FORUM GEOGRAFI
ISSN: 0852-0682 | E-ISSN: 2460-3945

HTTPS://JOURNALS.UMS.AC.ID/INDEX.PHP/FG/

Research article

Sustainable Management of Natural Resources at Disaggregated Levels with Insights from Landscape Dynamics

T V Ramachandra[1,2,3*], Paras Negi[1], Tulika Mondal[1], Bharath Setturu[1,4]

[1] Energy & Wetlands Research Group, CES TE 15, Environmental Information System, Center for Ecological Sciences (CES) Indian Institute of Science, New Bioscience Building, Third Floor, E-Wing, (Near D-Gate), Bangalore 560012, India; [2] Centre for Sustainable Technologies (Astra), Indian Institute of Science, Bangalore 560012, India; [3] Centre for Infrastructure, Sustainable Transportation and Urban Planning (CiSTUP), Indian Institute of Science, Bangalore, Karnataka 560012, India; [4] School of Mathematics and Natural Sciences, Chanakya University, Bengaluru, Karnataka, India.

*) Correspondence: tvr@iisc.ac.in

Citation:
Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B. (2025). Sustainable Management of Natural Resources at Disaggregated Levels with Insights from Landscape Dynamics. Forum Geografi. 39(2), 136-162.

Article history:
Received: 3 December 2024
Revised: 22 June 2025
Accepted: 18 July 2025
Published: 28 July 2025

Abstract

The burgeoning population, coupled with the resource demand and alterations in the climatic regime, have been posing serious challenges for the sustenance of natural resources. Natural Resource Rich Regions (NRRRs) are areas endowed with abundant natural resources, which maintain ecological balance and economic activities. These regions are pivotal for supporting the livelihoods of local communities by providing essential ecosystem services and resources. However, land degradation leading to deforestation due to unplanned developmental activities has escalated the carbon footprint, aggravated the vagaries of the climate, and posed significant challenges, especially for communities reliant on fragile, arid, and semi-arid ecosystems. The nexus of socio-economic disparity, persistent poverty, and unplanned developmental activities often poses severe challenges for realizing full economic potential with environmental sustainability. Land use (LU) changes with urbanization and agricultural expansion, leading to fragmentation, habitat loss, decline of native species, and disruption of ecological processes with a potential decline of biodiversity. The arid region in the northern part of Karnataka, located in Southern India, has been experiencing a sharp decline in the groundwater table due to frequent droughts and excessive groundwater extraction. The current study unveils actionable solutions for sustainable management of natural resource-rich regions by meticulously analyzing the nexus between rapid development, LU modifications, and their subsequent environmental ramifications. LU transitions are quantified using temporal-spatial data acquired through space-borne sensors through supervised machine learning classifiers based on the non-parametric algorithm Random Forest (RF). Land use dynamics assessment reveals that paved surfaces (area under buildings, roads) have increased from 186.22 sq. km (in 1973) to 1085.12 sq. km (in 2022). The study area has degraded forest patches, and the estimation through fragmentation metrics reveals that the intact forest has shown a decline from 3252.39 sq. km (1973) to 1508.12 sq. km (2022). The forests have continuously decreased from 2,154.20 sq. km (1973) to 1,096.34 sq. km (2022). In Northern Karnataka, the prioritization of NRRRs highlights the status of resource availability, with highly resource-rich zones represented by NRRR1 (67 grids) and NRRR2 (127 grids), followed by NRRR3 (304 grids) with moderate resource potential, and NRRR4 (522 grids) encompassing areas with comparatively scarcer resources. The prioritization of natural resource-rich regions emphasizes the need for prudent land management strategies, with holistic and integrated approaches considering social, economic, and environmental issues with degrees of sensitivity across arid regions.

Keywords: Natural Resource Rich Regions (NRRRs); arid regions, Land Use Land Cover (LULC); Machine Learning (ML); Random Forest (RF); landscape modelling.

1. Introduction

Anthropogenic-induced unplanned land use (LU) changes have contributed to land degradation and deforestation, which have impaired environmental quality and depletion of natural resources, posing critical challenges necessitating immediate interventions with prudent LU policies. The burgeoning demand of the swelling population has exerted pressure on the sustenance of natural resources, raising concerns about the potential exhaustion of finite resources with accelerating environmental degradation (Huo and Peng, 2023). Unrealistic pushes for economic development for short-term gains have been altering the fragile ecosystem integrity, leading to cascaded environmental consequences with land degradation, air and water pollution, deforestation, and soil erosion (IPCC, 2007). These environmental burdens pose a significant risk of negating the purported benefits of increased production and output, potentially jeopardizing the long-term well-being of future generations (World Bank, 2020) and necessitating a fundamental shift towards a sustainable development path.

Land degradation refers to irreversible degradation with a decline in productivity due to the deterioration of ecosystem functions (Bai *et al.*, 2008; del Barrio *et al.*, 2021). Alterations in the physical and chemical integrity of ecosystems due to direct and indirect anthropogenic influences have affected the biotic integrity (Chalise *et al.*, 2019; Olsson *et al.*, 2019). The expansion in agriculture and infrastructure, driven by the rapid increase in population, has accelerated the transitions in land cover (LC), leading to degradation (Wassie, 2020). Primary land degradation processes have resulted in vegetation decline, soil salinization, soil erosion, aridity, and the decline in organic carbon (Cherlet *et al.*, 2018; Prăvălie *et al.*, 2021), which are widely acknowledged as significant degradation forms in arable lands. Land degradation leading to vegetation decline indicates significant biomass loss and the consequent erosion in carbon sequestration capability (Mirzabaev *et al.*, 2019; Olsson *et al.*, 2019; Prăvălie *et al.*, 2023). LC refers to the physical characteristics of the land surface, such as vegetation and non-vegetation. LU refers to the anthropogenic use of the land for various activities, such as agriculture, etc. (Ramachandra *et al.*, 2022, 2023a). LU assessment helps in assessing the spatial extent of forests, agriculture, and other land use types. LU changes leading to deforestation and land degradation that alter the landscape structure, affecting ecosystem health, degrading ecosystems, shrinking habitats, and breaking them into smaller fragments, which results in the loss of biodiversity (Haddad *et al.*, 2015; UNCCD, 2016a and 2016b). Human-dominated actions, especially for economic purposes, reshape the landscape and cause a large-scale decline in biodiversity. LU changes are complex, triggering reactions in the system and increasing the environmental challenges affecting livelihood (Lambin *et al.*, 2003).

The transition from farmland to abandoned barren land is governed by macro and micronutrient content alterations in soil with climatic conditions in arid regions (Evans and Belnap, 1999; Kosmas *et al.*, 2000). In arid areas, continuous monitoring of LU modifications with physical and chemical attributes (of soil) helps to evaluate ecological risk at the regional scale. Monitoring environmental factors provide insights into theoretical frameworks toward effective LU management with mitigation strategies for lowering regional ecological risks (Zhang *et al.*, 2019). Climate change predictions have shown a rise in extreme climate events like floods, droughts, tropical storms, frosts, and heat waves (IPCC, 2013; Pontifes *et al.*, 2018). The arid and semi-arid regions with high temperatures and lower or scanty rainfall are vulnerable to these combined effects with the enhanced risk of desertification (Pontifes *et al.*, 2018). The consequences of climate change are a decline in ecosystem services, resulting in predominantly adverse effects on livelihoods, human health, and overall well-being (van der Geest *et al.*, 2019; Liu *et al.*, 2022). This effect is especially pronounced in semi-arid regions with limited adaptive capabilities (Mirzabaev *et al.*, 2022).

About 30% of the Earth's land surface has been identified as arid or semi-arid, and half of this land is utilized for pastoral or agricultural purposes, contributing significantly to the regional economy. In addition, these regions are endowed with minerals, which offer opportunities for the utilization of minerals for economic well-being and social advancement. However, unplanned extraction and exploration of these minerals would result in extensive environmental and societal impacts with inadequate management of processes that may lead to enduring effects (Gratzfeld, 2003; Scholes, 2020). Considering the looming threat of changes in the climate, the focus now is on the sustenance of ecosystem services, with an understanding of the dynamic interaction of human societies with ecosystems at a local scale (Turner *et al.*, 2016; Yang *et al.*, 2020; Sun *et al.*, 2021).

Karnataka State consists of a vast expanse of arid and semi-arid landscapes highly susceptible to climate change, which is evident from the recurring droughts over the past twenty years. In addition to these challenges, destructive floods, hailstorms, lightning, and thunderstorms during the pre-monsoon season have significantly damaged agriculture, particularly horticultural crops. These recurring calamities have contributed to food insecurity and illnesses, leading to chronic and acute undernutrition among the population. The cumulative economic loss due to these natural disasters is estimated at 1926.82 billion INR. Furthermore, the arid regions in the state, particularly in the North Interior Karnataka region, experience regular heat waves, as temperatures during the March-June period over the past two decades have shown a discernible upward trend, exacerbating stress-related health issues and fatalities (Economic Survey of Karnataka, 2022; 2023).

The significant progress in geoinformatics with the availability of temporal-spatial data (satellite remote sensing data) and machine learning techniques prove invaluable with the availability of LULC information, which is crucial for analyzing the status of natural resources and for formulating policies aimed at conserving natural resources for the attainment of the sustainable development goals (SDGs) related to food, nutrition, economic and environmental security (Rai *et al.*, 2022; Bell *et al.*, 2023). Remote sensing data provide spatial, spectral, and temporal information that is essential for monitoring natural resources through inventorying and mapping at a local and regional scale (West *et al.*, 2019) despite constraints of differing scales, a shortage of specific spatial or temporal details, and inconsistent time series (Pongratz *et al.*, 2018). Classification of LULC can be very challenging in arid and semi-arid regions due to significant spectral similarities between urban and non-urban features (Lasanta and Vicente-Serrano, 2012; Drusch *et al.*, 2012; Wambugu *et al.*, 2021; Ali and Johnson, 2022). Different classification techniques for LU mapping include traditional parametric classifiers such as ISO Clustering, Bayesian, and Maximum

Likelihood (Strahler, 1980; Otukei and Blaschke, 2010). Compared to this, non-parametric methods do not rely on either parameters or associated data distribution, making them increasingly adapted techniques (Evans *et al.*, 2011; Ahmadi *et al.*, 2020; Mancino *et al.*, 2023). Machine Learning (ML) is pivotal in assessing landscape dynamics and is most applied to pattern recognition (Talukdar *et al.*, 2021). ML techniques include Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Light Gradient Boosting Machine methods, and K-Nearest Neighbor (KNN) to analyze spatial data, derive information for acquiring knowledge to make well-informed decisions (Wang *et al.*, 2022).

An ensemble learning algorithm-based classifier, RF, is one of the widely used ML algorithms for LU classification (Breiman, 2001) and has overcome the problem of overfitting and instability in classification (Nguyen *et al.*, 2020; Adugna *et al.*, 2022). RF does process multi-dimensional data classification with minimal generalization errors (Belgiu and Drăguț, 2016) and achieves higher accuracy even when applied to data with noise (Rodriguez-Galiano *et al.*, 2012; Tian *et al.*, 2016; Ramachandra *et al.*, 2022, 2023a). Prediction and geovisualization of likely LU changes are crucial in effective landscape management. Dynamic representations of the LU and LC based on different scenarios and data sources can be created through this method, and it can provide valuable insights and guidance for landscape managers and decision-makers to formulate proactive strategies for conservation, urban planning, and sustainable resource management (Ramachandra *et al.*, 2023b). The CA integrated Markov chain model has outperformed all prediction models. The CA–Markov model is used extensively in modeling LULC dynamics and prediction (Beroho *et al.*, 2023). The CA-Markov method can predict multidirectional LU changes encompassing all available LU categories (Pontius and Malanson, 2005).

Natural resource-rich regions (NRRRs), especially in developing countries, despite harboring the potential for economic growth, encounter challenges of the inequitable distribution of development benefits and over-exploitation. NRRRs are endowed with abundant natural assets that significantly influence ecological balance and economic activities. These regions are pivotal for supporting the livelihoods of local communities by providing essential ecosystem services and resources (Wassie, 2020; Ramachandra *et al.*, 2024; Ramachandra and Negi, 2025). The nexus of socio-economic disparity, persistent poverty, and unplanned developmental activities for realizing full economic potential (Sugiri, 2009) often poses severe challenges to environmental sustainability. The growing understanding of the complex linkages of effective natural resource management and environmental sustainability necessitates robust prioritization frameworks for LU allocation. The traditional models employing economic models, trend analysis, and scenario building have served a purpose, but the lack of reliability underscores the need for more advanced approaches. Therefore, developing and implementing refined tools that leverage comprehensive and accurate data is crucial for identifying NRRRs considering ecological, bio-geoclimatic, and social factors, ensuring equitable and sustainable LU decision-making.

The current study identifies the NRRRs in arid and semi-arid regions of Karnataka, considering social, biological, geo-climatic, and ecological factors. Prioritization of NRRRs in arid regions through environmental, economic, and social considerations would aid in unlocking NRRRs' potential for sustainable development, improving livelihoods, and building resilient communities.

This research aims to: a) assess the spatiotemporal patterns of LU and LC in arid and semi-arid landscapes using temporal remote sensing data, b) evaluate the extent and condition of forest ecosystems from 1973 to 2022, c) predict likely LU changes by 2030 and 2038, and d) identify NRRRs at disaggregated levels by considering geo-climatic, ecological, biological, and social factors.

2. Research Methods

2.1. Study Area

The study was carried out in arid and semi-arid landscapes of Northern Karnataka, located between 13° 34' and 18° 28' N and 74° 59' and 77° 41' E across districts Vijayapura, Chitradurga, Bagalkot, Koppal, Bellary, Raichur, Kalaburagi, Yadgir, and Bidar covering an area of 71149.04 km^2 (Figure 1). The study area is a part of the Krishna Basin, situated on the Deccan Plateau at an elevation between 300 and 730 meters. The landscape is predominantly black and red soils, categorized as shallow, medium-deep, and deep, which supports the cultivation of key crops like green gram, pearl millet, sunflower, pigeon pea, sorghum, chickpea, and rabi sorghum. LU in the region is dominated by agriculture, fallow areas, wastelands, and degraded forests, with most of the terrain exhibiting slopes of less than 5%.

North Karnataka's hydrological network consists of the Krishna River Basin (Krishna River and tributaries, Bhima, Ghataprabha, Malaprabha, Vedavathi, and Tungabhadra), and the Godavari River Basin (Manjira and Karanja). These rivers serve as vital water resources for agriculture and support riparian ecosystems throughout the region.

This ecoregion extends northward into eastern Maharashtra, highlighting the ecological interconnectedness of the area. The region receives most rainfall during the monsoon season from June to September, ranging from 370 to 4200 mm annually. The region is also characterized by high temperatures, with summers often exceeding 40°C. Rising temperatures during March-June, especially in recent decades, have exposed North Karnataka to increasingly frequent heatwaves, posing a significant challenge to human and animal health. This region is prone to severe floods in the Krishna River basin.

The region possesses a rich historical legacy, evidenced by powerful dynasties (Kadamba, Rashtrakuta, Chalukya) and flourishing literary figures (Pampa, Ponna, Ranna). Extreme climatic events, high rates of anemia (50% in women, 65.5% in children), and malnutrition, particularly in districts like Kalburgi, Raichur, Yadgir, Koppala, Ballari, Bidar, and Gadag, further exacerbate the challenges. It is divided into two distinct sub-regions, Hyderabad-Karnataka (Bidar, Kalaburagi, Raichur, Yadgir, Bellary, and Koppal) and Mumbai-Karnataka (Vijayapura, Bagalkote), with lower socio-economic development.

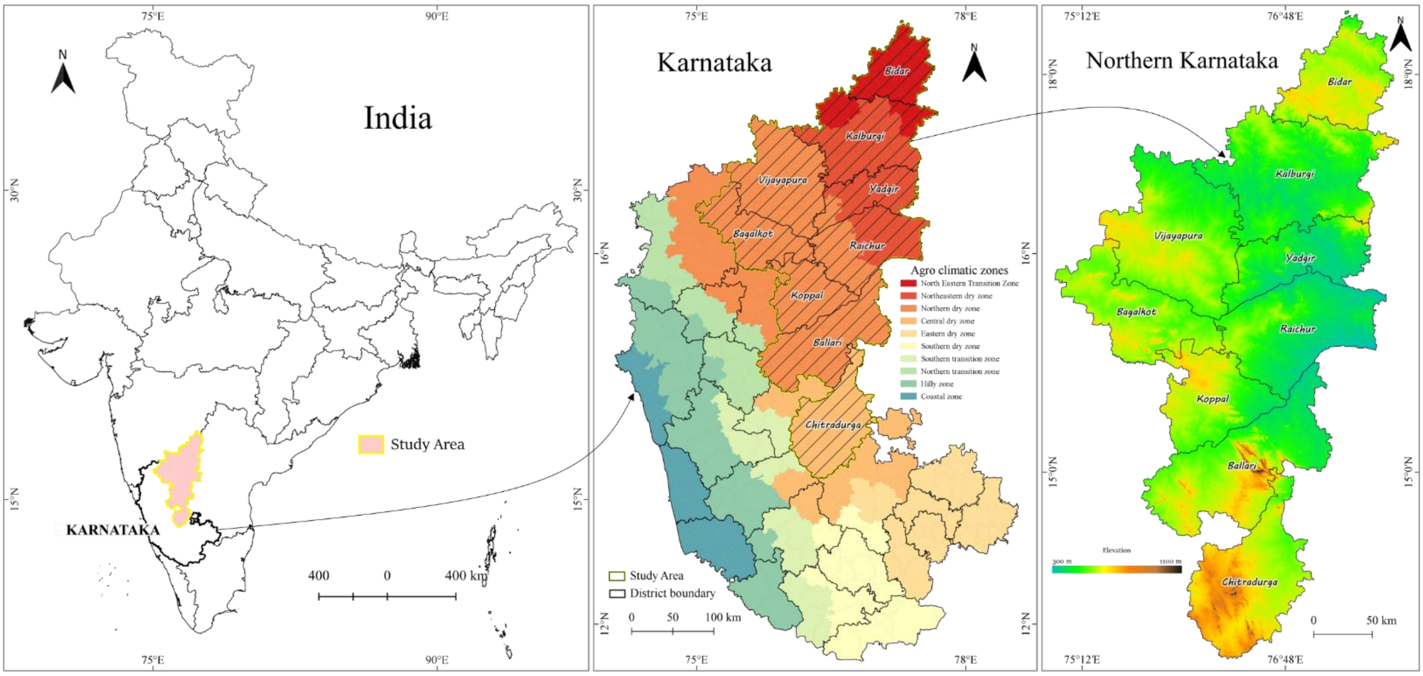


Figure 1. Study Area– Northern Karnataka arid regions, India.

2.2. Data

Spatial analyses were carried out using remote sensing (RS) data and collateral data. Temporal remote sensing data of Landsat MSS, TM, OLI-1, and OLI-2 were acquired from the spatial data portal of the United States Geological Survey (USGS - https://earthexplorer.usgs.gov/) for the 1970s, 1980s, 1990s, 2000s, 2010s, and 2020s, detailed in Supplementary Table 1. The Landsat program has been operational since 1972 and offers the most extensive medium spatial resolution satellite data collection. It has been extensively used in the assessment of LULC. The datasets were carefully chosen to ensure minimal cloud coverage (<10%). The data were pre-processed to rectify geometrical and radiometric discrepancies in the Google Earth Engine (GEE) Platform (https://earthengine.google.com/). Region-specific taluk and district administrative boundary maps were obtained from the K-GIS portal (https://kgis.gok.in).

Training data for LU classification were gathered from various locations within the study area using a handheld pre-calibrated global positioning system (GPS), online spatial portals (Google Earth - https://earth.google.com), and Bhuvan (https://bhuvan.nrsc.gov.in) with high-resolution remote sensing data. All these datasets corresponding to the study area were reprojected to a common geodetic datum, the World Geodetic System 1984 (WGS84), and Universal Transverse Mercator (UTM) within 43N zones, ensuring consistency in mapping. Road networks were extracted from Survey of India topographic maps at scales of 1:50,000 and 1:250,000 (https://www.surveyofindia.gov.in). The study considered Virtual online spatial maps such as Bhuvan (http://bhuvan.nrsc.gov.in) and high-resolution Google Earth (http://earth.google.com) to validate classified thematic maps.

Ecological, biological, geo-climatic, and resource data were compiled through field investigations, review of published literature, and reports. Elevation and slope maps were derived from the Shuttle Radar Topography Mission (SRTM) data with a 30-meter resolution (https://earthdata.nasa.gov).

2.3. Method

Figure 2 outlines the protocol for delineating NRRRs at disaggregated levels across the arid regions of North Karnataka. This entails (i) division of the study region into grids of 5'× 5' (or 9 km × 9 km), (ii) land cover and land use analyses, (iii) assessment of the condition of forests through fragmentation metrics, (iv) prediction of likely LUs, (iv) delineation of NRRRs at disaggregated levels (grids).

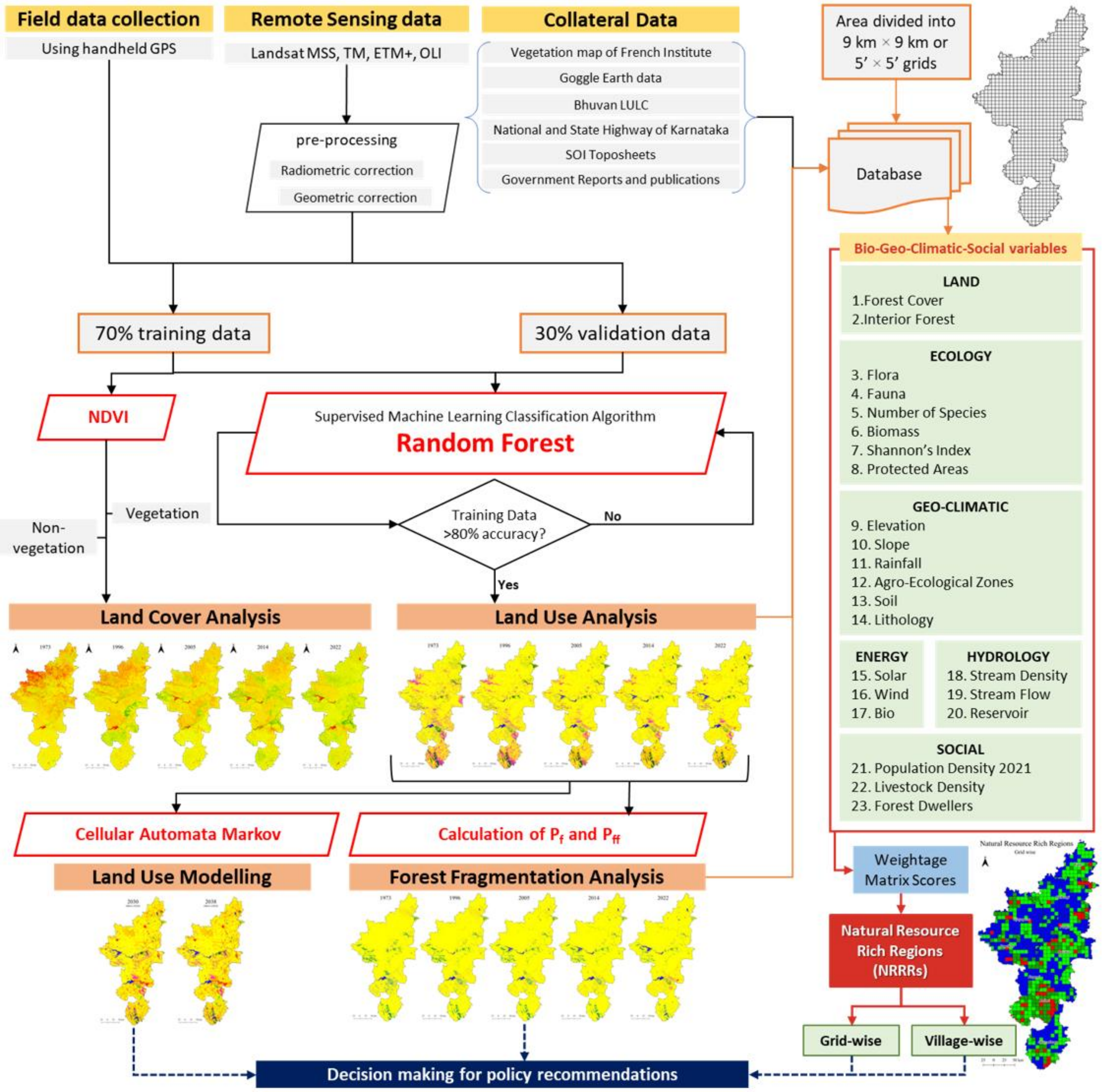


Figure 2. Method adopted for data analysis.

2.4. Land cover and Land use

The Normalized Difference Vegetation Index (NDVI) characterizes vegetation cover by assessing the difference in reflectance in the visible and near-infrared spectrum (land cover). It is widely employed for monitoring vegetation dynamics on various scales (Tucker, 1979; Ashok *et al.*, 2021). NDVI is exceptionally responsive to red reflectance, strongly influenced by density and green cover, whereas NIR reflectance is impacted by density alone, not green cover (Bremer *et al.*, 2011). Utilizing the red and NIR bands of Landsat data, NDVI values are computed, ranging from -1 to 1; values below zero signify dormant seasons (e.g., bare land, open land, cloud cover, snow, water bodies), while values above zero indicate vegetation cover during the growing season. Equation 1, detailed below, is used for the computation of NDVI.

$$NDVI = ((NIR - RED)) / ((NIR + RED)) \tag{1}$$

NIR and RED denote the electromagnetic spectrum corresponding to near-infrared and red wavelengths. The vegetation and non-vegetation have been categorized based on a threshold value (Supplementary Table 2). LU analysis involves generating FCC (false color composites) from remotely acquired data bands (NIR, Red, and Green) to identify heterogeneous landscape patches. The current study collected training polygons from the field using pre-calibrated handheld global positioning systems (GPS) and high spatial resolution data from Google Earth. Chosen training polygons represent all LU classes, covering 15% of the study, and are uniformly distributed throughout the study area. The attribute information for these training polygons was collected from the field using precalibrated handheld GPS devices and high spatial resolution data from Google Earth.

70% of training polygons are used for supervised classification, while the remaining (30%) are used for testing (Nguyen *et al.*, 2021). Spatial data (RS) were classified using a supervised machine learning algorithm, RF (Supplementary Figure 1a). RF is a novel technique employing a set of classifiers or a collection of multiple decision tree predictors. Each tree is constructed based on the randomly sampled feature vectors with replacement. It is independently generated with a uniform distribution shared across all decision trees to acquire high training data accuracy and enhance generalization accuracy as their complexity increases (Supplementary Figure 1b). These multiple classifiers are typically aggregated through a plurality voting scheme known as bagging (Breiman 1996).

RF can effectively handle multi-dimensional data while employing a substantial number of trees within the ensemble (Ramachandra *et al.*, 2022, 2023a). RF requires a significant amount of memory due to the storage of an N by ntree matrix in memory, and it is not computationally intensive; the trees are constructed without pruning (Gislason *et al.*, 2006; Rodriguez-Galiano *et al.*, 2012). The computational time for RF is computed as per Equation 2.

$$c * ntreeMN\, log(N) \tag{2}$$

Where c is the constant, $ntree$ represents the number of trees, M is the number of features, and N is the number of samples. A majority vote among the trees is employed in the prediction of the class of observation in the RF model. As ntree and M are two main hyperparameters in random forest, optimization of these parameters' aids in an increase in model accuracy. Increasing these parameters generally improves model performance but also increases computation time. The current study considered the $ntree$ based on the iterative method, ranging from 50 to 500 with an interval of 50, and prioritized 300 trees for best performance. M was considered as its default value (√M). Classified LU is validated using training data (30%) through computation of overall accuracy, producer accuracy, user accuracy, and kappa statistics.

2.5. Land Use Modelling

Markov chain (MC) analysis represents a heuristic modeling approach, which has been extensively used to examine LU change dynamics across various spatial scales (Halmy *et al.*, 2015). A Markov chain operates based on the principles of the probability of a system assuming a particular state at a given time can be ascertained based on its known prior state (Rimal *et al.*, 2018). Markov chain analysis involves the development of a transition probability matrix that accounts for LU change between two distinct periods (Fu *et al.*, 2018). The Markov chain model does not account for changes in spatial distribution. The cellular automata model, which is a spatially explicit model, can overcome these shortcomings by representing spatial attributes in mapping LU change compared to non-spatial models (Guan *et al.*, 2011). An integration of CA and Markov Chain (CA-Markov) model aids in predicting likely LU changes (Rimal *et al.*, 2017), based on the transition probability. A Markov chain determines the distribution of the LU class to another from time t to t+1 (Setturu and Ramachandra, 2021). The CA model detects changes in the spatial distribution at the cell level and captures interactions with neighboring cells. The Markov chain model enables the prediction of future spatiotemporal modifications (Equation 3) (Tariq *et al.*, 2023; Wang *et al.*, 2022).

$$S(t+1) = 〖P〗\_ij \ * S(t) \tag{3}$$

Where S represents the LU status at time t, S(t+1) denotes the LU status at time t+1, P_{ij} stands for the transition probability matrix within a specific state.

This matrix (Equation 4) is computed as described in previous studies (Singh *et al.*, 2021).

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \dots & \dots & P_{1n} \\ P_{21} & P_{22} & P_{23} & \dots & \dots & P_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & P_{n3} & \dots & \dots & P_{nn} \end{bmatrix} \tag{4}$$

Where P represents the transition probability, where P_{ij} signifies the probability of transitioning from state i to another state j in the subsequent period. P_n denotes the state probability at any given time. In this context, states with a low transition rate tend to have a probability close to 0, whereas high-growth states tend to have probabilities approaching 1 (Mumtaz *et al.*, 2020). Model validation: The accuracy of the model was validated by comparing current LU map of 2022 (reference map) with the simulated map of 2022. This validation process utilized an integrated VALIDATE module within IDRISI Selva 17.02 software (https://idrisi-selva.software.informer.com/) to assess the level of agreement between the classified and the simulated maps. The agreement metrics are based on the widely recognized Kappa Index of Agreement (KIA), which includes various metrics such as Kappa for location Strata ($K_{\text{locationStrata}}$), Kappa for location ($K_{\text{location}}$), and Kappa for no information (K_{no}). K_{no} was employed to assess the overall agreement between the proportions of the reference and modeled maps, which evaluated the precision of the spatial attributes, quantity, and locations of grid cells within specific LULC class categories (Ozturk, 2015).

2.6. Forest Fragmentation

An analysis of forest fragmentation quantifies the condition of forests, which determines the extent of structural and compositional changes in the forest ecosystem. The condition of forests in the study region is assessed through the computation of fragmentation indices, P_f, representing the proportion of forest pixels to non-water pixels (P_f) and P_{ff} represents the proportion of cardinal pixel pairs (both forest pixels) to pairs with at least one forest pixel (Riitters *et al.*, 2000; Riitters *et al.*, 2004; Ramachandra *et al.*, 2016).

This aided in assessing the condition of forests through pixel categorization based on the type of fragmentation (details are provided in Supplementary Table 3), as interior forest ($P_f = P_{ff} = 1$), transition (pertaining to pixels with $P_f < 0.6$ and $P_f > 0.4$), patch forest (for pixels with $P_f < 0.4$), perforated forest (applicable to pixels with $P_f > 0.6$ and ($P_f - P_{ff}$) < 0), edge forest (relevant for pixels with $P_f > 0.6$ and ($P_f - P_{ff}$) > 0), non-forest pixels encompass all pixels not classified as forest cover. This classification scheme serves as a structured framework for analyzing different types of forest fragmentation, providing a nuanced understanding of the diverse spatial patterns within the study area.

2.7. Prioritization of Natural Resource Rich Regions (NRRRs)

Analyzed hydrological, biological, geo-climatic, and socio-economic details at disaggregated levels in the arid region of Northern Karnataka for identifying Natural Resource Rich Regions (NRRRs). The region was divided into grids of 5′ × 5′ equivalent to approximately (9 × 9) km^2 (Ramachandra *et al.*, 2018), comparable to grids in the 1:50000 scale topographic maps (the Survey of India, Government of India). The spatial extent and occurrence of features for each variable have been assessed at the grid level, and the variable is assigned a weight based on the relative worth. This approach aided in combining multiple datasets and their significance in the landscape details in Supplementary Table 1. Weights for variables were assigned as per Supplementary Figure 2 and aggregated for each grid, as per Equation 5. The study area was grouped into four zones considering aggregated weights, which also highlights the ecosystem condition based on the availability and vulnerability of natural resources:

$$Weightage = \sum_{i=1}^{n} W_i V_i \tag{5}$$

where n is the number of factors or variables, W_i is the weight associated with criterion i, V_i is the associated value with that criterion.

Based on the aggregate weightage matrix, the study region is classified into four zones (NRRR 1 to 4). NRRR 1 represents natural resources rich region, requiring strict conservation and protection measures, NRRR 2 is less sensitive than NRRR 1, except for the degradation of some natural resource patches. NRRR 3 represents a moderate resource region, and NRRR 4 represents lower sensitivity with erosions in the ecosystem conditions.

3. Results and Discussion

3.1. Land Cover Analyses

The long-term analyses of LC changes using NDVI of the northern arid regions of Karnataka have been done to delineate the spatial extent of vegetation. The area under vegetation has shown an increasing trend, as depicted in Figure 3, increasing from 32.79% (in 1973) to 53.35% (in 2022), which suggests the intensification of agricultural and horticultural practices with increased water availability due to the construction of multiple reservoirs. The area under non-vegetation has shown a consistent decrease over the decades, from 67.21% (in 1973) to 46.65% (in 2022), as open spaces, including fallow land, were converted into croplands, horticultural lands, agroforestry, and forest plantations. The area under non-vegetation would decrease as detailed in Supplementary Table 4.

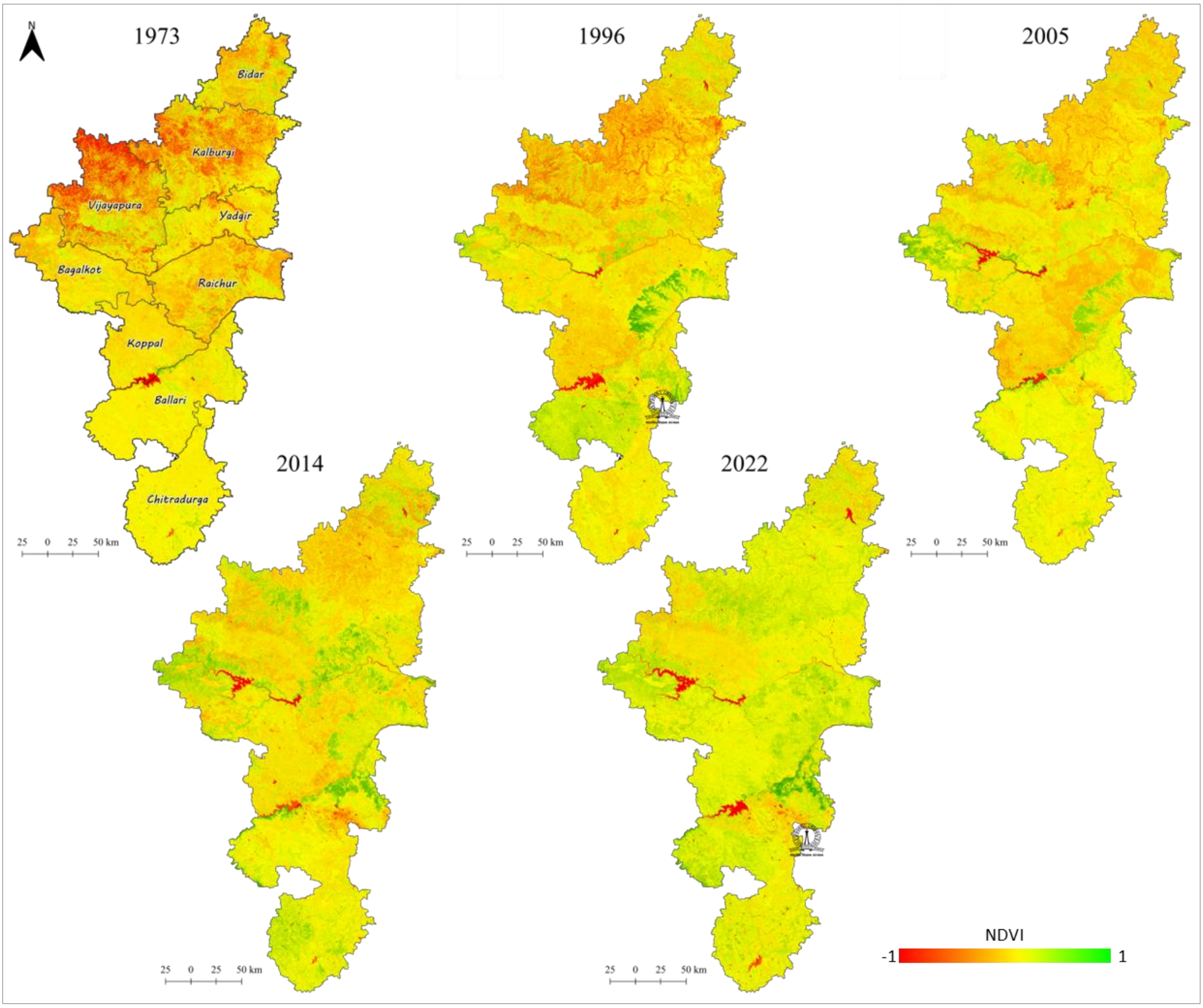


Figure 3. The spatial extent of vegetation (LC) was assessed through NDVI in Northern Karnataka's arid region (1973 to 2022).

3.2. Land Use Analyses

Temporal LUs (1973 to 2022) of the Northern arid regions of Karnataka illustrate that a predominant agrarian landscape has undergone intense anthropogenic changes since 1996 due to globalization and liberalization. The overall accuracy of the remote sensing analysis is 96% and the kappa coefficient is 0.91 (Supplementary Table 5). Highly elevated hills and plateaus are covered with dry deciduous forest and scrub forest in the lower regions of Chitradurga, Bellary, Koppal, and Bagalkote districts. Dry deciduous forest extent has shown a continuous trend of decrease (depicted in Figure 4), from 2,154.20 sq. km (1973) to 1,096.34 sq. km (2022), and details are provided in Supplementary Table 6. Scrub land, prevalent in semi-arid ecosystems, has shown a similar reduction, declining from 5,650.74 sq. km (7.94%) in 1973 to 2,260.19 sq. km (3.18%) in 2022. Bellary district has a reasonable spatial extent of dry deciduous forests in the Sandur forest range of Sandur taluk, and rampant iron ore mining in the Sandur taluk has impaired the integrity of forest ecosystems. These declines are attributed to land conversion for agriculture (witnessed in the Yadgir Reserved Forest area) and urban development. Some areas of degraded deciduous forest have been converted into scrubland.

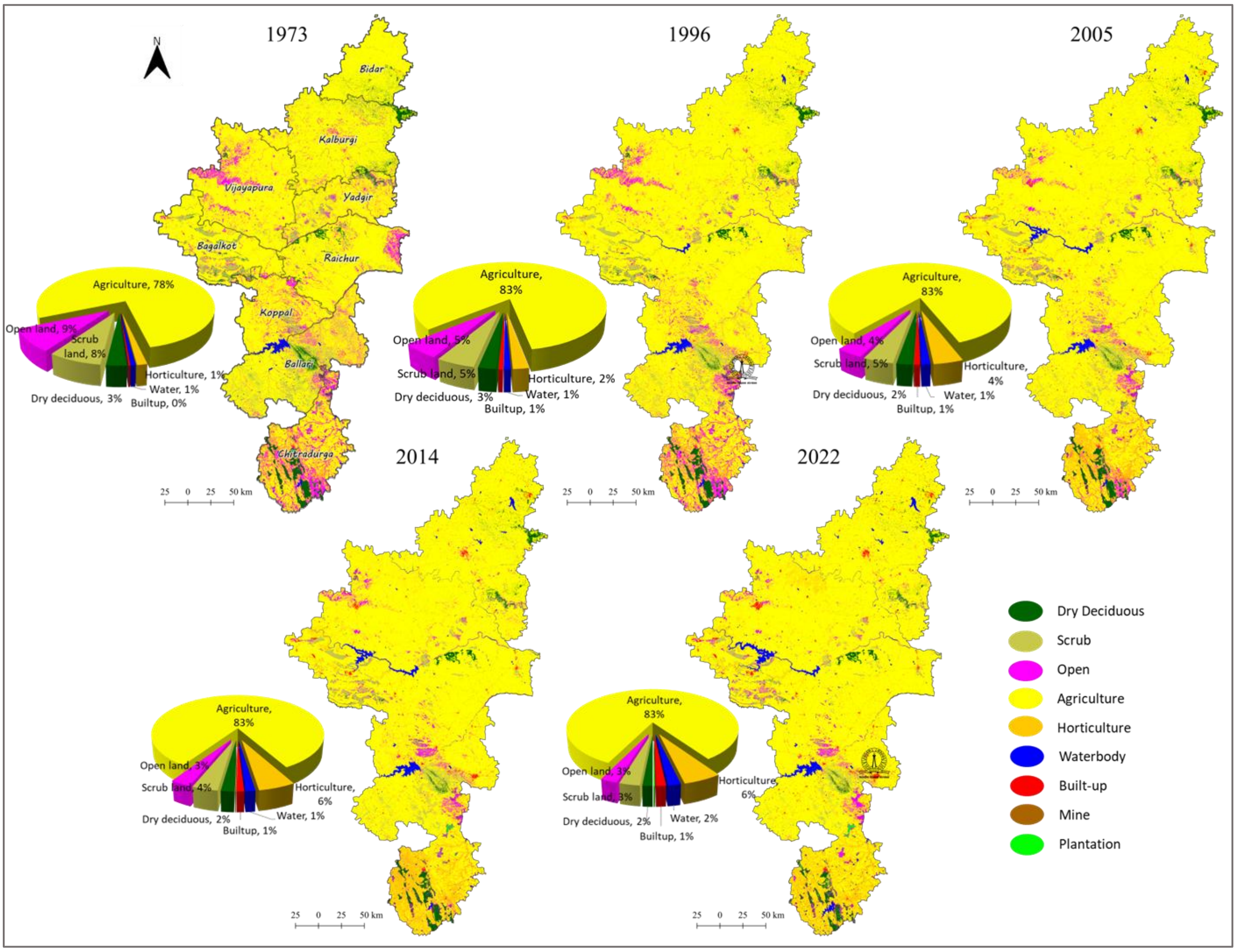


Figure 4. Land use analysis in Northern Karnataka's arid region (1973 to 2022).

The study region is principally agrarian, and Bellary, Raichur, and Koppal districts are popularly known as the "rice bowl of Karnataka". The extent of agricultural land increased from 78 % (in 1973) to 83.11% in 2022. The study area is enriched with the Krishna, Tungabhadra, Bhima, and Godavari rivers. The study region has witnessed a shift toward wet cultivation with enhanced water security due to multiple irrigation projects with the implementation of reservoirs like Almatti Reservoir, Basava Sagar Reservoir (Narayanpura), Karanja Reservoir, Jurala Reservoir, Vani Vilas Sagar in this region. The spatial extent of water bodies has increased markedly from 494.93 (1973) to 1,397.68 (2022) sq. km. The increased water security has expanded horticultural land from 1,089.35 sq. km (1.53%) in 1973 to 4,198.58 sq. km (5.90%) in 2022. The expansion of paved surfaces (built-up) from 186.22 sq. km (in 1973) to 1085.12 sq. km (in 2022) in the district reflects urbanization and infrastructure development. Cities are expanding due to urbanization in the core area and sprawl in the peri-urban area, with good connectivity of road networks. The growth of various industrial layouts in the core area aided as a catalyst for the expansion of the urban centers. Paved surfaces (built-up) in rural areas have been increasing at a constant rate.

Mining of iron ore is rampant in the Sandur-Hospet region of Bellary district, which is rich in iron ore reserves, and has increased post-2005, covering around 27.31 sq. km (in 2022). Plantation of exotic species like Acacia auriculiformis, Acacia catechu, Tectona grandis, Eucalyptus globulus, Casuarina equisetifolia L., and others have been increasing, reaching 131.08 sq. km (in 2022).

3.3. Forest Fragmentation Analyses

Forest ecosystems in the arid region of North Karnataka are undergoing fragmentation due to anthropogenic activity, with LU changes leading to land degradation. Fragmentation analysis emphasizes the loss of intact forest cover. The study area comprises degraded forest patches, and the results of fragmentation metrics also reveal that the interior/intact forest has declined from 3,252.39 (in 1973) to 1,508.29 sq. km (in 2022), and details are provided in Supplementary Table 7. Figure 5 highlights that the spatial extent of non-forests has increased from 63,819 (1973) to 66,543 sq. km (2022).

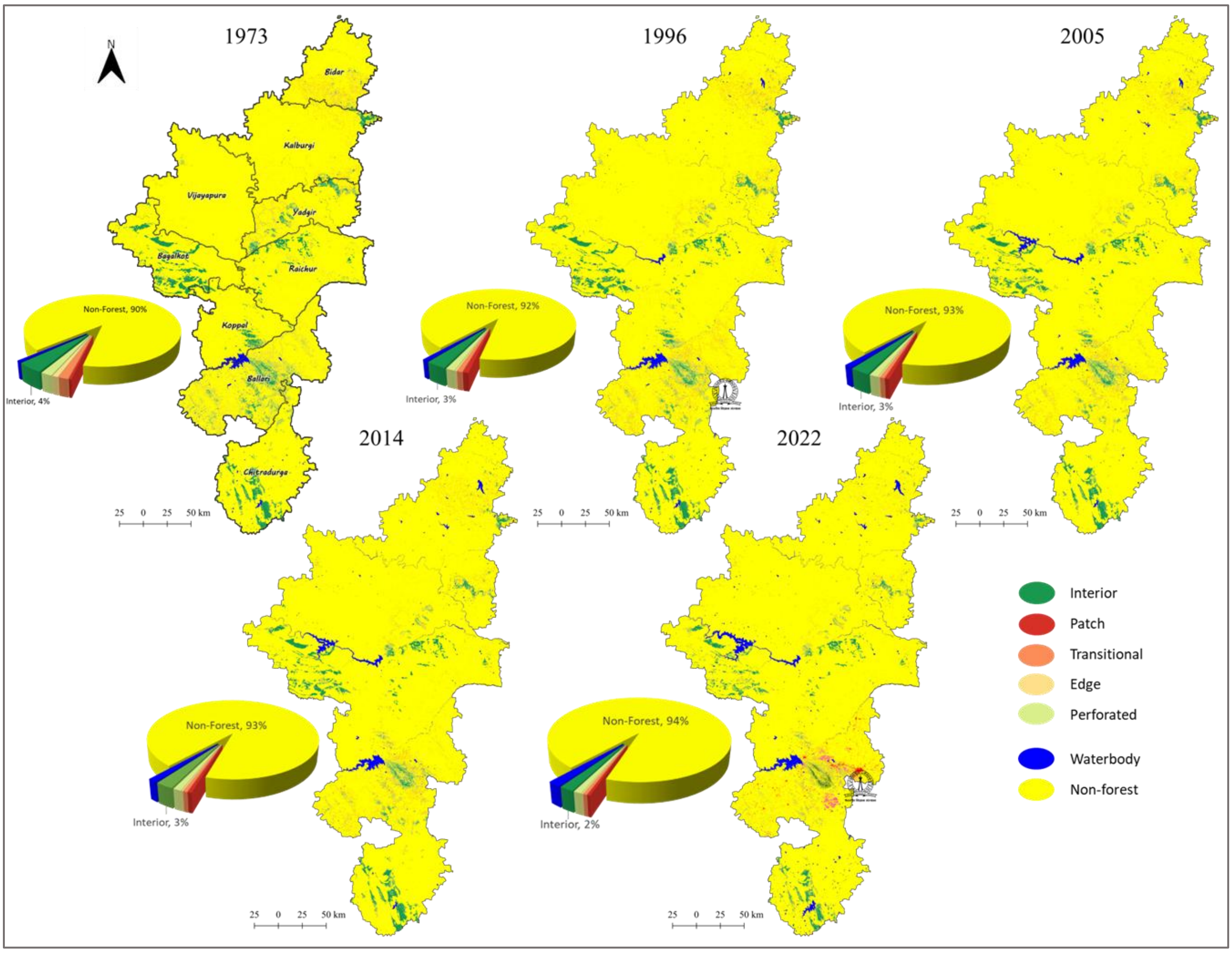


Figure 5. Forest Fragmentation in the arid region of North Karnataka (1973 to 2022).

3.4. Prediction of Land Uses for 2030 and 2038

Predictions of likely LU indicate the impact of the current rate of LU transitions in the next two decades with the help of CA-Markov techniques. Modeling is validated by comparing the simulated LU with the actual LU of 2022 and the computation of Kappa statistics. Kappa of 0.9 to 0.95 suggests agreement between the predicted and actual LU with high efficiency. The simulated LU showed a very minimal overestimation of water bodies in 2022.

The predicted LUs depicted in Figure 6 and details given in Supplementary Table 8 show a likely increase in built-up to the extent of 6.23% (in 2030) and 7.17% (in 2038). The likely built-up increase will be due to the rise in food processing, the food and beverage sector, and the expansion of roads or highways. The decline of scrubland to 11.63% and dry deciduous to 1.04% (in 2038) in a business-as-usual scenario highlights the likely continuation of forests and scrublands.

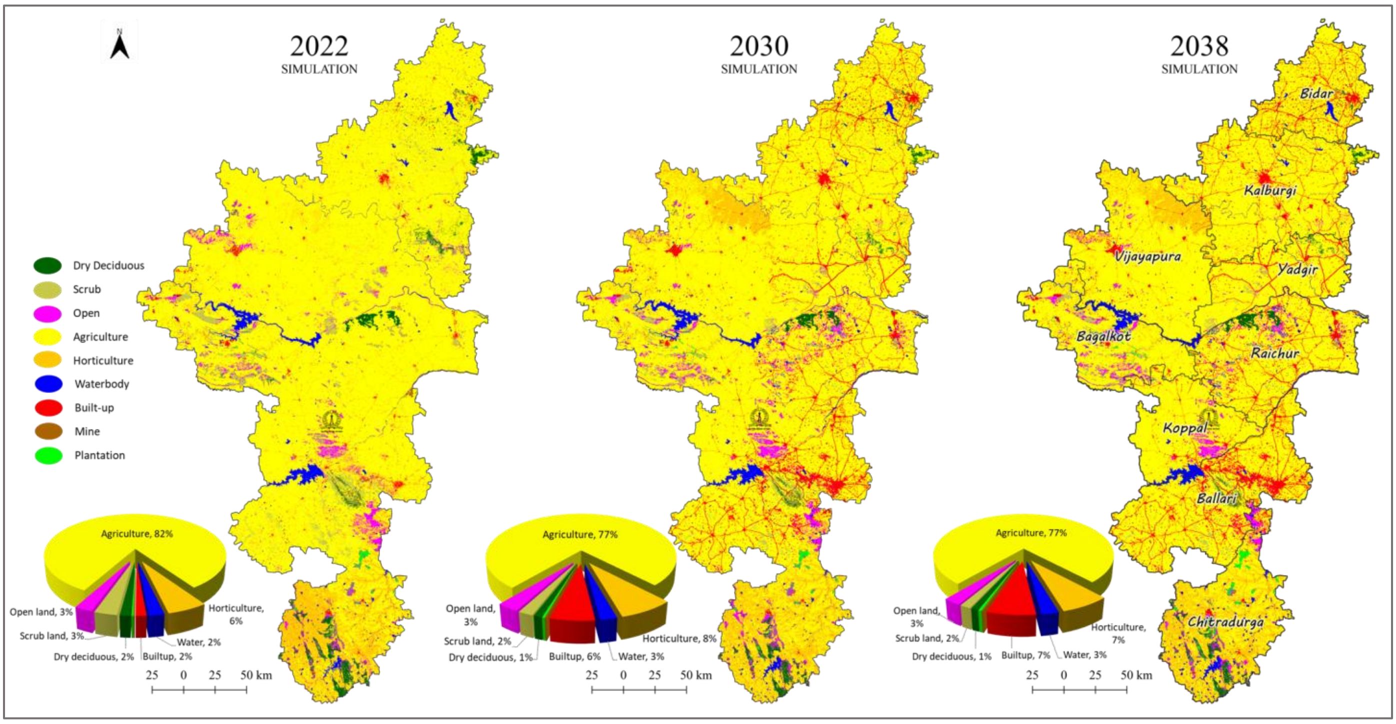


Figure 6. Land use simulation of 2022, 2030, and 2038.

3.5. Prioritization of NRRRs

Prioritization of NRRRs in the northern arid regions of Karnataka at disaggregated levels (grids and villages) was done through integrated assessment considering bio-geo-climatic, land, ecology, energy, environmental, and social variables compiled through field investigations and supplemented with the review of published literature. Weights were assigned to these variables at grid levels based on the relative significance at disaggregated levels.

Dry deciduous forests and scrubland in the hills of Chitradurga, Bellary, Bagalkolte, and Raichur account to 15% to 60% (Supplementary Figure 3a). Forest degradation in Vijaypura, Kalaburgi, and Yadgir is due to anthropogenic pressures with agricultural expansion. The intact/interior forests (Supplementary Figure 3b) are confined to higher-elevation regions and protected areas.

The ecological variables like endemic flora, fauna, forest biomass, species abundance, species diversity (Shannon diversity), and the presence of conservation reserves in the Northern Arid Karnataka were assessed, and Supplementary Figures 4a and 4b give the spatial distribution of flora and fauna, respectively. Shannon's diversity ranges from 1 to 2.5 (Supplementary Figure 4c), and Supplementary Figure 4d depicts species that range from 50 to 200. The region has dense, dry deciduous forests with a carbon sequestration potential up to 300 Gg (Supplementary Figure 4e). The protected areas in the study area are Malaksamudra Bird Sanctuary (Koppal), Yadahalli Chinkara Wild Life Sanctuary (Bagalkote), Bonal Bird Sanctuary (Yadgir), Yadgir reserved forest (Yadgir), Gudekote and Daroji Sloth Bear Sanctuary (Bellary), Ankasamudra Bird Sanctuary (Bellary), and Chincholi Wildlife Sanctuary (Kalaburagi) depicted in Supplementary Figure 4f.

The study area has the highest elevation of 750 m in Chitradurga and Bellary; Elevation in Koppal, Bagalkote, Vijaypura, and Bidar ranges from 500 to 750m, and elevation in Raichur, Yadgir, and Kalaburagi is at 250 to 500 m (Supplementary Figure 5a). The slope is less than 15% in the study region (Supplementary Figure 5b). The northern part of the study area (Bidar, Kalaburagi, Vijaypura, Yadgir, Bagalkote, Raichur, Koppal and partly Bellary) receives 1200 to 600 mm of rainfall, whereas part of Bellary and Chitradurga receives <600 mm of rainfall (Supplementary Figure 5c). Supplementary Figure 5d shows that Bidar, Kalaburagi, Vijaypura, Yadgir, Bagalkote, and Koppal have coarse loamy soil; Bidar, Kalaburagi, Vijaypura, Yadgir, and Bagalkote have sandy or sandy skeletal soil; Bagalkote, Raichur, Bellary, and Chitradurga have rocky outcrops or Fragmental soil; Kalaburagi, Vijaypura, Yadgir, and Bagalkote have clayey loamy or clayey skeletal soil; Koppal, Raichur, and Chitradurga have loamy or clayey soil. The middle part of Bagalkote is composed of Charnokities; Chitradurga, Bellary, Koppal, Raichur, and Yadgir are primarily composed of Peninsular Gneiss; the hills of the study area are composed of Dharwars or Granite; Bagalkote, Vijaypura, Kalaburagi, and Bidar are part of the Deccan trap (Supplementary Figure 5e). Bidar, Kalaburag, and Yadgir are in the arid zone; Vijaypura, Yadgir, Bagalkote, Raichur, and Chitradurga are majorly in the hot-dry semi-arid zone; and part of Vijaypura, Raichur, Koppal, Bellary, and north Chitradurga are in the hot-dry arid zone (Supplementary Figure 5f).

Krishna, Tungabhadra, Bhima, and Godavari Rivers flow, and the duration of water flow in streams (Supplementary Figure 6a) varies from 3 to 6 months in this region. The drainage density is higher (>2.5) in Raichur and Bellary (Supplementary Figure 6b). The major reservoirs of this district are Almatti, Basava Sagar (Narayanpura), Karanja, Jurala, and Vani Vilas Sagar (Supplementary Figure 6c).

Northern Arid Karnataka has the potential of more than 6 kWh/sq. m of solar energy (Supplementary Figure 7a). Multiple solar parks have been established in Chitradurga, Bellary, Bagalkote, and other districts. Kalaburagi, Raichur, and Yadgir have a high potential for wind energy with wind speeds of more than 3.5 to 4 m/sec throughout the year, and windmills are present in the hills of the districts (Supplementary Figure 7b). Also, there is scope for bioenergy (Supplementary Figure 7c) of 200-400 MKcal in Bidar, Kalaburagi, Vijaypura, Yadgir, Bagalkote, Raichur, Koppal, and Bellary; 200-600 MKcal in Chitradurga and Kalaburagi.

The population density is presented grid-wise in Supplementary Figure 8a, and livestock density is in Supplementary Figure 8b. The forest dwellers' settlements are mapped in Supplementary Figure 8c. in all districts of Northern arid Karnataka except Vijayapura.

The aggregated weightage metric score is computed for each grid, considering bio-geo-climatic, ecological, hydrological, energy, and social factors. Grids are grouped into four levels and presented in Figure 7 depending on the frequency of occurrences of aggregated scores. The NRRR1 (67 grids) and NRRR 2 (127 grids) are considered highly rich regions of natural resources, NRRR3 (304 grids) is moderate, and NRRR4 (522 grids) is less sensitive. Figure 7 shows, grid-wise and at village levels, NRRRs in the northern arid regions (districts) of Karnataka state, India. Policy recommendations are:

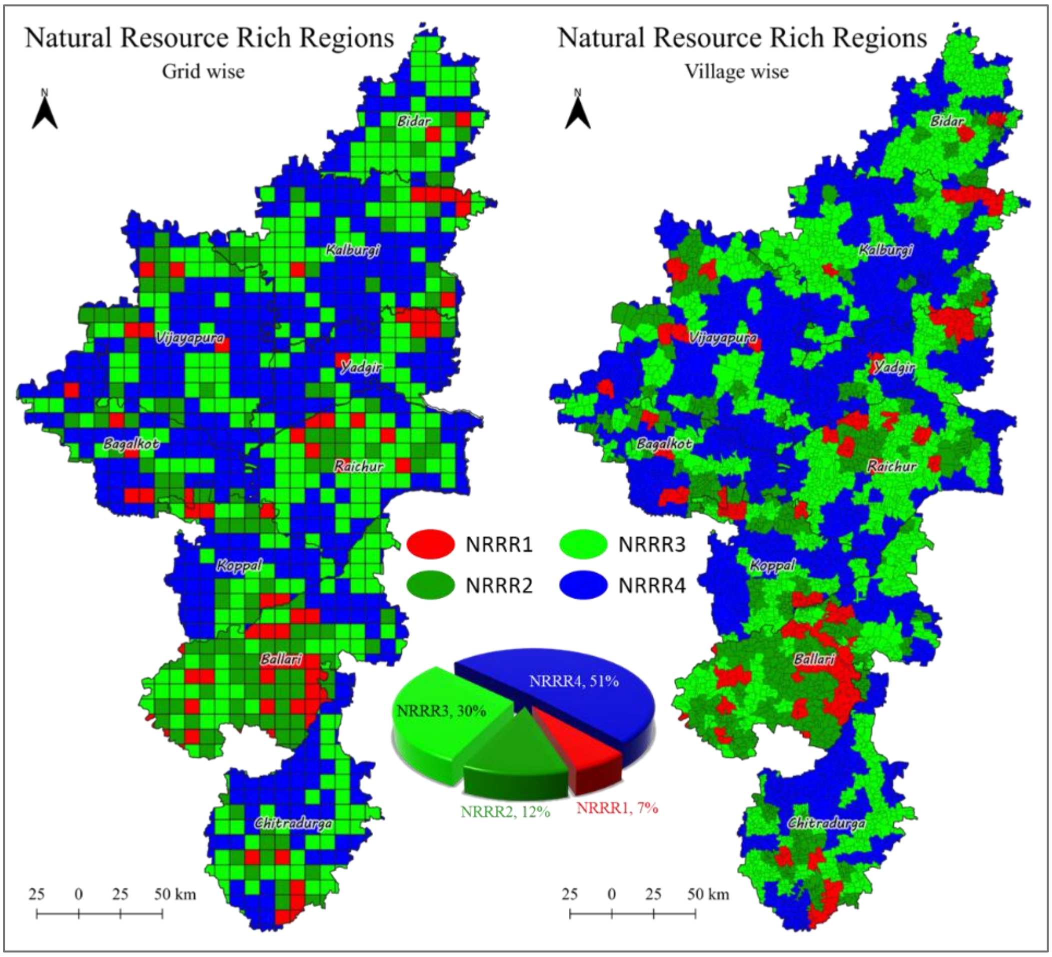


Figure 7. Natural Resource-Rich Regions of Northern Arid Karnataka (Grid level-left and Village level-right).

NRRR1 zones include the protected forest areas and interior forests, where the integrity of forests must be maintained without large-scale development projects such as mining. This region is highly fragile, and prudent management of natural resources through monitoring by regulatory authorities is required by including Village Forest Committees (VFCs) and Biodiversity Management Committee (BMC) at village Panchayath. NRRR1 regions are to be protected without any alterations in topography due to the linear projects (new / expansion) such as roads, and railway lines. Degraded forest patches to be revitalized with native species and regulation of monoculture plantations. Existing exotics and non-endemic plantations are to be replaced with native species. Needs to promote locally available renewable energy sources such as bioresources, solar, and wind. NRRR2 characterizes a zone of higher conservation as being a transition zone between NRRR1 and NRRR3, moderate conservation regions.

A regulated sustainable development path may be allowed in NRRR3 with stringent environmental norms and location-specific environmental management plans (EMP) to mitigate the impacts. Small-scale industries, like agro-based industries, are permitted to stimulate the rural economy. Incentives should be provided to youth and women self-help groups to encourage rural entrepreneurship and establishing agro-processing industries based on local resources.

NRRR4 represents the least diverse areas, where moderate developmental activities are allowed as per the requirement with the stringent regulatory norms.

3.6. Discussion

3.6.1. Landscape Dynamics in Northern Karnataka

The northern arid zones of Karnataka represent an agrarian landscape characterized by low rainfall, high temperature, and high evaporation. The implementation of water projects has escalated agricultural and horticultural practices during the past two decades. LU dynamics assessment using temporal RS data reveals a decline in the dry deciduous forests during post-1990 due to accelerated industrial developments and intense agricultural practices in response to globalization and liberalization of the economy. Agricultural (croplands and horticulture) expansion has resulted in declining forest ecosystems and fragmented contiguous forests. The forest cover of the state has declined from 32,875 ha (in 1985) to 27,968 ha (in 2019), mainly due to the conversion of forest land for non-forest purposes such as mining, irrigation, power projects, roads, railways (Ramachandra *et al.*, 2024).

The reduction in forest cover has resulted in the loss of biodiversity with the erosion in ecosystem services, such as carbon sequestration, soil nutrient retention, water regulation, and wildlife habitat (Ramchandra *et al.*, 2022; Mugari and Masundire, 2022). The principal agro-climatic zones are the (i) Northeastern dry zone (Kalburgi/Gulbarga, Yadgiri, and parts of Raichur); (ii) Northern dry zone (Bellary, Vijayapura, Raichur, Dharwad); and (iii) Central dry zone (Chitradurga). Construction of reservoirs such as Narayanpura Dam, Karanja Dam, Jurala Reservoir, Vani Vilas Sagar, Almatti Dam on Krishna River (Bagalkote), Tungabhadra Dam on Tungabhadra River (Koppal) has increased water availability in the districts prospering the irrigation system of the Karnataka Plateau region. The Upper Krishna Project was executed in distinct stages to address the irrigation needs of drought-prone districts in Northern Karnataka, including Kalaburagi, Raichur, Vijayapura, Yadgir, and Bagalkot.

The government has implemented various schemes and programs to improve the agricultural productivity and livelihood of the farmers in this region, such as watershed development, micro-irrigation, crop insurance, and soil health cards. However, these large-scale water projects have also caused some impacts on the ecosystem and the people. Moreover, the over-exploitation of water resources for irrigation has led to the problem of waterlogging and salinization of soils, reducing the agricultural productivity and quality of crops. Farmers have faced challenges of soil erosion, salinity, drought, and pest infestation in arid conditions. An evaluation of agricultural sustainability in Karnataka using the Sustainable Livelihood Security Index (SLSI) identified Bellary as moderately sustainable, while Bidar, Kalaburagi, Vijayapura, Bagalkote, Raichur, Chitradurga, and Koppal were classified as less sustainable for agricultural production (Sridhara *et al.*, 2022).

Burgeoning populations and haphazard development projects have spurred rapid urbanization marked by a critical lack of basic infrastructure in major cities, mainly district headquarters such as Bellary, Raichur, Bidar, Kalaburagi, Bagalkote, Vijayapura. A similar LULC change trend was reported earlier in major cities like Bidar, Kalaburagi, and Raichur in Northern Karnataka (Ramachandra and Aithal, 2013a, 2013b; Manna *et al.*, 2023; Ramachandra and Negi, 2025). Industrial corridors in Kalburagi-Bidar and Raichur industrial area, Special Economic Zones (SEZs) in

Kalaburagi, Bidar, Koppal, Vijayapura, and Bagalkote had attracted investments in engineering, automobiles, renewable energy, targets food processing, textiles, cement, and leather industries in response of State's Industrial policy, which spurred economic activity and job creation, drawing migrants seeking better livelihoods. The National Highway (NH) network in Karnataka has undergone a remarkable transformation with 100% increase in length and the addition of 372 km of new highways. However, NH development saw a sudden rise, from 6,750 km (in 2014) to 13,565 km (in 2018), including in-principle NHs (Ministry of Road Transport and Highways).

3.6.2. Change in the climatic regime of Northern Karnataka

Shifts in climate regimes were noticed due to the large-scale LU changes, across the diverse landscapes of Karnataka. South Vijayapura, Bagalkot, Koppal, and Chitradurga transitioned from arid to semi-arid (dry), potentially linked to irrigation projects and their effect on groundwater levels. Conversely, some parts of Chitradurga moved towards a drier semi-arid climate, with fewer rainy days, higher temperatures, and increased potential evapotranspiration (Sahu *et al.*, 2021). Factors such as limited agricultural opportunities and lack of amenities, coupled with the attraction of better education, healthcare, and employment prospects, are driving rural-urban migration. Farmers lack access to location-specific climate forecasts and reliable information on climate change, hindering their ability to adapt to changing climatic conditions or to climate-resilient cultivation practices. Additionally, they face challenges in obtaining critical inputs and fair prices for their produce. Improving field extension services, timely assistance, and updated climate information is crucial (Shanabhoga *et al.*, 2023).

3.6.3. Significance of Identification of NRRRs, Its Limitations, and Recommendations

Modelling and geo-visualization would aid in identifying areas of probable changes and their effect on the environment while delineating NRRRs. The delineation of NRRRs provides the quantitative and qualitative status of the environmental condition of the region, which is essential for restoration and management. Preventing NRRRs from degradation would ensure to attain higher productivity (Ramachandra and Negi, 2025). The management of the NRRRs should focus on permissible activities in agriculture, tourism, forestry, and urbanization. Unplanned developmental activities leading to unregulated resource use should be regulated to sustain natural resources, specifically NRRR1 and 2 (Ramachandra *et al.*, 2022; Uralovich *et al.*, 2023).

Insights into soil health and nutrient availability will empower farmers to make informed agricultural decisions, significantly improving productivity and sustainability through efficient water and nutrient management practices. Landsat's 30-meter spatial resolution may inadequately capture small-scale land use changes or fragmented ecosystems, particularly in heterogeneous arid landscapes where fine-grained features (e.g. sparse vegetation) are critical. Agent-based modelling that integrates socio-hydrological factors—such as farmer decision-making, groundwater management policies, and strategies for adapting to drought could more effectively simulate the dynamics of land-use transitions in the Northern Karnataka region. Additionally, engaging in participatory mapping with local communities can enhance this understanding.

Several key strategies to ensure sustainable management of natural resources can stimulate local economies through responsible extraction and use of resources, including (i) restrictions on large-scale LULC changes to preserve ecological and hydrological integrity, (ii) prohibition of large-scale mining, particularly of iron ore, (iii) restriction on monoculture plantations of exotic species like Eucalyptus and Acacia due to their high water consumption, which can lead to reduced groundwater recharge and lower water availability for local communities and agriculture in arid regions, resulting in desertification, (iv) restoration focussing on catchment area treatment plans to reduce silt yield, nutrient retention, etc., (v) promoting the cultivation of drought-resistant crops can significantly reduce crop failure risks and enhance agricultural resilience in these arid regions of Karnataka, (vi) implementing agroforestry techniques would improve soil health and biodiversity, which are essential for sustainable land management, (vii) participation of local communities in resource management and promoting diversified livelihoods.

Identifying NRRRs can enhance well-being, creating job opportunities and environmental awareness among local populations. Furthermore, encouraging non-agricultural activities and entrepreneurship can help diversify local economies, reducing dependence on a single sector and fostering economic stability. Setting up agro-processing and cottage industries can support local livelihoods, and adopting clustering approaches can enhance economic efficiency and sustainability. Providing comprehensive training and support to local populations is essential for equipping them with the skills needed to manage resources sustainably and adapt to climate change. Strengthening community organizations and social networks is equally vital for supporting economic development and resilience.

4. Conclusion

The spatiotemporal analyses of LU and LC of the arid region of Northern Karnataka have been done from 1973 to 2022 using RS data. The long-term analyses of LC changes provided invaluable insights into the dynamic interactions between human activities and the environment. The observed increase in areas under vegetation, particularly in agricultural and horticultural lands, reflects the positive impact of water resource development through reservoirs and dams. The temporal land-use analyses were done using a supervised non-parametric machine learning algorithm, the RF, highlighting the transformation of the predominantly agrarian landscape attributed to globalization and liberalization. Forest ecosystems, particularly dry deciduous and scrub lands, have faced degradation due to anthropogenic pressures, contributing to the decline in interior forest cover. The study identifies the impact of mining, plantation, and urbanization on LU patterns. Paved surfaces (built-up) have increased from 186.22 (in 1973) to 1085.12 sq. km (in 2022). The study area has degraded forest patches, and the results of fragmentation analyses reveal that the intact/interior forest has reduced from 3252.39 (1973) to 1508.12 (in 2022) sq. km. The prediction of likely LUs highlights an increase in paved surfaces (built-up) from 6.23% (in 2030) to 7.17% (in 2038). The LU modeling projections for 2038 highlight potential challenges, with a notable increase in built-up areas and continued encroachment on scrub and forest lands. The study has identified that NRRR1 (67 grids) and NRRR 2 (127 grids) are considered natural resources rich regions, NRRR3 (304 grids) moderate, and NRRR4 (522 grids) less sensitive. The prioritization of NRRRs emphasizes the need for conservation strategies with varying degrees of sensitivity across grids and villages. Strategic planning with regulatory measures is essential to ensure sustainable development, conservation of biodiversity, and the preservation of NRRRs (natural resources-rich regions). The study provides valuable insights for policymakers, environmentalists, and local communities to make informed decisions for the future well-being of the northern arid regions of Karnataka.

Acknowledgements

We thank Indian Institute of Science for the infrastructure and academic support

Author Contributions

Conceptualization: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.; **methodology**: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.; **investigation**: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.; **writing—original draft preparation**: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.; **writing—review and editing**: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.; **visualization**: Ramachandra, T. V., Negi, P., Mondal, T., Setturu, B.. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

Authors do not have any conflicts of interest, either financial or non-financial.

Data availability

Data are archived at our data portal https://wgbis.ces.iisc.ac.in.

Funding

We are grateful to the EIACP (ENVIS) Division, the Ministry of Environment, Forests and Climate Change, the Government of India, for the research grant to meet field expenses.

References

Adugna, T., Xu, W., & Fan, J. (2022). Comparison of random forest and support vector machine classifiers for regional land cover mapping using coarse resolution FY-3C images. *Remote Sensing*, 14(3), 574. doi: 10.3390/rs14030574

Ahmadi, K., Kalantar, B., Saeidi, V., Harandi, E. K., Janizadeh, S., & Ueda, N. (2020). Comparison of machine learning methods for mapping the stand characteristics of temperate forests using multi-spectral sentinel-2 data. *Remote Sensing*, 12(18), 3019. doi: 10.3390/rs12183019

Ali, K., & Johnson, B. A. (2022). Land-Use and Land-Cover Classification in Semi-arid Areas from Medium-Resolution Remote-Sensing Imagery: A Deep Learning Approach. *Sensors*, 22(22), 8750. doi: 10.3390/s22228750

Ashok, A., Rani, H. P., & Jayakumar, K. V. (2021). Monitoring of dynamic wetland changes using NDVI and NDWI based landsat imagery. *Remote Sensing Applications: Society and Environment*, 23, 100547. doi: 10.1016/j.rsase.2021.100547

Bai, Z. G., Dent, D. L., Olsson, L., & Schaepman, M. E. (2008). Proxy global assessment of land degradation. *Soil use and management*, 24(3), 223-234. doi: 10.1111/j.1475-2743.2008.00169.x

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing*, 114, 24-31. doi: 10.1016/j.isprsjprs.2016.01.011

Bell, W., Hoffman, M. T., Visser, V., & Kirsten, T. (2023). Modelling land condition to augment Land Degradation Neutrality assessments-The succulent Karoo biome of South Africa as a case study. *Journal of Arid Environments*, 219, 105086. doi: 10.1016/j.jaridenv.2023.105086

Beroho, M. Briak, H. Cherif, E. K. Boulahfa, I. Ouallali, A. Mrabet, R. Kebede, F. Bernardino, A. Aboumaria, K. (2023). Future Scenarios of Land Use/Land Cover (LULC) Based on a CA-Markov Simulation Model: Case of a Mediterranean Watershed in Morocco. *Remote Sensing*, 15, 1162. doi: 10.3390/rs15041162

Breiman, L. (1996). Bagging predictors. *Machine learning*, 24, 123-140. doi: 10.1007/BF00058655

Breiman, L. (2001). Random forests. *Machine learning*, 45, 5-32. doi: 10.1023/A:1010933404324

Bremer, D. J., Lee, H., Su, K., & Keeley, S. J. (2011). Relationships between normalized difference vegetation index and visual quality in cool-season turfgrass: II. Factors affecting NDVI and its component reflectances. *Crop science*, 51(5), 2219-2227. doi: 10.2135/cropsci2010.12.0729

Census of India. (2025). Retrieved From https://censusindia.gov.in/

Chalise, D., Kumar, L., & Kristiansen, P. (2019). Land degradation by soil erosion in Nepal: A review. *Soil systems*, 3(1), 12. doi: 10.3390/soilsystems3010012

Cherlet, M., Hutchinson, C., Reynolds, J., Hill, J., Sommer, S. and Von Maltitz, G. (2018). *World Atlas of Desertification, Publications Office of the European Union, Luxembourg.* ISBN 978-92-79-75350-3, doi:10.2760/9205, JRC111155

del Barrio, G., Sanjuan, M. E., Martínez-Valderrama, J., Ruiz, A., & Puigdefábregas, J. (2021). Land degradation means a loss of management options. *Journal of Arid Environments*, 189, 104502. doi: 10.1016/j.jaridenv.2021.104502

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., ... & Bargellini, P. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote sensing of Environment*, 120, 25-36. doi: 10.1016/j.rse.2011.11.026

Karnataka. (2023). *Economic Survey 2022-23.* Retrieved From https://des.karnataka.gov.in/storage/pdf-files/Economic%20Survey%202022-23%20English.pdf

Evans, J.S., Murphy, M.A., Holden, Z.A., Cushman, S.A. (2011). *Modeling Species Distribution and Change Using Random Forest. In: Drew, C., Wiersma, Y., Huettmann, F. (eds) Predictive Species and Habitat Modeling in Landscape Ecology. Springer, New York, NY*. Retrieved From https://doi.org/10.1007/978-1-4419-7390-0

Evans, R. D., & Belnap, J. (1999). Long-term consequences of disturbance on nitrogen dynamics in an arid ecosystem. *Ecology*, 80(1), 150-160. doi: 10.1890/0012-9658(1999)080[0150:LTCODO]2.0.CO;2

Fu, X., Wang, X., & Yang, Y. J. (2018). Deriving suitability factors for CA-Markov land use simulation model based on local historical data. *Journal of environmental management*, 206, 10-19. doi: 10.1016/j.jenvman.2017.10.012

Ghosh, P., Mukhopadhyay, A., Chanda, A., Mondal, P., Akhand, A., Mukherjee, S., ... & Hazra, S. (2017). Application of Cellular automata and Markov-chain model in geospatial environmental modeling-A review. *Remote Sensing Applications: Society and Environment*, 5, 64-77. doi: 10.1016/j.rsase.2017.01.005

Gidey, E., Dikinya, O., Sebego, R., Segosebe, E., & Zenebe, A. (2017). Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. *Modeling Earth Systems and Environment*, 3, 1245-1262. doi: 10.1007/s40808-017-0397-6

Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern recognition letters*, 27(4), 294-300. doi: 10.1016/j.patrec.2005.08.011

Gratzfeld, J. (Ed.). (2003). *Extractive industries in arid and semi-arid zones: Environmental planning and management. IUCN*. Retrieved From https://doi.org/10.2305/IUCN.CH.2004.CEM.1.en

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., & Hokao, K. (2011). Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecological modelling*, 222(20-22), 3761-3772. doi: 10.1016/j.ecolmodel.2011.09.009

Haddad, N. M., Brudvig, L. A., Clobert, J., Davies, K. F., Gonzalez, A., Holt, R. D., ... & Townshend, J. R. (2015). Habitat fragmentation and its lasting impact on Earth's ecosystems. *Science advances*, 1(2), e1500052. doi: 10.1126/sciadv.1500052

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, 63, 101-112. doi: 10.1016/j.apgeog.2015.06.015

Huo, J., & Peng, C. (2023). Depletion of natural resources and environmental quality: Prospects of energy use, energy imports, and economic growth hindrances. *Resources Policy*, 86, 104049. doi: 10.1016/j.resourpol.2023.104049

IPCC, (2007). Climate change 2007: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press, United Kingdom*, 976 pp.

IPCC, (2013). Climate change 2013: The physical science basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, United Kingdom, 1535 pp.

Kosmas, C., Gerontidis, S., & Marathianou, M. (2000). The effect of land use change on soils and vegetation over various lithological formations on Lesvos (Greece). *Catena*, 40(1), 51-68. doi: 10.1016/S0341-8162(99)00064-8

Karnataka. (2022). Krishna Bhagya Jala Nigam Limited (KBJNL), India. Retrieved From https://kbjnl.karnataka.gov.in/storage/pdf-files/Progrss%20Report%20Eng%20as%20on%2030062022.pdf

Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual review of environment and resources*, 28(1), 205-241. doi: 10.1146/annurev.energy.28.050302.105459

Lasanta, T., & Vicente-Serrano, S. M. (2012). Complex land cover change processes in semi-arid Mediterranean regions: An approach using Landsat images in northeast Spain. *Remote Sensing of Environment*, 124, 1-14. doi: 10.1016/j.rse.2012.04.023

Liu, M., Wei, H., Dong, X., Wang, X. C., Zhao, B., & Zhang, Y. (2022). Integrating land use, ecosystem service, and human well-being: A systematic review. *Sustainability*, 14(11), 6926. doi: 10.3390/su14116926

Mancino, G., Falciano, A., Console, R., & Trivigno, M. L. (2023). Comparison between Parametric and Non-Parametric Supervised Land Cover Classifications of Sentinel-2 MSI and Landsat-8 OLI Data. *Geographies*, 3(1), 82-109. doi: 10.3390/geographies3010005

Manna, H., Sarkar, S., Hossain, M., & Dolui, M. (2023). Modeling and predicting spatio-temporal land use land cover changes and urban sprawling in Kalaburagi City Corporation, Karnataka, India: a geospatial analysis. *Modeling Earth Systems and Environment*, 1-24. doi: 10.1007/s40808-023-01814-2

Karnataka Rising. (2018). Ministry of Road Transport and Highways. https://morth.nic.in/sites/default/files/PragatiKiNayiGati/pdf/karnataka.pdf

Mirzabaev, A., Stringer, L. C., Benjaminsen, T. A., Gonzalez, P., Harris, R., Jafari, M., ... & Zakieldeen, S. (2022). Cross-chapter paper 3: deserts, semi-arid areas and desertification. *Climate Change*, 2195-2231.

Mirzabaev, A., Wu, J., Evans, J., Garcia-Oliva, F., Hussein, I. A. G., Iqbal, M. H., Kimutai, J., Knowles, T., Meza, F., Nedjroaoui, D., Tena, F., Türkeş, M., Vázquez, R. J. & Weltz, M. (2019). *Desertification. In P. R. Shukla, J. Skeg, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, S. van Diemen, M. Ferrat, E. Haughey, S. Luz, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi & J. Malley, Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Retrieved From https://philarchive.org/rec/NGCD

Mugari, E., & Masundire, H. (2022). Consistent Changes in Land-Use/Land-Cover in Semi-arid Areas: Implications on Ecosystem Service Delivery and Adaptation in the Limpopo Basin, Botswana. *Land*, 11(11), 2057. doi: 10.3390/land11112057

Mumtaz, F., Tao, Y., de Leeuw, G., Zhao, L., Fan, C., Elnashar, A., ... & Wang, D. (2020). Modeling spatio-temporal land transformation and its associated impacts on land surface temperature (LST). *Remote Sensing*, 12(18), 2987. doi: 10.3390/rs12182987

Nguyen, L. H., Joshi, D. R., Clay, D. E., & Henebry, G. M. (2020). Characterizing land cover/land use from multiple years of Landsat and MODIS time series: A novel approach using land surface phenology modeling and random forest classifier. *Remote Sensing of Environment*, 238, 111017. doi: 10.1016/j.rse.2018.12.016

Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., ... & Stringer, L. (2019). *Land degradation: IPCC special report on climate change, desertification, land 5 degradation, sustainable land management, food security, and 6 greenhouse gas fluxes in terrestrial ecosystems. In IPCC special report on climate change, desertification, land 5 degradation, sustainable land management, food security, and 6 greenhouse gas fluxes in terrestrial ecosystems (p.1). Intergovernmental Panel on Climate Change (IPCC).* Retrieved From https://doi.org/10.1017/9781009157988.006

Otukei, J. R., & Blaschke, T. (2010). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation*, 12, S27-S31. doi: 10.1016/j.rse.2018.12.016

Ozturk, D. (2015). Urban growth simulation of Atakum (Samsun, Turkey) using cellular automata-Markov chain and multi-layer perceptron-Markov chain models. *Remote Sensing*, 7(5), 5918-5950. doi: 10.3390/rs70505918

Pongratz, J., Dolman, H., Don, A., Erb, K. H., Fuchs, R., Herold, M., ... & Naudts, K. (2018). Models meet data: Challenges and opportunities in implementing land management in Earth system models. *Global change biology*, 24(4), 1470-1487. doi: 10.1111/gcb.13988

Pontifes, P. A., García-Meneses, P. M., Gómez-Aíza, L., Monterroso-Rivas, A. I., & Caso-Chávez, M. (2018). Land use/land cover change and extreme climatic events in the arid and semi-arid ecoregions of Mexico. *Atmósfera*, 31(4), 355-372. doi: 10.20937/ATM.2018.31.04.04

Pontius, G. R., & Malanson, J. (2005). Comparison of the structure and accuracy of two land change models. *International Journal of Geographical Information Science*, 19(2), 243-265. doi: 10.1080/13658810410001713434

Prăvălie, R., Niculiță, M., Roșca, B., Marin, G., Dumitrașcu, M., Patriche, C., ... & Bandoc, G. (2023). Machine learning-based prediction and assessment of recent dynamics of forest net primary productivity in Romania. *Journal of Environmental Management*, 334, 117513. doi: 10.1016/j.jenvman.2023.117513

Prăvălie, R., Patriche, C., Borrelli, P., Panagos, P., Roșca, B., Dumitrașcu, M., ... & Bandoc, G. (2021). Arable lands under the pressure of multiple land degradation processes. A global perspective. *Environmental Research*, 194, 110697. doi: 10.1016/j.envres.2020.110697

Rai, P. K., Mishra, V. N., & Singh, P. (2022). *Geospatial Technology for Landscape and Environmental Management. Springer Singapore.* Retrieved From https://doi.org/10.1007/978-981-16-7373-3

Ramachandra, T. V., & Aithal, B. H. (2013a). Understanding urban sprawl dynamics of Gulbarga-Tier II city in Karnataka through spatio-temporal data and spatial metrics. *International Journal of Geomatics and Geosciences*, 3(3), 388-404.

Ramachandra, T. V., & Aithal, B. H. (2013b). Urbanisation and sprawl in the Tier II City: metrics, dynamics and modelling using spatio-temporal data. *International Journal of Remote Sensing Applications*, 3(2), 65-74.

Ramachandra, T. V., Bharath, S., Subash Chandran, M. D., & Joshi, N. V. (2018). Salient ecological sensitive regions of central Western Ghats, India. *Earth Systems and Environment*, 2, 15-34. doi: 10.1007/s41748-018-0040-3

Ramachandra, T. V., Mondal, T., Settur, B., & Aithal, B. H. (2023b). Environmental Consequences in the Neighbourhood of Rapid Unplanned Urbanisation in Bangalore City. *Advances in Environmental and Engineering Research*, 4(4), 1-17. doi: 10.21926/aeer.2304052

Ramachandra, T. V., Negi, P., & Setturu, B. (2022). Insights from Big Spatial Data through Machine Learning Techniques for Prudent Management of Natural Resources. *Journal of Resources, Energy and Development*, 19(1-2),1-18. doi: 10.3233/RED-191201

Ramachandra, T. V., Setturu, B. & Subash Chandran, M. D. (2016). Geospatial analysis of forest fragmentation in Uttara Kannada District, India. For. *Ecosyst.* 3, 10. doi: 10.1186/s40663-016-0069-4

Ramachandra, T.V., Aithal, B.H., Setturu, B., Vinay, S., Asulabha, K.S., Sincy, V. (2024). *Valuation of Ecosystem Services, Karnataka State, India. In: Natural Capital Accounting and Valuation of Ecosystem Services, Karnataka State, India. Springer, Singapore*. Retrieved From https://doi.org/10.1007/978-981-97-2405-5_3

Ramachandra, T.V., Mondal, T. & Setturu, B. (2023a). Relative performance evaluation of machine learning algorithms for land use classification using multispectral moderate resolution data. *SN Appl. Sci.*, 5, 274. doi: 10.1007/s42452-023-05496-4

Ramachandra, T.V., & Negi, P. (2025). Geoinformatics-based prioritisation of natural resources rich regions at disaggregated levels for sustainable management. *Discov Sustain* **6**, 195. doi: 10.1007/s43621-025-00964-w

Riitters, K. H., Wickham, J. D., & Coulston, J. W. (2004). A preliminary assessment of Montreal process indicators of forest fragmentation for the United States. *Environmental Monitoring and Assessment*, 91, 257-276. doi: 10.1023/B:EMAS.0000009240.65355.92

Riitters, K.H., Wickham, J.D., O'Neill, R., Jones, B., & Smith, E. (2000). Global-scale patterns of forest fragmentation. *Conservation ecology*, 4(2).

Rimal, B., Zhang, L., Keshtkar, H., Haack, B. N., Rijal, S., & Zhang, P. (2018). Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and markov chain. *ISPRS International Journal of GeoInformation,* 7(4), 154. doi: 10.3390/ijgi7040154

Rimal, B., Zhang, L., Keshtkar, H., Wang, N., & Lin, Y. (2017). Monitoring and modeling of spatiotemporal urban expansion and land-use/land-cover change using integrated Markov chain cellular automata model. *ISPRS International Journal of GeoInformation*, 6(9), 288. doi: 10.3390/ijgi6090288

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS journal of photogrammetry and remote sensing*, 67, 93-104. doi: 10.1016/j.isprsjprs.2011.11.002

Roy, P. S., Ramachandran, R. M., Paul, O., Thakur, P. K., Ravan, S., Behera, M. D., ... & Kanawade, V. P. (2022). Anthropogenic land use and land cover changes—A review on its environmental consequences and climate change. *Journal of the Indian Society of Remote Sensing*, 50(8), 1615-1640. doi: 10.1007/s12524-022-01569-w

Sahu, N., Reddy, G. O., Dash, B., Kumar, N., & Singh, S. K. (2021). Assessment on spatial extent of arid and semi-arid climatic zones of India using GIS. *Journal of Agrometeorology*, 23(2), 189-193. doi: 10.54386/jam.v23i2.66

Scholes, R. J. (2020). The future of semi-arid regions: A weak fabric unravels. *Climate*, 8(3), 43. doi: 10.3390/cli8030043

Setturu, B., & Ramachandra, T.V. (2021). Modeling landscape dynamics of policy interventions in Karnataka State, India. *Journal of Geovisualization and Spatial Analysis*, 5(2), 22. doi: 10.1007/s41651-021-00091-w

Shanabhoga, M. B., Krishnamurthy, B., Suresha, S. V., Dechamma, S., & Kumar, R. V. (2023). Climate change adaptation constraints among paddy growing farmers in Kalyana-Karnataka region of Karnataka State. *Indian Journal of Extension Education*, 59(2), 124-127. doi: 10.48165/IJEE.2023.59227

Sridhara, S., Gopakkali, P., Manoj, K. N., Patil, K. K. R., Paramesh, V., Jha, P. K., & Prasad, P. V. V. (2022). Identification of sustainable development priorities for agriculture through sustainable livelihood security indicators for Karnataka, India. *Sustainability*, 14(3), 1831. doi: 10.3390/su14031831

Strahler, A. H. (1980). The use of prior probabilities in maximum likelihood classification of remotely sensed data. *Remote sensing of Environment*, 10(2), 135-163. doi: 10.1016/0034-4257(80)90011-5

Sugiri, A (2009). *Redressing Equity Issues in Natural Resource-Rich Regions: A Theoretical Framework for Sustaining Development in East Kalimantan, Indonesia. Weber, Estelle L. (Ed.), 2009. Environmental Ethics, Sustainability and Education, Oxford: Inter-disciplinary Press, p. 107-34, ISBN: 978-1-904710-74-5, Available at SSRN*. Retrieved From https://ssrn.com/abstract=2038246

Sun, Q., Qi, W., & Yu, X. (2021). Impacts of land use change on ecosystem services in the intensive agricultural area of North China based on Multi-scenario analysis. *Alexandria Engineering Journal*, 60(1), 1703-1716. doi: 10.1016/j.aej.2020.11.020

Talukdar, S., Eibek, K. U., Akhter, S., Ziaul, S. K., Islam, A. R. M. T., & Mallick, J. (2021). Modeling fragmentation probability of land-use and land-cover using the bagging, random forest and random subspace in the Teesta River Basin, Bangladesh. *Ecological indicators*, 126, 107612. doi: 10.1016/j.ecolind.2021.107612

Tariq, A., Mumtaz, F., Majeed, M., & Zeng, X. (2023). Spatio-temporal assessment of land use land cover based on trajectories and cellular automata Markov modelling and its impact on land surface temperature of Lahore district Pakistan. *Environmental Monitoring and Assessment*, 195(1), 114. doi: 10.1007/s10661-022-10738-w

Tian, S., Zhang, X., Tian, J., & Sun, Q. (2016). Random forest classification of wetland landcovers from multi-sensor data in the arid region of Xinjiang, China. *Remote Sensing*, 8(11), 954. doi: 10.3390/rs8110954

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote sensing of Environment*, 8(2), 127-150. doi: 10.1016/0034-4257(79)90013-0

Turner, K. G., Anderson, S., Gonzales-Chang, M., Costanza, R., Courville, S., Dalgaard, T., ... & Wratten, S. (2016). A review of methods, data, and models to assess changes in the value of ecosystem services from land degradation and restoration. *Ecological Modelling*, 319, 190-207. doi: 10.1016/j.ecolmodel.2015.07.017

UNCCD. (2016a). *The UNCCD: Securing Life on Land (2016–2017). Bonn. United Nations.* Retrieved From https://www.unccd.int/sites/default/files/documents/25072016_Securing%20Life%20on%20Land_ENG.pdf.

UNCCD. (2016b). *Global Land Outlook; UNCCD: Bonn, Germany, 2022.* Retrieved From https://www.unccd.int/sites/default/files/documents/2017-09/GLO_Full_Report_low_res.

Uralovich, K. S., Toshmamatovich, T. U., Kubayevich, K. F., Sapaev, I. B., Saylaubaevna, S. S., Beknazarova, Z. F., & Khurramov, A. (2023). A primary factor in sustainable development and environmental sustainability is environmental education. *Caspian Journal of Environmental Sciences*, 21(4), 965-975. doi: 10.22124/CJES.2023.7155

Van de Ven, D. J., Capellan-Peréz, I., Arto, I., Cazcarro, I., de Castro, C., Patel, P., & Gonzalez-Eguino, M. (2021). The potential land requirements and related land use change emissions of solar energy. *Scientific reports*, 11(1), 2907. doi: 10.1038/s41598-021-82042-5

Van Der Geest, K., De Sherbinin, A., Kienberger, S., Zommers, Z., Sitati, A., Roberts, E., & James, R. (2019). The impacts of climate change on ecosystem services and resulting losses and damages to people and society. *Loss and damage from climate change: Concepts, methods and policy options*, 221-236. doi: 10.1007/978-3-319-72026-5_9

Wambugu, N., Chen, Y., Xiao, Z., Wei, M., Bello, S. A., Junior, J. M., & Li, J. (2021). A hybrid deep convolutional neural network for accurate land cover classification. *International Journal of Applied Earth Observation and Geoinformation*, 103, 102515. doi: 10.1016/j.jag.2021.102515

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of the Total Environment*, 822, 153559. doi: 10.1016/j.scitotenv.2022.153559

Wassie, S. B. (2020). Natural resource degradation tendencies in Ethiopia: a review. *Environmental systems research*, 9(1), 1-29. doi: 10.1186/s40068-020-00194-1

Weng, L., Qian, M., Xia, M., Xu, Y., & Li, C. (2020). Land use/land cover recognition in arid zone using a multi-dimensional multi-grained residual Forest☆. *Computers & Geosciences*, 144, 104557. doi: 10.1016/j.cageo.2020.104557

West, H., Quinn, N., & Horswell, M. (2019). Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. *Remote Sensing of Environment*, 232, 111291. doi: 10.1016/j.rse.2019.111291

Winkler, K., Fuchs, R., Rounsevell, M., & Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nature communications*, 12(1), 2501. doi: 10.1038/s41467-021-22702-2

World Bank. (2020). *World Development Report 2020: Trading for Development in the Age of Global Value Chains. World Bank.* Retrieved From http://hdl.handle.net/10986/32437 License: CC BY 3.0 IGO.

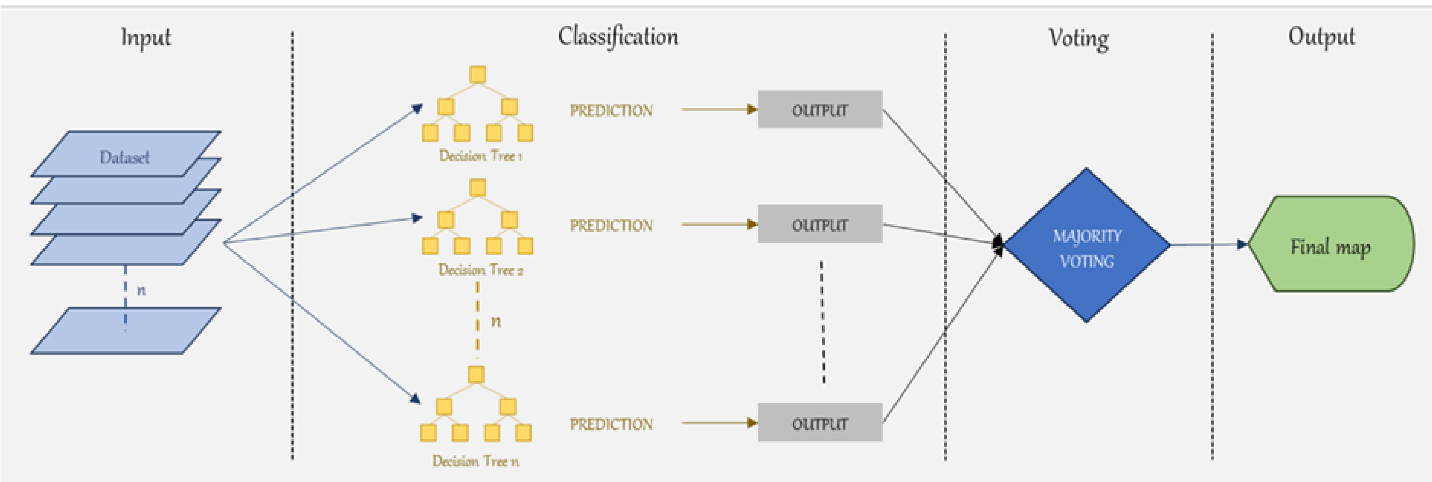
Yang, Y., Wang, K., Liu, D., Zhao, X., & Fan, J. (2020). Effects of land-use conversions on the ecosystem services in the agro-pastoral ecotone of northern China. *Journal of Cleaner Production*, 249, 119360. doi: 10.1016/j.jclepro.2019.119360

Zhang, A., Venkatesh, V. G., Liu, Y., Wan, M., Qu, T., & Huisingh, D. (2019). Barriers to smart waste management for a circular economy in China. *Journal of Cleaner Production*, 240, 118198. doi: 10.1016/j.jclepro.2019.118198

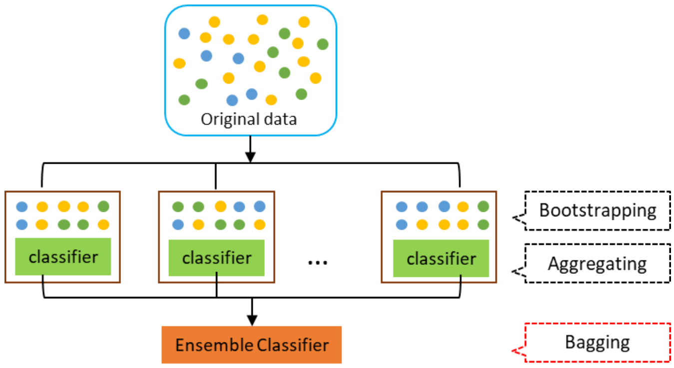
Nguyen, Q. H., Ly, H. B., Ho, L. S., Al-Ansari, N., Le, H. V., Tran, V. Q., ... & Pham, B. T. (2021). Influence of data splitting on performance of machine learning models in prediction of shear strength of soil. *Mathematical Problems in Engineering*, 2021, 1-15. doi: 10.1155/2021/4832864

Supplementary Data

Sustainable Management of Natural resources at disaggregated levels with insights from landscape dynamics



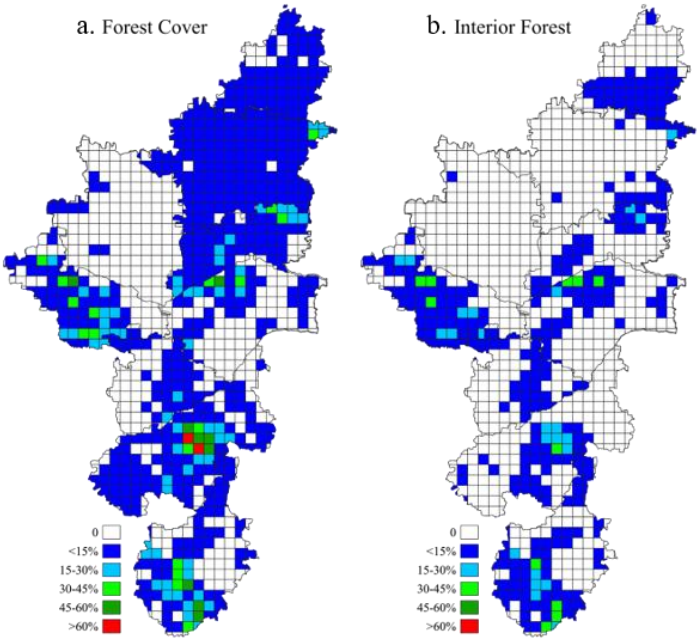
Supplementary Figure 1a. Random Forest Classifier.



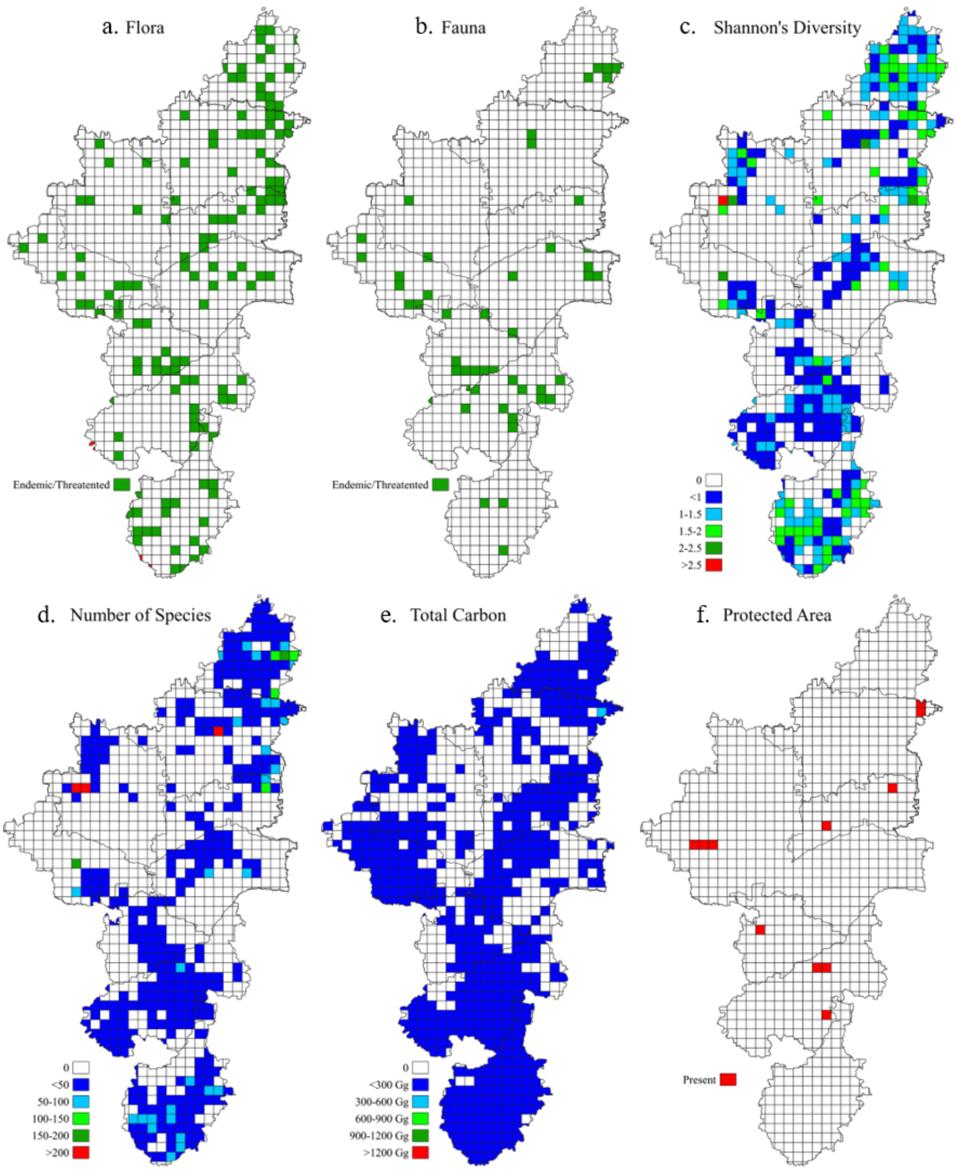
Supplementary Figure 1b. Bagging in Random Forest.

Variables		Weights 0	2	4	6	8	10
LAND	Forest	0	<15%	15-30%	30-45%	45-60%	>60%
	Interior forest	0	0-15%	>15 & <30%	>30 & <45%	>45 & <60%	60-100%
ECOLOGY	Biomass (total Carbon in Gg)	0	<300	>300 &<600	600-900	900-1200	>1200
	Shannon's Diversity	0	<1	1-1.5	1.5-2	2-2.5	>2.5
	No of species	0	<50	50-100	100-150	150-200	>200
	Flora	–	Non-endemic	–	–	Endemic/ Threatened	–
	Fauna	–	Non-endemic	–	–	Endemic/ Threatened	–
	National Park	outside NP	–	–	–	inside NP	–
	Protected Area	outside PA	–	–	–	inside PA	–
GEO-CLIMATIC	Altitude (m)	–	–	<250	250–500	500–750	>750
	Slope (%)	–	–	–	–	>15%	>30%
	Rainfall (mm)	–	<600	600-1200	1200-1800	1800-2400	>2400
	Agroclimatic Zone	–	Hot Dry Arid	Arid	Hot Dry Semi-Arid	Hot Dry Sub Humid	Hot Moist Sub-Humid or Sahyadris
	Lithology	–	–	Charnokites	Penninsular Gneiss	Dharwars or Granite	Deccan Trap
	Soil	–	coarse loamy	sandy or sandy skeletal	Fragmental or Rocky outcrops	Clayey loamy or Clayey Skeletal	Loamy or Clayey
HYDROLOGY	Stream density	<0.5	0.5-1	1-1.5	1.5-2	2-2.5	>2.5
	Stream flow	-	<3 months	3 months	4 months	5 months	>6 months
	Reservoir	not present	–	–	–	–	present
ENERGY	Solar energy (kWh)	–	-	-	-	<6	>6
	Wind energy (m/sec)	–	<1.5	1.5-2	2-3.5	3.5-4	>4
	Bio energy (Mkcal)	–	<100	100-200	200-400	400-600	>600
SOCIAL	Population Density (persons per sq. km)	–	>1000	1000-500	500-250	250-100	<100
	Livestock Density (animals/ha)	–	<0.75	0.75-1.5	1.5-2.25	2.25-3	>3
	Forest Dwellers	not present	–	–	–	–	present

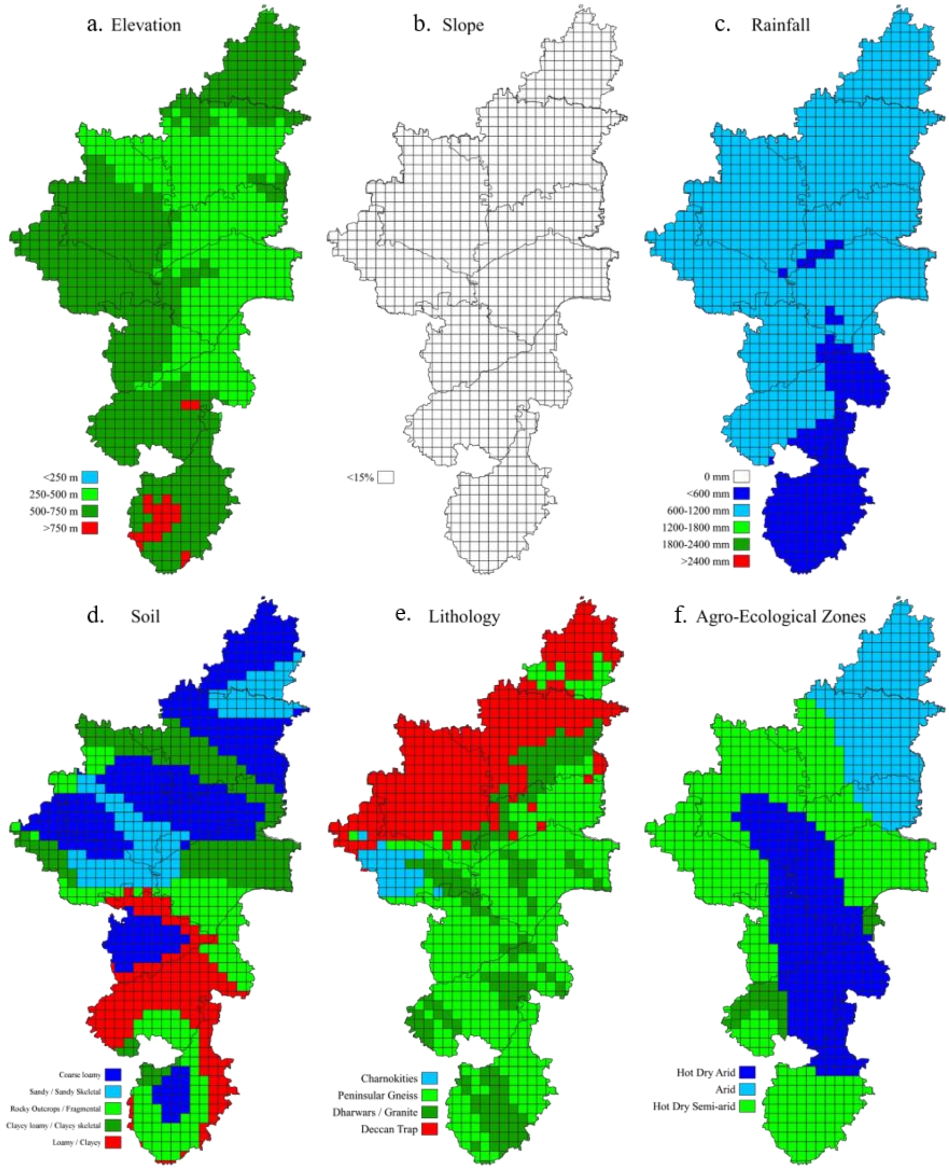
Supplementary Figure 2. Weights assigned to bio-geo climatic, social and environmental parameters based on the significance / relevance.



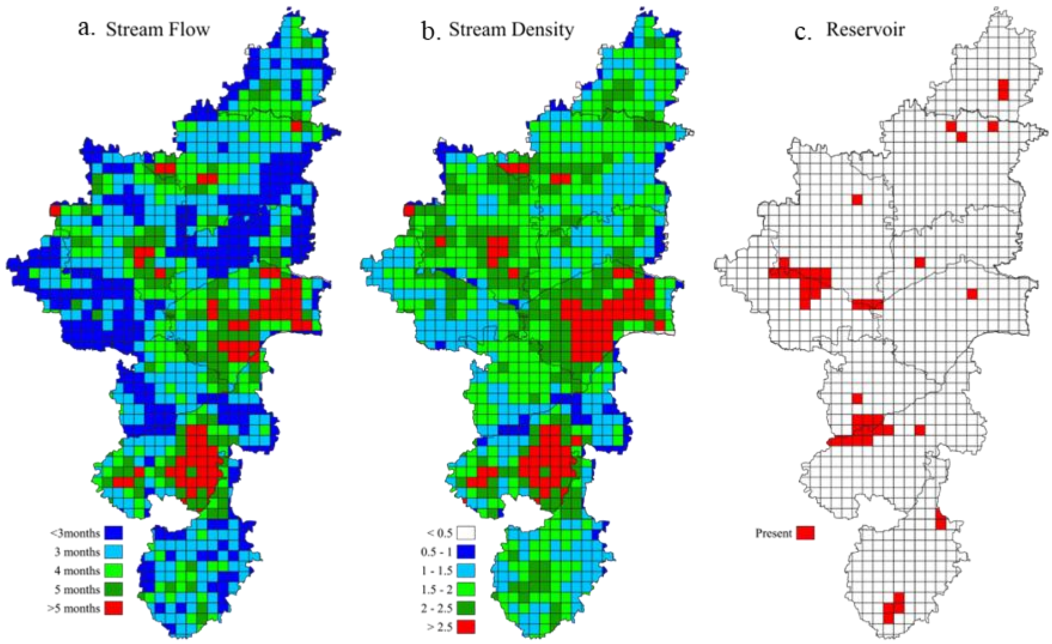
Supplementary Figure 3. Spatial extent of forest and interior forest



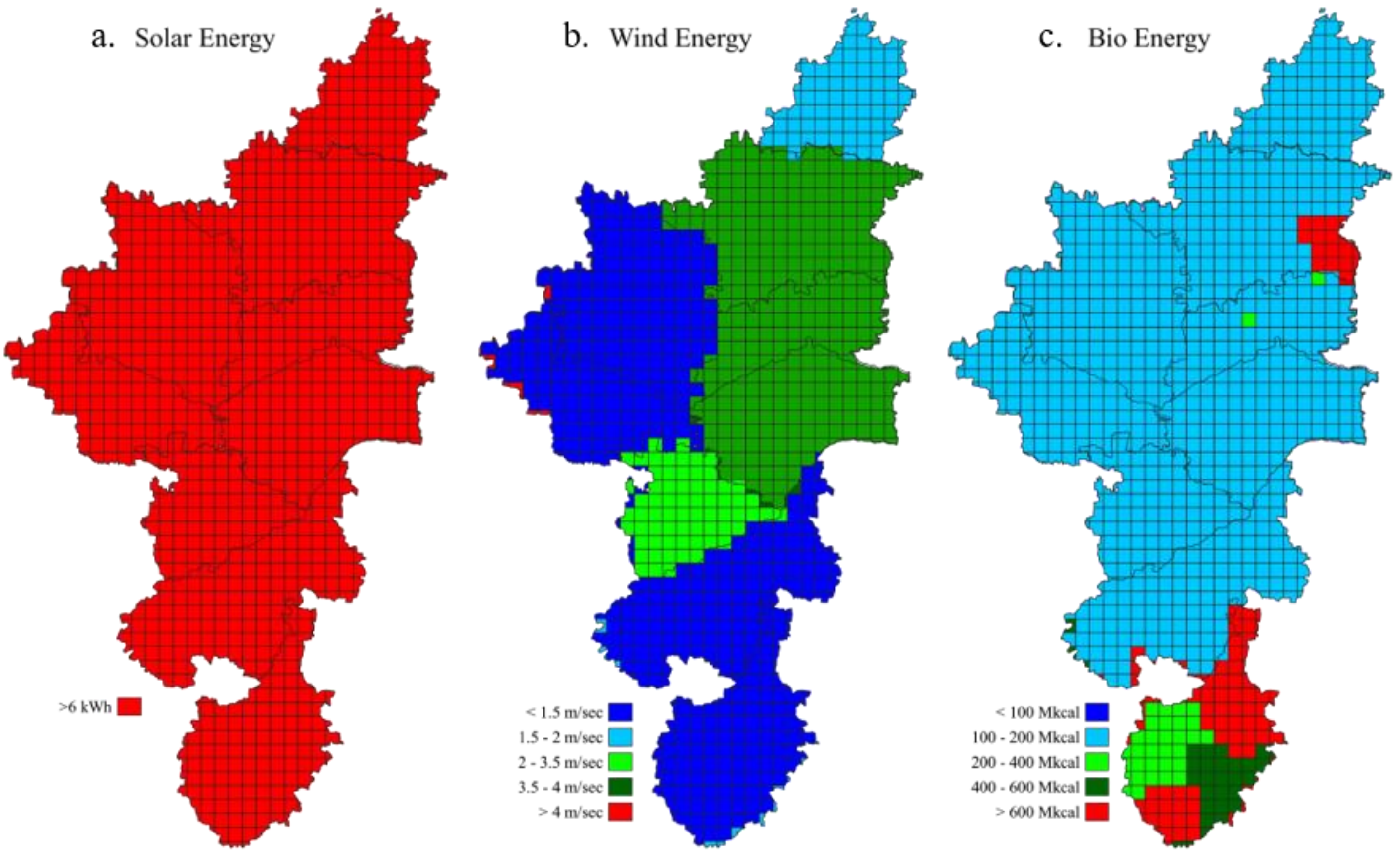
Supplementary Figure 4. Distribution of ecological variables.



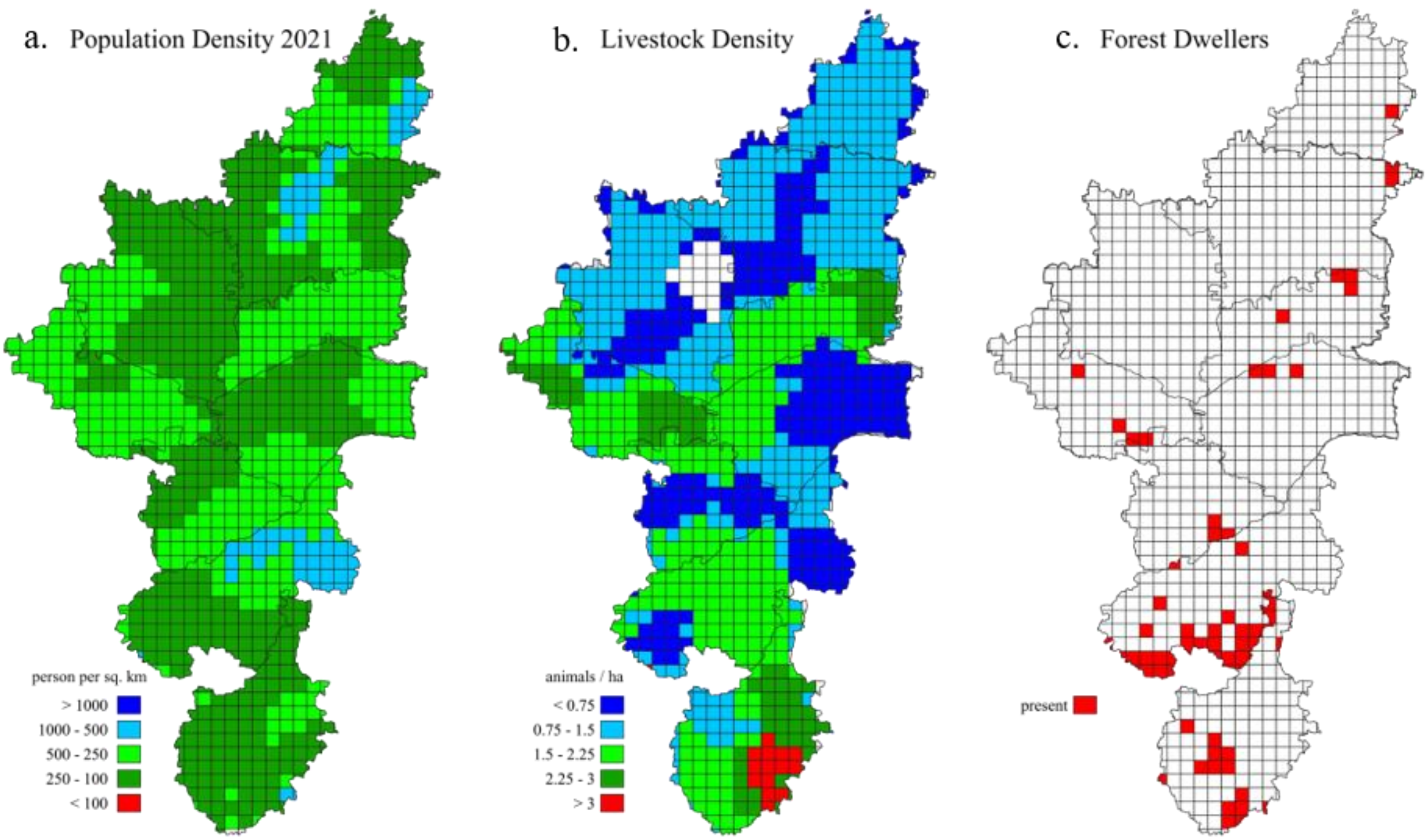
Supplementary Figure 5. Spatial extent of geo-climatic variables



Supplementary Figure 6. Spatial extent of hydrological variables



Supplementary Figure 7. Potential of renewable energy variables



Supplementary Figure 8. Distribution of social variables.

Supplementary Table 1. Data used for assessing the extent and condition of.

Remote sensing data

Data	Source	Bands	Spatial resolution	Temporal resolution	Year
Landsat Multispectral Sensor (MSS)	U.S. Geological Survey https://earthexplorer.usgs.gov/	Band 4, 5, 6	30 m	16 days	1973
Landsat Thematic Mapper (TM)	U.S. Geological Survey https://earthexplorer.usgs.gov/	Band 1, 2, 3, 4,5,7	30 m	16 days	1996, 2005
Landsat Operational Land Imagery (OLI)	U.S. Geological Survey https://earthexplorer.usgs.gov/	Band 2,3,4,5,6,7	30 m	16 days	2014, 2022
Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM)	U.S. Geological Survey https://earthexplorer.usgs.gov/		30 m		2014

Collateral Data

Data	Source	Spatial resolution	Year
KGIS K-GIS Portal	https://kgis.gok.in		
Survey of India Toposheet	surveyofindia.gov.in	1:50000	2005-06
Survey of India Toposheet	surveyofindia.gov.in	1:250000	1964-66
Google Satellite	Google Earth https://earth.google.com/	0.1-5 m	1985-2023
National Remote Sensing Centre (NRSC) Land Use	Bhuvan https://bhuvan.nrsc.gov.in/home/index.php	1:50,000	2005-06, 2011-12, 2015-16

Data used for identification of NRRRs

Variable	Source of Data	Data	Description
Forest Cover	Author	Land Use classification map (2022)	Spatial quantification of forested areas within the defined grid
Interior Forest	Author	Forest class derived from land use map (2022)	Spatial quantification of interior forest within the defined grid
Biomass (Total Carbon)	https://wgbis.ces.iisc.ac.in	Empirical field data and synthesis of literature	Estimation of total carbon stored in biomass across the grid
Shannon's Diversity	https://wgbis.ces.iisc.ac.in	Empirical field data and synthesis of literature	Calculation of Shannon diversity index based on species abundance and distribution within the grid
Number of Species	https://wgbis.ces.iisc.ac.in	Empirical field data and synthesis of literature	Enumeration and spatial mapping of species diversity within the grid
Flora	https://wgbis.ces.iisc.ac.in	Empirical field data and synthesis of literature	Spatial representation of endemic plant species distributed across the grid
Fauna	https://wgbis.ces.iisc.ac.in	Empirical field data and synthesis of literature	Spatial representation of endemic animal species distributed across the grid
Elevation (m)	https://www.nrsc.gov.in/	Cartosat DEM data (1 arc second = 30m resolution)	Extraction of elevation profiles and contour features from DEM data within the grid
Rainfall (mm)	Indian Meteorological Data (IMD)	Historical daily rainfall records (1901-2010) from rain gauge stations	Conversion of point-based rainfall observations into spatially interpolated datasets for the grid
Agro-Climatic Zone	https://e-krishiuasb.karnataka.gov.in/	Karnataka Agriculture Portal	Classification and spatial delineation of agro-climatic zones specific to the grid area
Lithology	https://nbsslup.icar.gov.in/	National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)	Geological characterization of lithological units based on parent rock material within the grid
Soil	https://nbsslup.icar.gov.in/	National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)	Identification, classification, and spatial mapping of soil types within the grid
Stream Density	https://www.nrsc.gov.in	Cartosat DEM data (1 arc second = 30m resolution)	Quantitative analysis of stream network density using hydrological modeling in the grid
Stream Flow	https://www.nrsc.gov.in	Cartosat DEM data (1 arc second = 30m resolution)	Temporal assessment of water flow duration in streams present within the grid

Reservoir	Author	Land Use classification map (2022)	Identification and spatial mapping of reservoirs present within the grid

Supplementary Table 1. Continued.

Data used for identification of NRRRs			
Variable	**Source of Data**	**Data**	**Description**
Solar Energy (kWh)	Ramachandra et al., 2011; Ramachandra, T.V., 2006	Empirical field data and synthesis of literature	Quantification of solar radiation potential based on global solar energy measurements in the grid
Wind Velocity (m/sec)	Ramachandra, T.V., & Shruthi, B.V., 2005	Empirical field data and synthesis of literature	Measurement and spatial analysis of wind speed dynamics across the grid
Bioenergy (Mkcal)	Ramachandra, T.V., 2007	Empirical field data and synthesis of literature	Estimation of bioenergy potential derived from fuelwood availability in the grid area
Population Density (persons per sq. km)	Census of 2011 (http://censusindia.gov.in)	Census of India 2011	Spatial analysis of human population density per square kilometer within the grid area
Livestock Density (animals/ha)	Animal Husbandry Departments of the states and union territories	20th Livestock Census of India	Spatial distribution and density of livestock within the grid area
Forest dwellers	Census of 2011 (http://censusindia.gov.in)	Census of India 2011	Spatial distribution and statistics of forest dwellers within the grid area

Supplementary Table 2. Quantification of area under vegetation and non-vegetation through NDVI thresholding.

Bagalkote				
Year	**Scene**	**Minimum value**	**Threshold value**	**Maximum value**
2022		-1	0.4	1
2014		-1	0.3	0.88
2005	Scene 1	-0.89	0.25	0.87
	Scene 2	-1	0.25	0.87
1998		-1	0.11	1
1973		-0.63	0.09	0.7
Bellary				
2022	Scene 1	-0.73	0.27	0.84
	Scene 2	-0.27	0.24	0.66
	Scene 3	-0.29	0.24	0.74
2014	Scene 1	-0.38	0.23	0.77
	Scene 2	-0.34	0.22	0.76
	Scene 3	-0.31	0.19	0.74
2007	Scene 1	-0.1	0.13	0.74
	Scene 2	-0.19	0.11	0.63
	Scene 3	0.06	0.13	0.69
2000	Scene 1	-0.5	0.16	1
	Scene 2	-0.52	0.19	0.78
	Scene 3	-0.73	0.2	0.8
1973	Scene 1	-0.54	0.13	0.69
	Scene 2	-0.42	0.11	0.61
	Scene 3	-1	0.8	0.61
	Scene 4	-1	0.8	0.66
Bidar				
2022	Scene 1	-0.24	0.12	0.52
	Scene 2	-0.24	0.1	0.52
2014	Scene 1	-0.13	0.13	0.36
	Scene 2	-0.21	0.12	0.5
2007	Scene 1	-0.1	0.13	0.44
	Scene 2	-0.13	0.13	0.41

	Scene 3	-0.1	0.15	0.44
1999	Scene 1	-0.3	0.23	0.71
	Scene 2	-0.4	0.27	0.77

Supplementary Table 2. Continued.

Bidar				
Year	**Scene**	**Minimum value**	**Threshold value**	**Maximum value**
1973	Scene 1	-1	0.07	0.57
	Scene 2	-0.87	0.1	0.73
	Scene 3	-1	0.1	0.74
	Scene 4	-1	0.06	0.64
Chitradurga				
	2021	-0.1	0.4	0.48
	2013	-0.25	0.3	0.54
	1998	-0.44	0.25	0.58
	1991	-0.14	0.11	0.47
	1973	-0.93	0.09	0.68
Kalaburagi				
2022	Scene 1	-0.2	0.21	0.51
	Scene 2	-0.15	0.19	0.47
2014	Scene 1	-0.12	0.17	0.48
	Scene 2	-0.14	0.21	0.48
2005	Scene 1	-0.64	0.06	0.73
	Scene 2	-0.46	0.01	0.72
1996	Scene 1	-1	0.05	1
	Scene 2	-0.33	0.01	0.2
1973	Scene 1	-1	0.08	0.65
	Scene 2	-0.58	0.06	0.8
Koppal				
2021		-1	0.4	0.66
2013		-0.27	0.4	0.52
2006		-0.17	0.4	0.46
1998		-0.33	0.4	0.58
1973		-1	0.4	0.66
Raichur				
2022	Scene 1	-0.19	0.16	0.49
	Scene 2	-1	0.31	1
2014	Scene 1	-0.17	0.16	0.52
	Scene 2	-0.48	0.32	0.88
2009	Scene 1	-0.66	0.15	0.82
	Scene 2	-0.09	0.1	0.45
1999	Scene 1	-0.29	0.12	0.48
	Scene 2	-0.37	0.12	0.58
1973	Scene 1	-0.47	0.14	0.79
	Scene 2	-1	0.13	0.66
Vijayapura				
2022	Scene 1	-1	0.31	0.87
	Scene 2	-0.57	0.29	0.85
2014	Scene 1	-1	0.33	0.88
	Scene 2	-0.7	0.24	0.88

Vijayapura				
2005	Scene 1	-0.81	0.2	0.89
	Scene 2	-0.38	0.21	0.79

Supplementary Table 2. Continued.

Vijayapura				
Year	**Scene**	**Minimum value**	**Threshold value**	**Maximum value**
	Scene 3	-0.25	0.19	0.77
1996	Scene 1	-0.45	0.22	0.77
	Scene 2	-1	0.17	0.81
	Scene 3	-0.49	0.19	0.81
1973		-0.26	0.11	0.52
Yadgir				
2022		-0.62	0.34	1
2014		-0.47	0.34	0.86
2005		-1	0.25	1
1996		-0.54	0.3	0.81
1973	Scene 1	-0.86	0.08	0.61
	Scene 2	-1	0.14	0.67

Supplementary Table 3. Forest fragmentation analysis by computation of $\boldsymbol{P_f}$ and $\boldsymbol{P_{ff}}$

Fragmentation Classes	**Computation**	**Description**
Interior	Pf = 1	Forest pixels that are surrounded by non-forested pixels and are located far from the boundaries of both forested and non-forested areas.
Perforated	Pf > 0.6 and Pf-Pff > 0	Forest pixels that serve as boundaries between interior forest pixels and perforated areas.
Edge	Pf > 0.6 and Pf-Pff < 0	Forest pixels that act as boundaries between interior forest pixels and non-forested areas.
Transitional	0.4 < Pf < 0.6	Pixels that lie between edge pixels and non-forested pixels.
Patch	Pf < 0.4	Forested pixels that are surrounded by non-forested pixels.

$$P_f = \frac{proportion\ of\ number\ of\ forest\ pixels}{total\ number\ of\ non - water\ pixels\ in\ the\ window} \tag{6}$$

$$P_{ff} = \frac{proportion\ of\ number\ of\ forest\ pixel\ pairs}{total\ number\ of\ adjacent\ pairs\ of\ at\ least\ one\ forest\ pixel} \tag{7}$$

Supplementary Table 4. Land cover in arid regions of Northern Karnataka from 1973 to 2022.

Land Cover (NDVI)	**1973**		**1996**		**2005**		**2014**		**2022**	
	sq. km	**%**	**sq. km**	**%**	**sq. km**	**%**	**sq. km**	**%**	**sq. km**	**%**
Non-vegetation	47815.19	67.21	42441.14	59.66	40428.81	56.83	36050.38	50.67	33187.19	46.65
Vegetation	23328.22	32.79	28702.27	40.34	30714.60	43.17	35093.03	49.33	37956.22	53.35

Supplementary Table 5. Accuracy assessment of land use classification of 2022.

	Reference (Google)										
	Dry Deciduous	**Scrub**	**Open**	**Agricul-ture**	**Horticul-ture**	**Water-body**	**Built-up**	**Mine**	**Plantation**	**row sum**	**UA**
Dry Deciduous	50	4	0	2	1	0	0	0	0	57	0.88
Scrub	6	86	0	1	1	0	0	0	1	95	0.91
Open	0	1	42	6	0	0	2	1	0	52	0.81
Agriculture	2	14	6	1452	2	0	1	0	0	1477	0.98
Horticulture	2	2	0	6	114	0	0	0	0	124	0.92
Waterbody	0	0	0	0	0	56	0	0	0	56	1.00
Built-up	0	0	5	1	0	0	61	0	0	67	0.91
Mine	0	1	1	0	0	0	0	8	0	10	0.80

Plantation	1	0	0	0	0	0	0	0	7	8	0.88
column sum	61	108	54	1468	118	56	64	9	8	1876	
PA	0.82	0.80	0.78	0.99	0.97	1.00	0.95	0.89	0.88		0.96

Supplementary Table 6. Change in LU from 1973 to 2022 in arid region of Northern Karnataka.

Land Use	1973		1996		2005		2014		2022	
	sq. km	%	sq. km	%	sq. km	%	sq. km	%	sq. km	%
Dry deciduous	2154.2	3.03	1755.9	2.47	1583.29	2.23	1416.63	1.99	1096.34	1.54
Scrub land	5650.74	7.94	3773.37	5.3	3093.85	4.35	2817.06	3.96	2260.19	3.18
Open land	6159.02	8.66	3830.62	5.38	2815.79	3.96	2215.26	3.11	1822.05	2.56
Agriculture	55399.64	77.87	59082.51	83.05	59040.72	82.99	58709.19	82.52	59125.07	83.11
Horticulture	1089.35	1.53	1569.86	2.21	3054.14	4.29	4033.5	5.67	4198.58	5.9
Water	494.93	0.7	693.82	0.98	910.46	1.28	1053.27	1.48	1397.68	1.96
Built-up	186.22	0.26	402.42	0.57	606.24	0.85	804.78	1.13	1085.12	1.53
Mining	0	0	0.89	0	3.42	0	16.3	0.02	27.31	0.04
Plantation	9.3	0.01	34.02	0.05	35.5	0.05	77.44	0.11	131.08	0.18
Total	71143.41	100	71143.41	100	71143.41	100	71143.41	100	71143.41	100

Supplementary Table 7. Forest Fragmentation Indices from 1973 to 2022 in the arid region of North Karnataka.

Forest fragmentation	1973	1996	2005	2014	2022
	sq. km	sq. km	sq. km	sq. km	sq. km
Patch	520.81	790.34	565.35	507.58	365.87
Transitional	1357	714.41	549.73	506.68	419
Edge	883.32	263.34	217.47	200.71	163.73
Perforated	1596.3	1180.5	1043.8	956.64	868.86
Interior	3447.6	2580.7	2300.8	2062.1	1539.1
Total forest area	7804.9	5529.3	4677.1	4233.7	3356.5

Supplementary Table 8. Land use change simulation from 2022 to 2038.

Land use Modelling	2022 actual		2022 sim		2030 sim		2038 sim	
	sq. km	%	sq. km	%	sq. km	%	sq. km	%
Dry deciduous	1096.34	1.54	1081.51	1.52	798.01	1.12	736.71	1.04
Scrub land	2260.19	3.18	2376.56	3.34	1469.71	2.07	1157.46	1.63
Open land	1822.05	2.56	1856.62	2.61	2232.61	3.14	1873.37	2.63
Agriculture	59125.07	83.11	58626.39	82.41	54648.15	76.81	54758.82	76.97
Horticulture	4198.58	5.90	4192.18	5.89	5522.32	7.76	5221.57	7.34
Water	1397.68	1.96	1600.42	2.25	1678.19	2.36	1819.60	2.56
Built-up	1085.12	1.53	1111.39	1.56	4432.20	6.23	5098.30	7.17
Mining	27.31	0.04	118.15	0.17	120.92	0.17	152.86	0.21
Plantation	131.08	0.18	180.19	0.25	241.29	0.34	324.71	0.46
Total	71143.41	100.00	71143.41	100.00	71143.41	100.00	71143.41	100.00