2.04	1.9	1.68	1.08
Scrub land					
sq. km	274.47	169.03	102.49	78.47	51.55
%	5.03	3.1	1.88	1.44	0.94
Open land					
sq. km	10.54	0	0	0	0
%	0.19	0	0	0	0
Mining					
sq. km	0	0	0.25	7.73	7.09
%	0	0	0	0.14	0.13

transition of forest land into scrubland and agricultural land have contributed to the fragmentation of forests. Plantation of non-native species such as *Eucalyptus, Acacia auriculiformis, Tectona grandis and Cassia siamea*) raised by the forest department are part of forest categories.

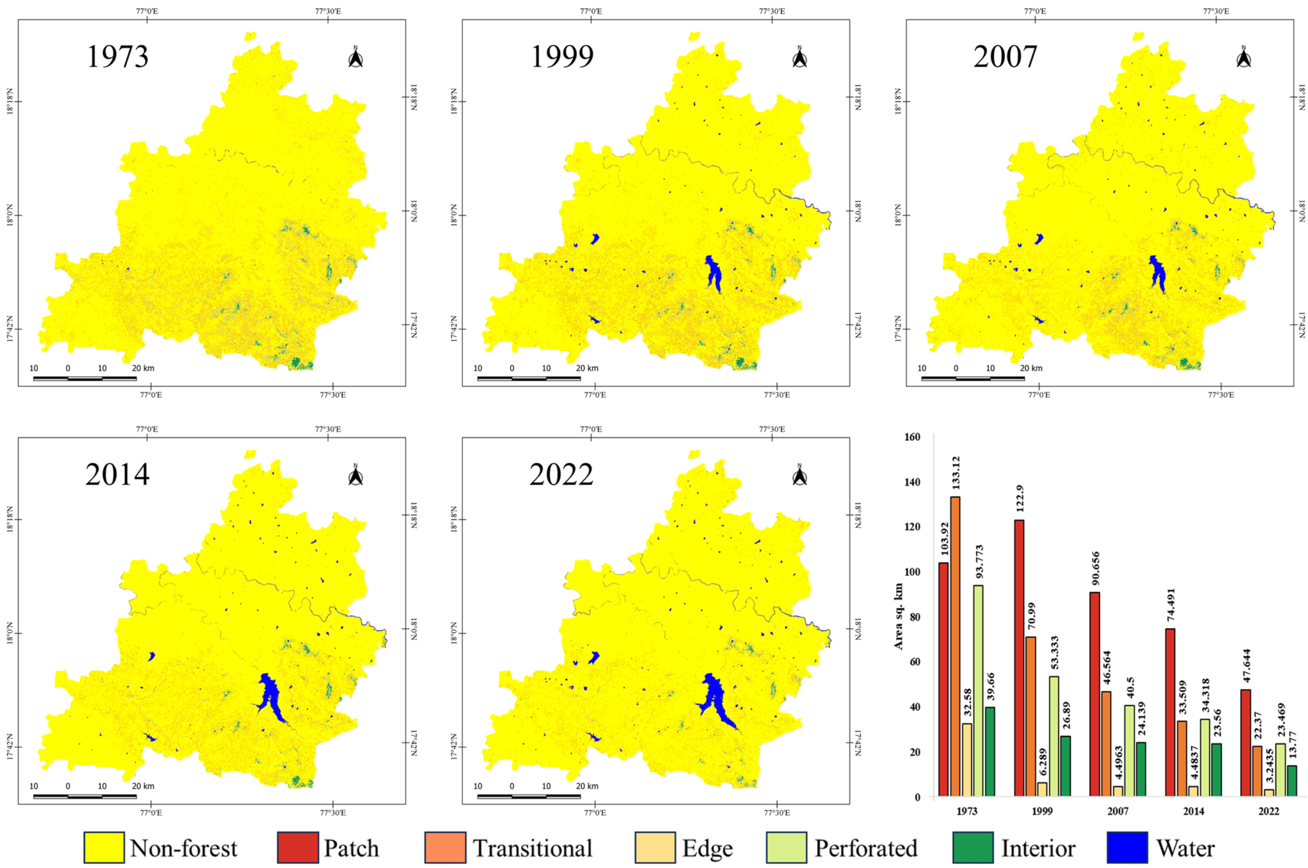


Fig. 7 Assessment of fragmentation in the forest ecosystem of Bidar district from 1973 to 2022

Table 5 Assessment of Forest fragmentation in the forest ecosystem of Bidar district from 1973 to 2022

Forest fragmentation	1973	1999	2007	2014	2022
Non-forest					
sq. km	5047.2	5120.3	5186.9	5207.6	5245.7
%	92.49	93.83	95.05	95.43	96.13
Patch					
sq. km	103.92	122.9	90.656	74.491	47.644
%	1.9	2.25	1.66	1.37	0.87
Transitional					
sq. km	133.12	70.99	46.564	33.509	22.37
%	2.44	1.3	0.85	0.61	0.41
Edge					
sq. km	32.58	6.289	4.4963	4.4837	3.2435
%	0.6	0.12	0.08	0.08	0.06
Perforated					
sq. km	93.773	53.333	40.5	34.318	23.469
%	1.72	0.98	0.74	0.63	0.43
Interior					
sq. km	39.66	26.89	24.139	23.56	13.77
%	0.73	0.49	0.44	0.43	0.25
Water					
sq. km	6.757	56.32	63.732	79.071	100.82
%	0.12	1.03	1.17	1.45	1.85

3.4 Prediction of likely LUs (2022, 2030, and 2038)

The LU for 2022 is simulated using CA-Markov and compared with the actual LUs (Fig. 8). The validation highlights the overall agreement of the actual with the simulated L.U. of 2022 is 0.96. Predicated and actual LUs for 2022 are presented in Table 6. Based on this, LUs are predicted for 2030 and 2038.

Bidar is predominantly an agricultural district, with 93% of the landscape covered with croplands. The district is rapidly urbanizing, mainly in the Bidar metropolitan area. Kolhar industrial area is the largest industrial area of Bidar city. The modeling results for Bidar district in 2030 and 2038 (Fig. 8) indicate that there is a likely increase in the built-up area by 11.80% (in 2030) and 12.88% (in 2038) primarily due to the expansion of agro and food processing industries. The recent industrial policy of the State for the period 2020–2025 aims to sustain a growth rate of 10 percent per year by promoting balanced, inclusive, and sustainable industrial development. As part of the economic growth strategy, agricultural land is expected to be converted into built-up areas between 2022 and 2030 to support the growth of Tier II / III cities in the State. This is intended to stimulate the development and advancement of the MSME (Micro, Small and Medium Enterprises) sector. Consequently, there would be a decline in agricultural land, to the extent of 83.83% (in 2030) and 83.47% (in 2038), to facilitate the development and promotion of MSME sector.

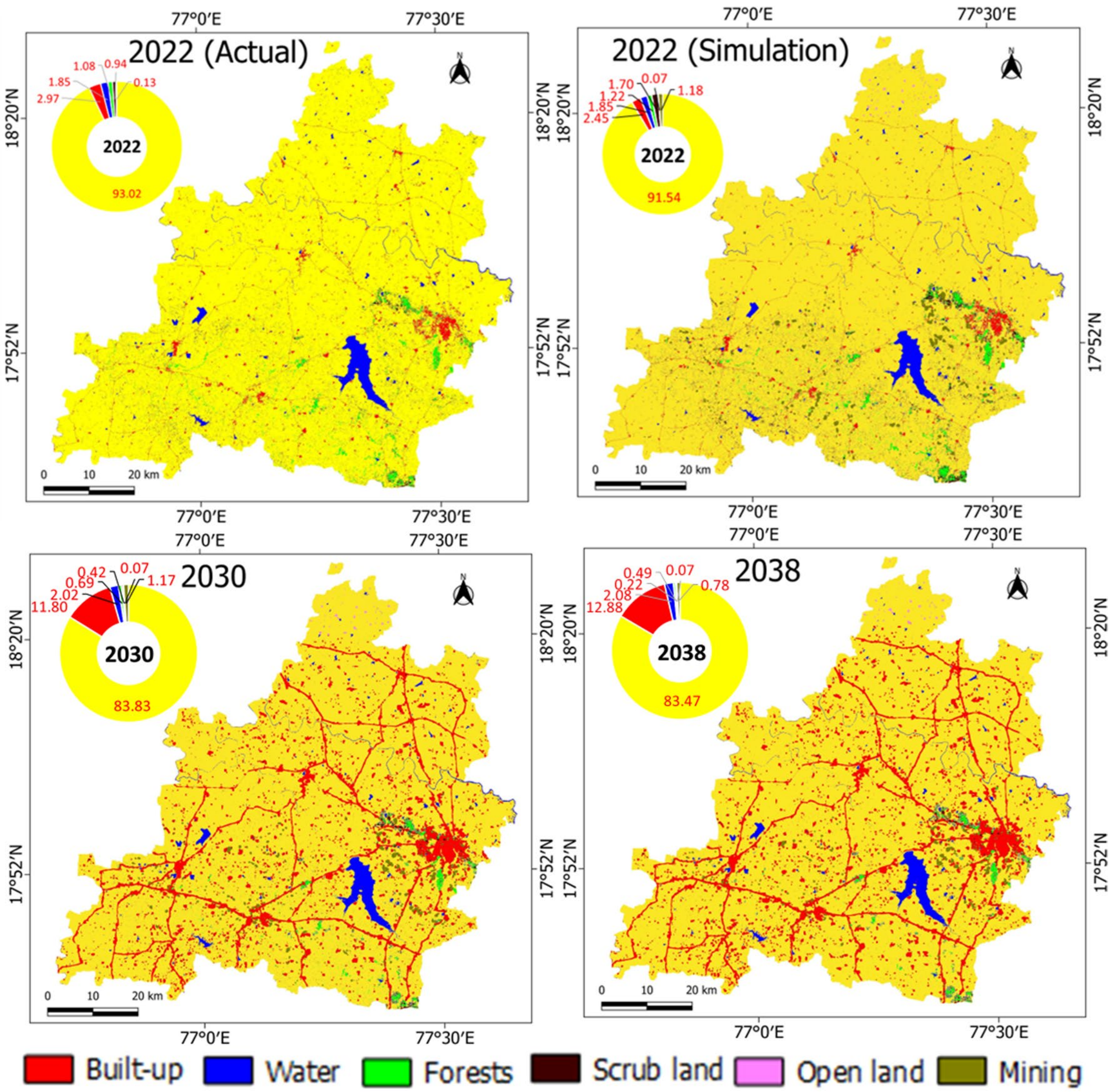


Fig. 8 Predicted LUs in 2030 and 2038 for Bidar district

Table 6 Modeling LU for 2022 of Bidar district

Land use	2022 (Actual)		2022 (Simulation)	
	sq. km	%	sq. km	%
Agriculture	5076.29	93.02	4995.33	91.54
Built-up	162.30	2.97	133.51	2.45
Water	100.82	1.85	100.83	1.85
Forests	58.95	1.08	66.45	1.22
Scrub land	51.55	0.94	92.51	1.70
Open land	0.00	0.00	4.08	0.07
Mining	7.09	0.13	64.22	1.18

3.5 Prioritising natural resource rich regions (NRRRs)

The extent of forest in the district at disaggregated grid levels is depicted in Fig. 9, indicating that the district has much less forest cover (< 15%) and less than 15% cover of the intact contiguous forest. The district has Chitta Reserved Forest in Bidar taluk.

The flora distribution in Fig. 10a illustrates that flora species are distributed mainly at the center of Bidar, spreading across Chittagupppa, south of Bhalki, north of Basavakalyan, and Aurad taluks. Fauna is distributed mainly in the Bidar Taluk (Fig. 10b). Shannon's diversity (Fig. 10d) and the number of species (Fig. 10c) computed for the Bidar, Bhalki, and northern parts of Humnabad. Chittaguppa and Bidar regions highlight that the Bidar region has the highest number of species (150–200). The district has a biomass of less than 300 Gg (Fig. 10e) in Bidar, Humnabad, Chittaguppa, and Basavakalyan taluks.

The elevation map in Fig. 11a shows that the district has an elevation range of 500–700 m. The spatial distribution of rainfall (Fig. 11b) shows the district receives more than 600 mm. The district falls in arid agro-climatic zones (Fig. 11c), so only dry crops are grown. The Deccan trap and Peninsular gneiss type dominate the lithology of the district (Fig. 11d). Soil found in the district (Fig. 11e) is mainly coarse loamy, and Sandy is in Humnabad and Chittaguppa taluks.

Figure 12a shows the higher stream flow (more than five months) in Humnabad, Aurad, and the northern part of Basavakalyan and stream density of more than 2 (Fig. 12b) in these regions. Karanja Dam is the main reservoir (Fig. 12c), which meets the irrigation demand in the district.

The potential of solar energy depicted in Fig. 13a highlights very high potential in the district (> 6 kWh). The wind velocity in the entire district ranges between 1.5 and 2 m/s (Fig. 13b) denotes moderate potential, and southern regions have higher wind velocity (3.5–4 m/s) for Wind energy production. The whole region of the district has a moderate biomass potential of 100–200 Mkcal (Fig. 13c).

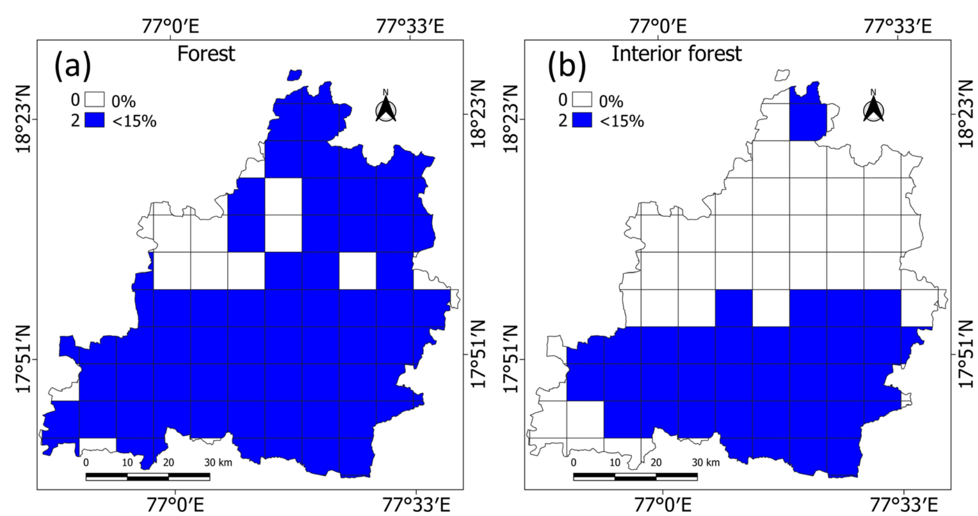


Fig. 9 Land variable: **a** forest, and **b** Interior forest

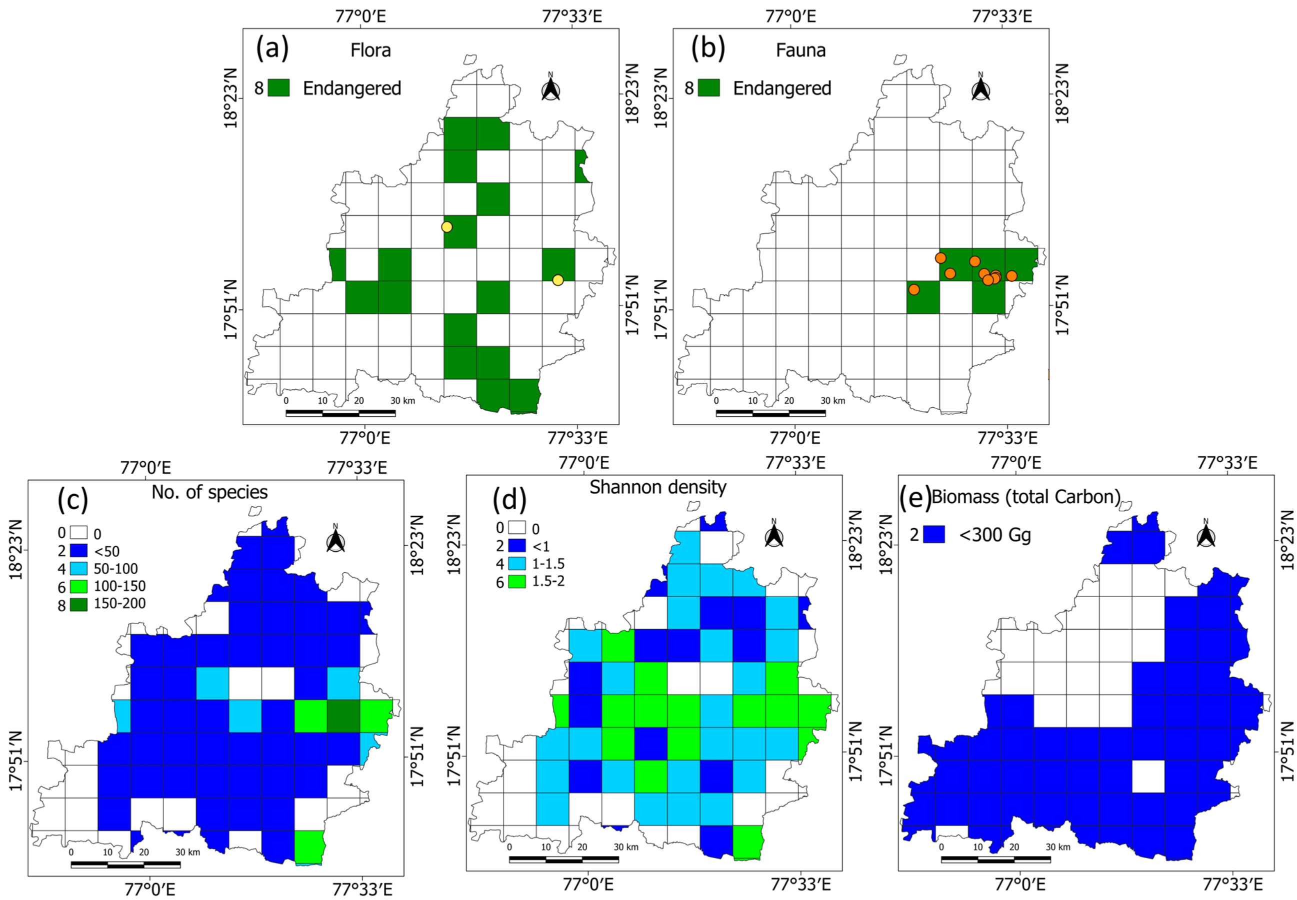


Fig. 10 Ecological variables: **a** flora, **b** fauna, **c** number of species **d** Shannon diversity, and **(e)** Biomass (total carbon)

Population density (2021 census) information depicted in Fig. 14a shows Bidar is highly populated (500–1000 persons per sq. km). Aurad and Bhalki taluks have lower population density (100–250 persons per sq. km), and based on that, they ranked higher. Basavakalyan and Humnabad taluk have population density (250–500 persons per sq. km), and Chitapur taluk have population density between (250–500 persons per sq. km). The livestock density (Fig. 14b) illustrates that most parts have livestock density between (0.75–1.5 animals/ha). The forest dweller distribution in Fig. 14c shows dominance in the Chitta Reserved Forest.

Figure 15 presents NRRRs at a disaggregated level (grids), which highlights that 3% of the geographical area in the district is NRRR 1 (4 grids), 9% area is NRRR 2 (6 grids), 54% of the area is NRRR 3 (42 grids), and 35% of the area is NRRR 4 (42 grids). No more degradation is permitted within NRRR 1, a zone of maximum conservation to ensure the sustenance of natural resources. NRRR 2 could eventually become NRRR 1, provided conservation norms are implemented with stringent regulatory measures and protection is given to forests and the surrounding areas.

3.6 Discussion

NRRRs delineation accounts for biotic, abiotic, and anthropological factors, which helps to assess the current State of fragile landscapes and their role in ecosystem balance. The study region is categorized into four distinct groups (NRRR 1-4) based on ecological, social, and bio-geo-climatic factors to account for varying levels of ecological sensitivity and natural resource availability. Similar approaches were adopted earlier for prioritizing ecologically sensitive regions at disaggregated levels in the Western Ghats for conservation and protection [13, 14, 17, 20, 59].

The development in the Bidar district reflects a dynamic interplay of economic, social, and infrastructural factors. Bidar is situated in the northeastern part of Karnataka, with a rich historical and cultural heritage contributing to its unique identity. Bidar ranks second from last amongst all 30 districts in the State, with a value of ₹133,935 for the year 2021–22. Similarly, the district's Gross Domestic District Product (GDDP) of ₹2,444,017 lakh and the district is at the 24th position

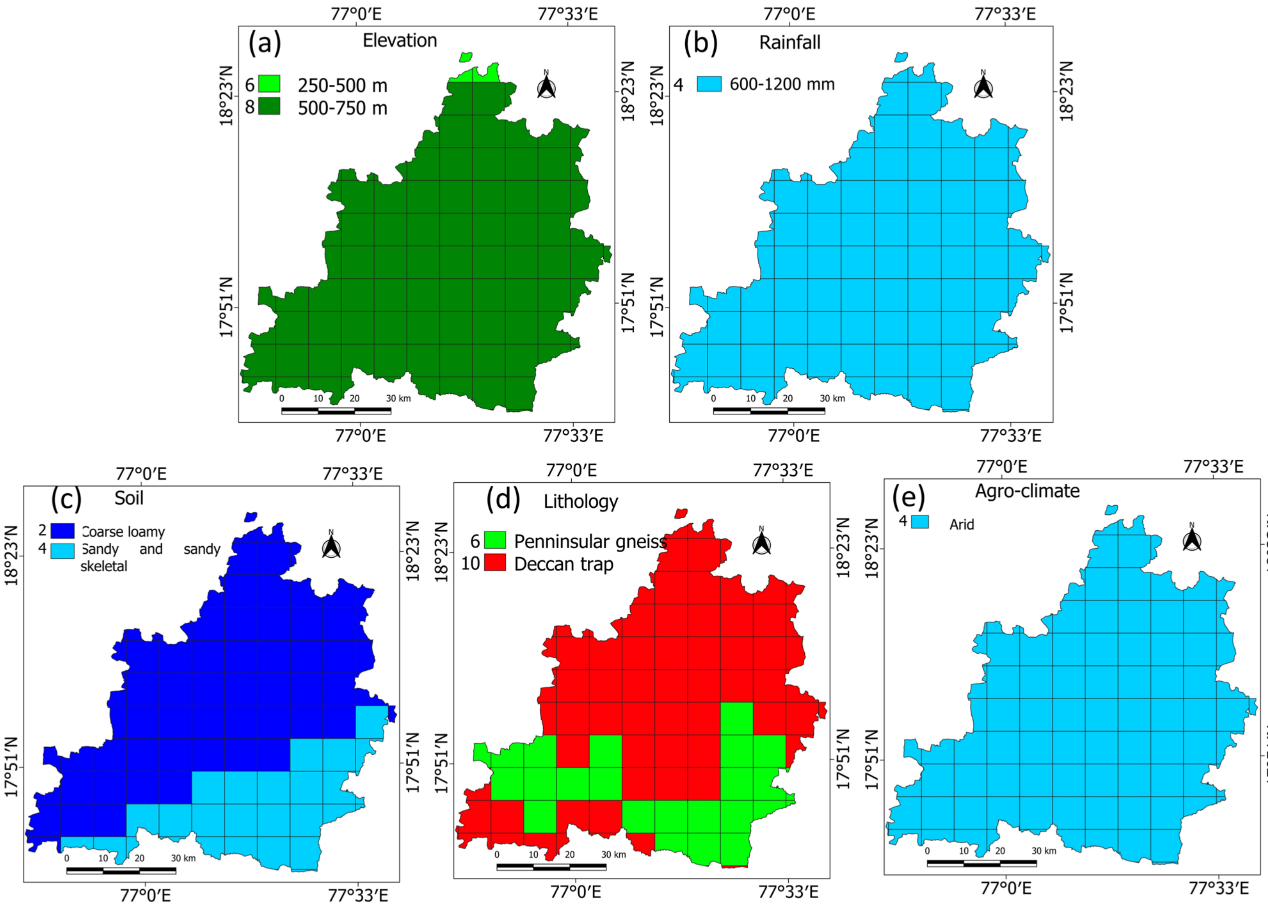


Fig. 11 Geo-climatic **a** Elevation, **b** Rainfall, **c** Soil, **d** Lithology, and **e** Agro-climate

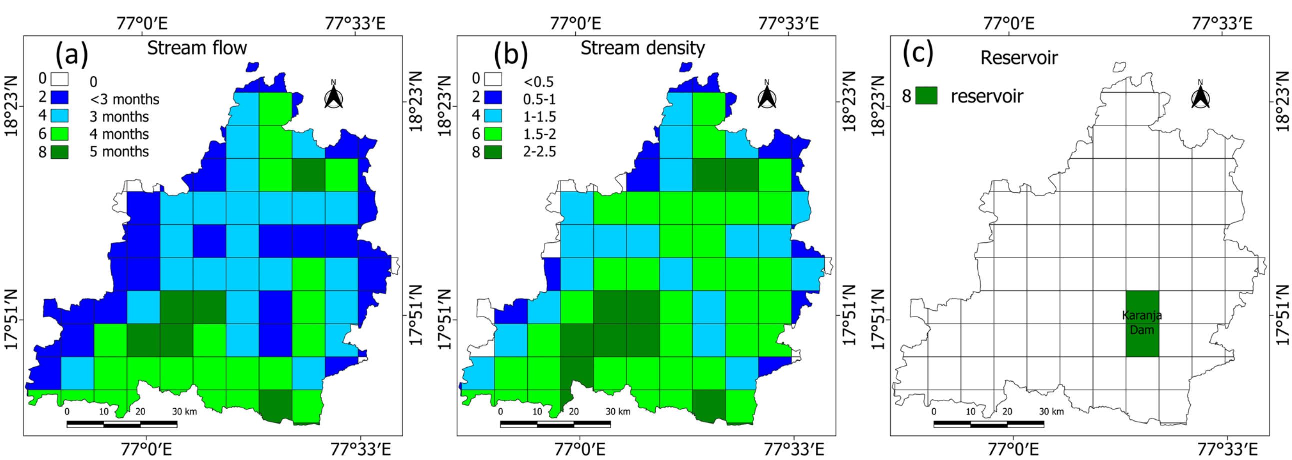


Fig. 12 Hydrology **a** Stream flow **b** Stream density, and **c** Reservior

among all districts in the State [65]. Human Development Indices (HDI) highlight substantial deficiencies in literacy, education, infrastructure, healthcare access, and various other crucial societal aspects [66]. The non-profit nature of farming and the better opportunities for youth in other districts are the prime drivers of migration. LU planning in India centers around agriculture and livestock management. Bidar falls in agro-ecological Regions 6 (AER 6) based on the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) classification, with the lowest agricultural productivity Rs.

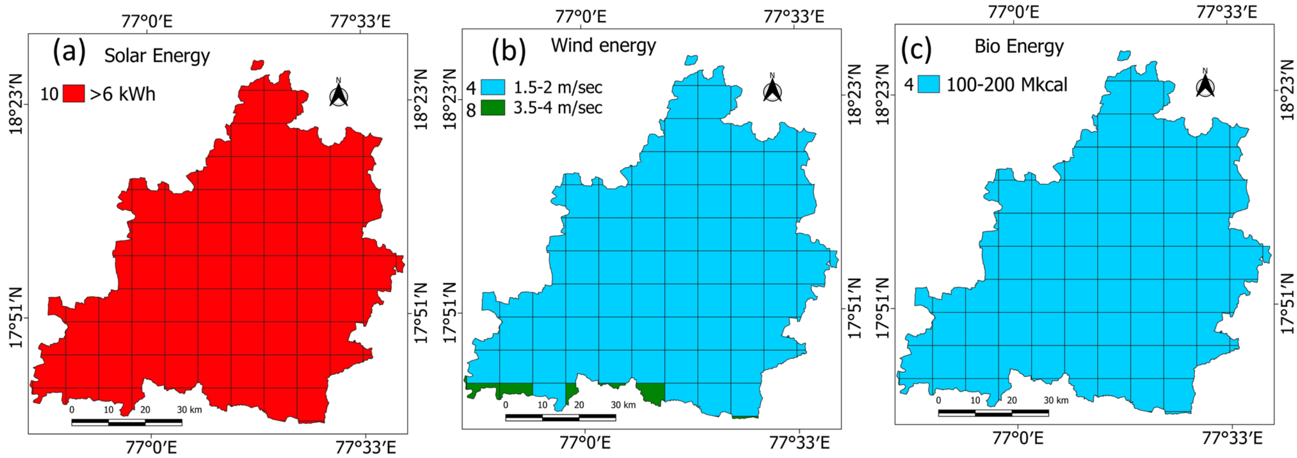


Fig. 13 Energy variables **a** Solar, **b** Wind, and **c** Bioenergy

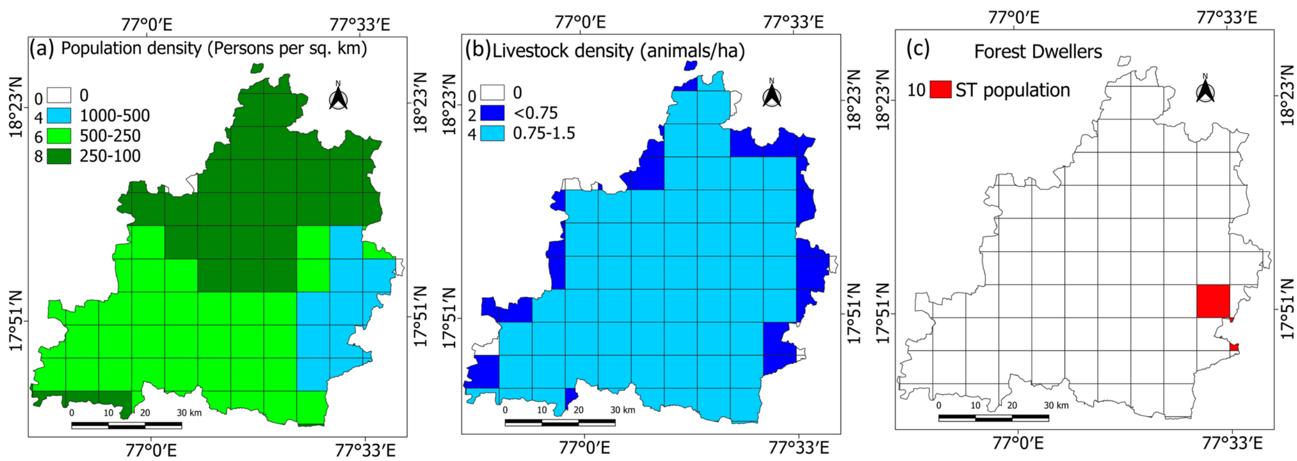
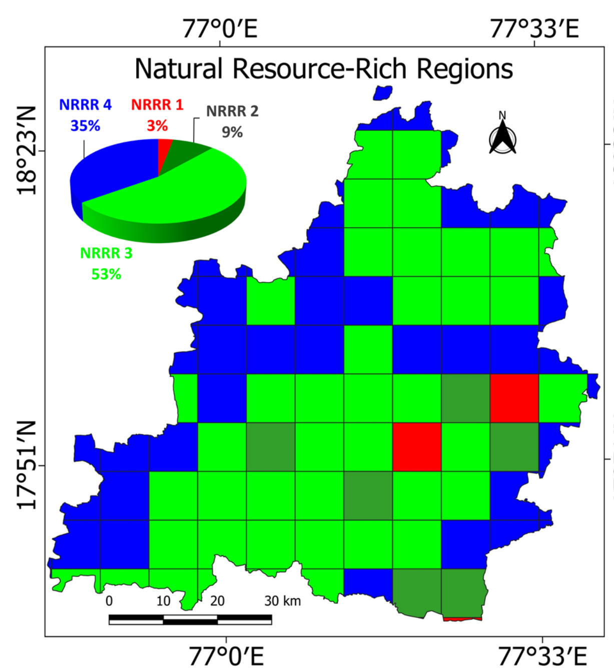


Fig. 14 Social variables **a** Population density, **b** Livestock density, and **c** forest dwellers

Fig. 15 NRRRs in Bidar district



12,687 ha^{-1} in Karnataka [67]. This study examining the socio-economic factors driving agricultural laborer migration in the district revealed a higher prevalence of individual migration (around 44%) within the 15–30 years age group compared to entire family migration and migration accounts for approximately 50% of individuals with significant correlation between the size of a household's land holdings and their decision to migrate [68]. Economic, and ecological crises and agrarian distress are mainly [69] attributed to multiple historically determined, geographically influenced, and socioeconomically influenced factors. Bidar district is part of the semiarid and drought-prone belt of Northern Karnataka and is susceptible to periodic drought, and only 8 percent of cultivated area is irrigated [70]. Similarly, a survey conducted to assess the fertility status of soils revealed that soil pH ranged from slightly acidic to strongly alkaline, and organic carbon content varied from low to medium. Also, soil nutrients such as nitrogen, phosphorus, and potassium exhibited spatial variation, ranging from low to high levels [71].

Improvements in farming practices, encompassing soil and water management, and optimized use of cultivation techniques, crop rotations, cover cropping, fertilization strategies, and agricultural chemical handling practices, would ensure climate-resilient, sustainable agriculture with a reduced carbon footprint, and biodiversity conservation. The integrated farming approach fosters productive agricultural systems, ensuring a sustainable food supply and a healthy environment for future generations [72]. Achieving food security and preserving agricultural resources for future generations necessitates maintaining the ecological integrity of the land to sustain human well-being [73].

The district shows a decline in the deciduous forest cover, comparable with an earlier study in Gadag, Karnataka, with similar climatic conditions, which showed 0.33% of forest cover decline from 1989 to 2019 [74]. Similar results were observed in Bellary district, highlighting the decline of deciduous forests with agricultural expansion in the northern part of Karnataka [32]. Shifts in vegetation cover within arid and semiarid landscapes constitute a critical driver of biogeochemical cycling at local, regional, and global scales. Consequently, understanding vegetation dynamics in these environments is paramount to elucidating their influence on the carbon cycle, water cycle, and energy exchange [75]. Biodiversity conservation is a challenge in Karnataka's dry zones, due to threats like habitat loss and fragmentation, development projects, resource overexploitation, pesticide use, and climate change are severely affecting the biodiversity of semiarid landscape and require a landscape-level conservation strategy [76]. Vegetation cover plays a critical role as a natural flow barrier and promotes increased soil water retention, which aids in mitigating run-off and erosion processes [77, 78]. Also, the district has grasslands with indigenous grass species that offer promising solutions for water retention and groundwater recharge. Also, these grasses possess diverse morphophysiological mechanisms to tolerate harsh conditions, including high light intensity, wind speeds, evapotranspiration, limited precipitation, and poor soil moisture/nutrient content. Their inherent resilience makes them ideal for arid environments [79]. Dry forest exhibits great potential for supplying a diverse array of ecosystem services, with a particular emphasis on regulating services [80] such as water regulation and soil retention were the most important services provided by these forests. LULC and ecosystem service value have an interrelationship in arid and semiarid regions. The study [81] highlighted that grassland and watersheds emerged as crucial contributors, accounting for 45% and 30% of the total. These ecosystems play a vital role in supporting biodiversity, soil preservation, water regulation, and purification, highlighting the need for their conservation. Specifically, native species in arid ecosystems offer a broader spectrum of services, such as soil carbon storage, and has higher water use efficiency [82]. Additionally, arid/semiarid lands, due to a rich evolutionary history, exhibit intra-species diversity, contrasting richness, or inter-species variation [83]. Mosaic landscapes comprising grasslands, forest patches, and agricultural fields provide a suitable habitat for black buck (classified as near threatened in India). A pioneering study conducted from 2012 to 2014 [84], revealed a population of approximately 886 blackbuck individuals within the district, which is the second highest in Karnataka after the Ranebennur Blackbuck Sanctuary.

Landscape dynamics assessment shows an increase in built-up area from 18.53 km^2 (in 1973) to 162.30 km^2 (in 2022). The outskirts of the main cities and core parts of major cities in the region have witnessed rapid expansion, driven by the growth of the National Investment & Manufacturing Zone (NIMZ). The increase in built-up area comparable to the urban growth in the neighboring district of Kalaburagi [85, 86] highlights substantial urban expansion over the past three decades. This expansion is in response to the increasing demand for industries in chemicals, agriculture, pharmaceuticals, and others. A similar trend is noticed in the neighboring Kalaburagi city, with the burgeoning population coupled with the demand for infrastructure, which has led to an increase in built-up areas at the expense of agricultural and barren land [87]. In terms of infrastructure, developments in transportation and connectivity have played a crucial role. Road network improvements and enhancing public transportation facilities have contributed to better accessibility within the district and connectivity to neighboring regions. The expansion of urban areas and planned urban development initiatives have reshaped the landscape in the district. Agriculture is a vital component of the economy in arid and semiarid climatic conditions, but these regions suffer from land and water resource degradation due to uncoordinated planning, inadequate management practices, etc., and a similar situation prevails across vast swathes of agricultural land in developing countries [88]. Changes in the climate, lower productivity, and water scarcity in arid and semiarid regions exacerbate land degradation and biodiversity loss, which have enhanced the susceptibility of rural communities [89].

The district has witnessed sustained attempts to boost agro-based industries, tapping agricultural potential and fostering economic growth. While contributing to economic development, the emphasis on agricultural growth and agro-based industries has led to increased demands on water resources for irrigation. The water supply in the area relies on the drainage systems of two river basins: the Godavari River basin, encompassing the majority of the district, and the Krishna River basin. A notable transformation in the cropping pattern has occurred, transitioning from a predominantly dry cropping system to one with increased water security, facilitated by the Karanja Dam and the Karanja Irrigation Project. Karanja reservoir has helped the farmers of the southern part of the district with irrigation facilities, boosting the cultivation of water-intensive crops. The region is primarily covered by Deccan Traps, with basalts and laterites as the dominant lithology. Highly fractured and jointed basalts and laterites exhibit exceptional water transmission characteristics. The basin exhibits a dendritic to sub-dendritic drainage pattern, indicating low drainage density and high permeability. The low slope and gentle relief suggest the potential for groundwater recharge with good to very good (25.23%), moderate (3.36%), poor (5.39%), and poor to nil (22.89%) groundwater potential [90].

The recent industrial policy of the Government of Karnataka, spanning from 2020 to 2025, visualizes an annual growth rate of 10 percent by fostering balanced, inclusive, and sustainable industrial development [91]. As a component of the economic growth strategy, agricultural lands are converted into built-up areas to facilitate the expansion of Tier II / III cities in the state. This strategic shift is designed to catalyze the progress and enhancement of the Micro, Small, and Medium Enterprises (MSME) sector. Urbanization and infrastructural expansion have altered LU patterns, impacting ecosystems and biodiversity [92, 93]. Efforts to balance economic development and environmental conservation are crucial, especially considering the need to address challenges such as water scarcity and the preservation of natural habitats. The forest ecosystem declined due to the expansion of area under agriculture. Mining of non-metallic minerals (Bauxite, Kaolin, and red ochre) has increased post-2005 in the district, mainly in the south of Basavakalyan taluk, Bidar, and Aurad taluks. Participatory watershed management approaches integrating engineering, ecological, and social measures present a promising avenue for enhancing rain-fed agriculture. This approach contributes to meeting the growing food demand and offers numerous collateral benefits, including improvements in livelihoods, addressing equity concerns, and promoting biodiversity conservation [94–96].

Sustainable development practices and eco-friendly initiatives are essential to mitigate adverse impacts on the delicate ecological balance of Bidar district, fostering a harmonious coexistence between human activities and preserving its natural resources. Sustainable development in natural resource-rich regions is imperative for the preservation of ecological integrity and the well-being of local communities. Conservation measures in these regions focus on the responsible management of resources, promoting biodiversity, and minimizing environmental degradation. Prioritizing natural resources rich regions (NRRRs) at disaggregated levels would aid in adopting eco-friendly practices, embracing renewable energy sources, and implementing robust policies that safeguard ecosystems. Fostering a harmonious relationship between human activities and the environment would ensure sustainable development, ensuring the sustainability of natural resources while supporting the resilience and vitality of these landscapes.

3.6.1 Limitations

The current study has identified the natural rich resource regions based on bio-geoclimatic, hydrological, and ecological variables at the disaggregated level. Delineation of monoculture plantations from natural forests is possible with field data along with high spatial and spectral resolution data, which is required to better understand the ecosystem services. Use of high resolution (spatial, and spectral) will also improve the accuracy of classification, which aids in the validation of the effectiveness of afforestation initiatives. Visualisation of likely land uses is done through CA-Markov. Accounting for agents of transition through agent-based or scenario-based modeling by considering agents and constraints would allow more complex scenarios with insights into drivers of LU changes.

3.6.2 Recommendation

The natural resource-rich regions are prioritised at disaggregated levels to frame better LU policies and empower decision-making per the Biodiversity Act 2002, Government of India. Active participation of local communities in conservation initiatives would foster a sense of ownership and encourage sustainable land management practices. Incentivizing farmers to integrate conservation goals with agricultural production would promote better land-use practices with agroforestry, drought-resilient farming practices, harvesting solar energy, water use efficiency with location-specific climate-resilient crops, organic farming, etc. Implementing robust monitoring systems through remote sensing data would help track deforestation rates, soil health, biodiversity, etc., and would aid in the timely identification of emerging threats and timely interventions to implement stricter regulations on land-use change, promoting afforestation programs with native species and soil conservation practices. Climate resilient strategies (being implemented as part of an extension program in partnership with the regional agricultural institute) include (i) awareness programs to educate farmers and communities of the impacts of climate change, (ii) incentives to empower to adopt adaptation strategies, (iii) skill development for training local youth to process agriproducts (iv) promoting entrepreneurship and small businesses, (v) rainwater harvesting, (vi) promoting efficient irrigation practices and (viii) foster collaboration among stakeholders-researchers, policymakers, and local communities to ensure that policies are evidence-based and address local needs.

4 Conclusion

Information on LULC changes and their impacts on natural resource rich regions are vital for conserving and restoring natural resources. The region witnessed a sharp increase in the impervious surface due to enhanced industrial development and economic activities. The region has experienced rapid growth in the rural built-up area and periphery of the main cities due to the expansion of the National Investment & Manufacturing Zone [NIMZ] to cater to the demand of the industries in sectors like chemical, agro, pharma, etc. Built area increased from 0.34 to 3% in the last five decades. The extent of water bodies has increased from 0.12% to 1.85% from 1973 to 2022 due to the construction of dams and reservoirs. Karanja reservoir has helped the farmers of the southern part of the district with irrigation facilities to grow water intense crops. Forest fragmentation indices reveal that the forest has degraded due to anthropogenic interventions. The intact forest of the region shows a decline during the study period. Modeling of likely LUs for 2030 and 2038 depicts that built-up would increase to 11.80% and 12.88%, respectively, due to the increase in agro and food processing industries, transport, trade, hotel sectors and other servicing units. The increasing trend of built-up is predicted to continue due to the accomplishment of a target to achieve higher and sustainable industrial infrastructure, and skill upgradation in response for maintaining the industrial growth rate of 10 percent per annum by promoting sustainable, balanced and inclusive industrial growth as proposed by the state new industrial policy. Focusing on the development through promotion of the MSME sector in Tier II/III cities of the states as an engine of economic growth.

Prioritization of Natural Resource Rich Regions (NRRRs) at disaggregated levels highlights that 12% of the total geographical area of the district is under NRRR 1 and NRRR 2, 54% of the total geographical area under NRRR 3, and the rest of the region under NRRR 4. The study highlights that NRRR1 and 2 are of high concern, requiring the attention of the district's authorities for the preservation and conservation of natural resources. NRRRs help preserve and conserve biodiversity, water, ecological values, social and cultural values. Identification of NRRRs aids in framing effective policies, which assist the decision-making process at the local and regional levels to achieve sustainable development goals (SDGs).

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Author contributions T V Ramachandra—concept design, data collection. analyses, manuscript writing, review and editing Paras Negi—Field data collection, Spatial data analyses, writing, implementing revision.

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Data availability Data is archived at https://wgbis.ces.iisc.ac.in.

Code availability Not applicable.

Declarations

Ethics approval and consent to participate All authors have read, understood, and have complied as applicable with the statement on 'Ethical responsibilities of Authors' as found in the Instructions for Authors. *Not applicable. This work did not describe experiments with animals, human subjects, or human tissue samples.*

Consent for publication All authors have read and approved the manuscript.

Competing interests The authors declare no competing interests.

Annexure

See Tables 7, 8 and 9.

Table 7 NDVI threshold value used for computation of vegetation and non-vegetation

Year	Scenes	Minimum value	Threshold value	Maximum value
1973	Scene 1	– 0.06	0.07	0.53
	Scene 2	– 0.02	0.1	0.64
	Scene 3	– 0.05	0.1	0.54
	Scene 4	– 0.02	0.06	0.54
1999	Scene 1	– 0.02	0.23	0.71
	Scene 2	0	0.27	0.76
2007	Scene 1	– 0.1	0.13	0.39
	Scene 2	– 0.1	0.13	0.39
	Scene 3	– 0.01	0.15	0.35
2014	Scene 1	– 0.01	0.13	0.36
	Scene 2	– 0.002	0.12	0.50
2022	Scene 1	– 0.02	0.12	0.52
	Scene 2	– 0.02	0.1	0.52

Table 8 Accuracy assessment of land use classification 2022

		Reference								
		Agriculture (1)	**Builtup (2)**	**Water (3)**	**Forest (4)**	**Scrub (5)**	**Mining (7)**	**Row total**	**Commission error**	**User Accuracy**
Classified	**Agriculture (1)**	**49**	0	0	0	3	0	52	0.06	94.23
	Built-up (2)	10	**129**	2		2	6	149	0.13	86.58
	Water (3)	0	0	**80**	0	0	0	80	0.00	100.00
	Forest (4)	6	0	0	**50**	9	0	65	0.23	76.92
	Scrub (5)	13	0	0	2	**35**	0	50	0.30	70.00
	Mining (7)	0	0	0	0	2	**2**	4	0.50	50.00
	Column total	78	129	82	52	51	8	400		
	Omission Error	0.37	0.00	0.02	0.04	0.31	0.75	**Overall Accuracy**		**86.25**
	Producer Accuracy	62.82	100.00	97.56	96.15	68.63	25.00	**Kappa**		**0.82**

Diagonal elements (shaded cells) with bold values are the correctly classsified pixles

Table 9 Data—ecological, bio-geo-climate, and environmental with the source of data

Variables	Data	Values	Source
Forest Cover	LU classification map for 2022	Spatial extent of forest cover in the grid	Current assessment
Interior forest	Forest class from land use map of 2022	Spatial extent of interior forest cover in the grid	Current assessment
Biomass (total Carbon)	field data and literature review	total biomass stored in the grid	https://wgbis.ces.iisc.ac.in
Shannon's Diversity	field data and literature review	based on the distribution of flora with relative abundance in grids	https://wgbis.ces.iisc.ac.in
No. of species	field data and literature review	Spatial distribution of species in the grid	https://wgbis.ces.iisc.ac.in
Flora	field data and literature review	Spatial distribution of endemic flora in the grid	https://wgbis.ces.iisc.ac.in
Fauna	field data and literature review	Spatial distribution of endemic fauna in the grid	https://wgbis.ces.iisc.ac.in
Elevation (m)	Cartosat DEM (1 arc second = 30 m)	Prominent contour in the grid	https://www.nrsc.gov.in/
Rainfall (mm)	point based daily rainfall data from (1901–2010) from various rain gauge station	point data extrapolated into spatial data in the grid	Indian Metrological data (IMD)
Agro-Climatic Zone	Karnataka agri Portal	agro-climatic condition in the grid	https://e-krishiuasb.karnataka.gov.in/
Lithology	National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)	based on the parent material (rock) present in the grid	https://nbsslup.icar.gov.in/
Soil	National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)	type of soil present in the grid	https://nbsslup.icar.gov.in/
Stream density	Cartosat DEM (1 arc second = 30 m)	number of streams present in the grid	https://www.nrsc.gov.in
Stream flow	Cartosat DEM (1 arc second = 30 m)	duration of water flow in a stream (if present in the grid)	https://www.nrsc.gov.in
Reservoir	LU classification for 2022	if present in the grid	Author
Solar energy (kWh)	field data and literature review	quantum of global solar radiation in the grid	Ramachandra et al. [97]; Ramachandra [98]
Wind (m/sec)	field data and literature review	wind velocity in the grid	Ramachandra and Shruthi [99]
Bio (Mkcal)	field data and literature review	based on the fuelwood available in the grid	Ramachandra [100]
Pop. Density (persons per sq. km)	Census of India 2011	number of people present in the grid	Census of 2011 (http://censusindia.gov.in)
Livestock Density (animals/ha)	20th Livestock Census of India	number of livestock present in the grid	Animal Husbandry Departments of the states and union territories
Forest dwellers	Census of India 2011	statistics of forest dwellers in the grid	Census of 2011 (http://censusindia.gov.in)

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