Machine Learning-based Identification of Livelihood Lifeline Regions in Chikamagaluru District, Central Western Ghats

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Abstract

Livelihood lifeline regions are ecologically fragile regions that sustain natural resources but are vulnerable even to minor disturbances and hence require prudent management to maintain the region's integrity. Identification of ecologically fragile regions is possible considering landscape dynamics with bio-geo-hydro-climatic-social variables. Objectives of the current study are to (i) evaluate landscape dynamics through assessment of Land Use Land Cover (LULC) and (ii) identify and prioritize Livelihood Lifeline Regions (LLR) or Environmental Fragile Regions (EFRs) through integrated approaches considering ecological, biological, geo-climatic, and social variables. The current research focuses on the use of an Artificial Intelligence (AI) based Random Forest algorithm, a supervised Machine Learning (ML) classifier using temporal remote sensing data (1973 to 2021) of Chikamagaluru district, Karnataka state, India. Land use classification showed a decrease in forest cover (48.91 per cent) with an increase in agriculture (6.13 per cent), horticulture (43.14 per cent), and built-up cover (2.10 per cent). Livelihood lifeline regions (EFR1 to EFR 3) are to be protected to sustain the livelihood of local people with the sustenance of natural resources, and EFR4 denotes the least environmental fragility. The outcome of the current research would aid in policy-making toward optimizing local livelihood and economy through the prudent management of natural resources.

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1. Introduction

The sustenance of natural resources depends on a region's ecological fragility, which indicates the degree of vulnerability that alters species abundance and composition. The extent of vulnerability is assessed by considering agents and impacts on the ecosystem. Ecological fragility assessment helps to identify the quantitative and qualitative vulnerable status of the region (França *et al.*, 2022), helps to visualize and plan for regulating disastrous anthropogenic activities through prudent ecosystem management with the active participation of all stakeholders to sustain livelihood lifeline systems (Ramachandra *et al.*, 2022a). Conservation of ecosystems requires insights of ecological, biological, and cultural dimensions. The ecological dimension refers to the natural environment, such as ecosystems and ecological processes, while the cultural dimension refers to the political, social, technological, and economic aspects (Ramachandra *et al.*, 2018). Delineation of Environmental Fragile Regions (EFRs)/Livelihood Lifeline Regions (LLR) considering bio-geo-hydro-climatic variables with environmental and social aspects is essential to evolve strategies for enduring ecosystem processes to sustain biodiversity. Multiple levels of EFR or LLR (with grids prioritized based on the cumulative eco-sensitive metrics score) help the decision-makers opt for eco-friendly development measures and aid in effective regional planning.

Landscape comprises heterogeneous elements with diverse ecological, biological, geological, hydrological, social, economic, and environmental characteristics. The ecological processes in a region depend on the landscape structure or characteristics. The mosaic of interacting landscape elements is vital for sustaining ecosystem processes or activities, which are termed Environmental Fragile Regions (EFRs) or Livelihood Lifeline Regions (Ramachandra *et al.*, 2022b). The ecological processes deteriorate due to the sustained anthropogenic interferences with unplanned developmental activities (Hu *et al.*, 2021).

Alterations in the structure of a landscape due to natural or anthropogenic activities are accounted for through temporal land cover (LC) and land uses (LU). A quantitative analysis of LU and LC determines the extent and condition of ecosystems (Ramachandra and Bharath, 2012), indicating the level of human interactions and associated changes. The availability of spatial data at regular intervals through space-borne sensors and advancements in geoinformatics with machine learning algorithms have been aiding in the provision of information required for assessing landscape dynamics.

Unplanned developmental activities have altered the structure of the landscape, inducing fragmentation of contiguous forests, which are detrimental to the sustenance of biodiversity, carbon sequestration potential, and other ecological services at local and global scales (Liu *et al.*, 2019). Fragmentation of forests creates disturbances in ecological and socio-economic processes with habitat loss, distribution of habitats into patches, a decrease in habit patch size, loss of species diversity, etc., leading to disruptions in wildlife habitats and aggravating human-wildlife conflicts (Ritters *et al.*, 2000). Hence, information on landscape dynamics focusing on the extent and condition aids in prioritizing the area for planning, managing, and conserving biodiversity to sustain livelihood support socio-economic activities (Chughtai *et al.*, 2021; Ramachandra and Kumar, 2011). The structure and composition of the landscape are ascertained through spatial matrices.

Recurring mudslides and landslides in recent years have necessitated identifying and prioritizing Livelihood Lifeline Regions (LLR) and Environmental Fragile Regions (EFR) in Chikamagaluru district of Karnataka. There have been significant efforts to understand the landscape dynamics, including ecosystem conditions, through fragmentation assessment (Chughtai *et al.*, 2021; Ramachandra and Kumar, 2011; Hu *et al.*, 2021; Liu *et al.*, 2019; Khalidkar, 2019; Ramachandra *et al.*, 2019), but mapping environmentally fragile regions at disaggregated levels considering ecological, biological, geo-climatic, and social variables would facilitate in the sustainable management. The novelty of the research is assessing and geo-visualizing LLR and EFR in a heterogeneous landscape, by taking advantage of recent advances in geoinformatics through spatial big data and machine learning algorithms.

The availability of long-term, multi-resolution remote sensing data (spatial big data) helps to identify and quantify land use dynamics and understand the impacts of unplanned anthropogenic interventions. Integrating land use information with collateral data through a Geographic Information System (GIS) aids in comprehending land use information with agents of change, including policy interventions (Vivekananda, 2021). Recent advancements in the classification of big data (spatial) through artificial intelligence (Khalidkar, 2019) based on machine learning aid in making an informed optimal decision due to the availability of accurate land use information in less time. Random Forest classifier (RFC) based on ensemble methods like bagging and boosting is the most widely used ML algorithm (Breiman, 1996). RFC provides accurate LU classification for heterogeneous landscapes through a set of decision trees from a randomly selected subset of the training set and aggregates decisions for deciding the final class. RFC randomly selects variables from training samples at each node to determine the best split to construct a tree based on the Gini index measure that gives a measure of impurity within a node. The accuracy of the classifier is assessed through samples (not used for training), which provide unbiased error estimates. The performance of three supervised learning non-parametric techniques (Random Forest classifier (RFC), Support Vector Machine (SVM)), and parametric technique (Maximum Likelihood classifier (MLC)) were assessed, and results reveal that non-parametric based RFC performed better with an overall accuracy and kappa value (Ramachandra *et al.*, 2023). Integrated landscape assessments considering bio-geo-climatic, with ecological, environmental, and social characteristics, are required to delineate Environmental Fragile Regions (EFRs). Prioritization of EFRs at disaggregated levels is essential for planning interventions to ensure sustainable development and maintain the ecological balance in the environment.

1.1 Objectives

Objectives of the current study include: (i) assessing landscape dynamics through LULC in Chikamagaluru district, Karnataka State, India using temporal remote sensing data and (ii) identification and prioritization of Livelihood Lifeline Regions (LLR) or Environmental Fragile Regions (EFRs) considering ecological, biological, geo-climatic and social variables.

2. Materials and Method

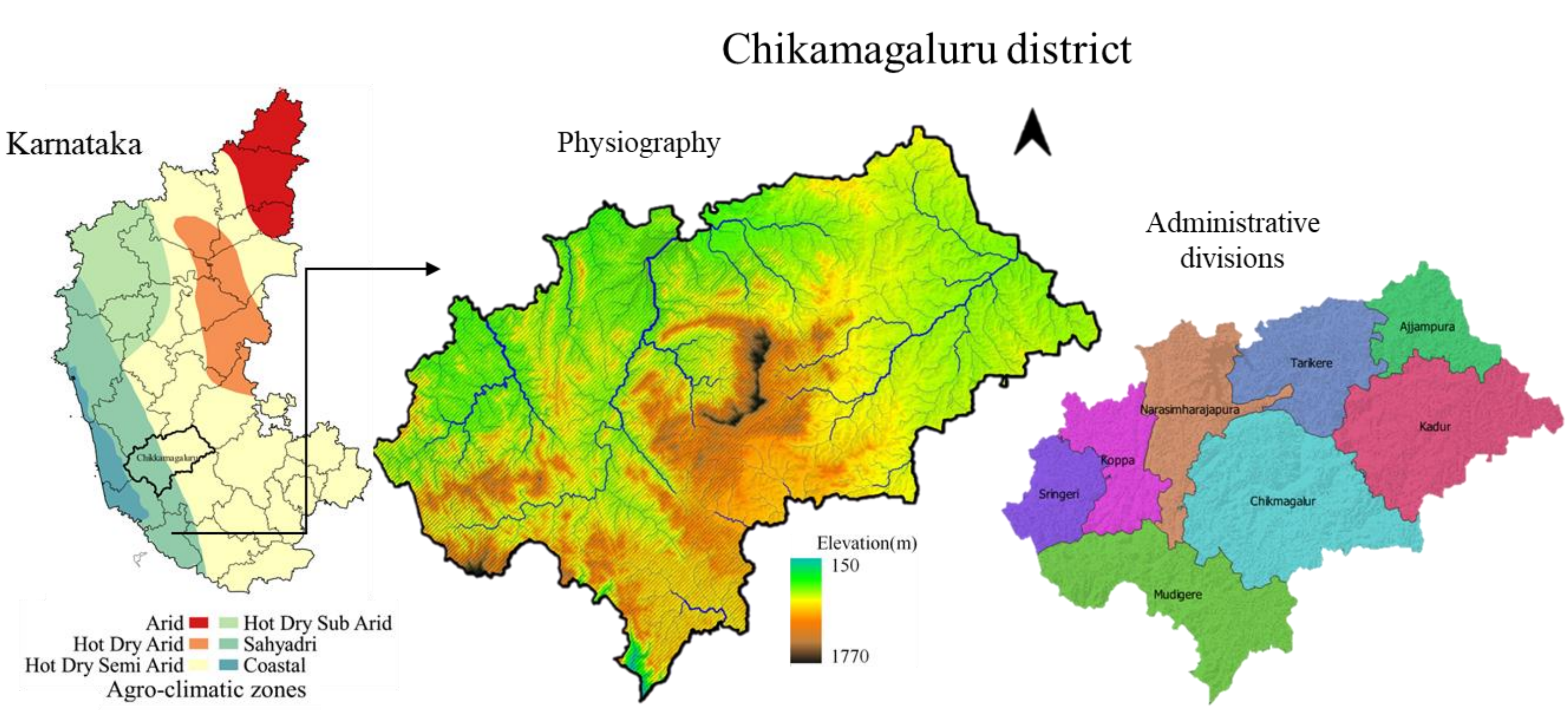
2.1. Study Area

Chikamagaluru district, with a spatial extent of 7101 sq. km (3.8% of Karnataka), lies in the south-western part of Karnataka between 12° 54' 42" and 13° 532 53" N and 75° 04' 46" and 76° 212 50" E (Fig 1). The district landscape spans three agro-climatic zones the hilly zone (Chikamagaluru, Koppa, Mudigere, Narashimharajpura, and Sringeri), the central dry zone (Kadur), and southern transition zone (Tarikere). The district of Chikamagaluru is divided into two distinct regions, the western part being a forested hilly area known as the 'Malnad' area. In contrast, the eastern part is dominated by a plain region or 'Maidan' area. The forest cover in the district is managed by five administrative forest divisions, including Chikamagaluru, Koppa, Bhadravathi, Kudremukh National Park, and Bhadra Wildlife Sanctuary. The vegetation in the district can be broadly categorized into four types: dry deciduous hill type, moist deciduous type, evergreen type, and Sholas and Grassland type. Mullayanagiri, the highest peak in the district, rises 1926 meters above MSL. The major rivers in the district are Tunga and Bhadra, while other perennial rivers include Hemavati, Netravati, and Vedavathi.

The major horticulture crops grown in the district are areca nut, coconut, black pepper, banana, mango, cardamom, ginger, and vegetables. Due to the presence of extensive hilly areas, the climate in the district is pleasant, with April being the hottest month, with a mean daily maximum temperature of 36°C and a mean daily minimum temperature of 19°C. The average annual rainfall in the Chikamagaluru district is 1925 mm, ranging from 595 mm to 2379 mm.

Chikmagaluru district consists of seven administrative taluks - Chikamagaluru, Kadur, Koppa, Mudigere, Narashimharajapura, Sringeri, and Tarikere (Ajjampura and Tarikere taluks as per the 2021 statistical report). According to the 2011 Census, the district has a total population of 1137961, accounting for 1.9 per cent of the state's population, and ranks 25th in Karnataka. About 81 per cent of the population lives in rural areas, while the remaining 19 per cent live in urban areas. The district is well-connected by road to Hassan, Mysore, Bangalore, Shivamogga, Udupi, and Mangaluru, and the nearest airports are Mysore and Mangalore. There are two railway junctions at Kadur and Birur. The economy of the district is primarily based on rural agriculture and supplemented by tourism income.

Figure 1: Location of Study Area – Chikamagaluru District, Karnataka, India



Source: Authors' Compilation

2.2 Method

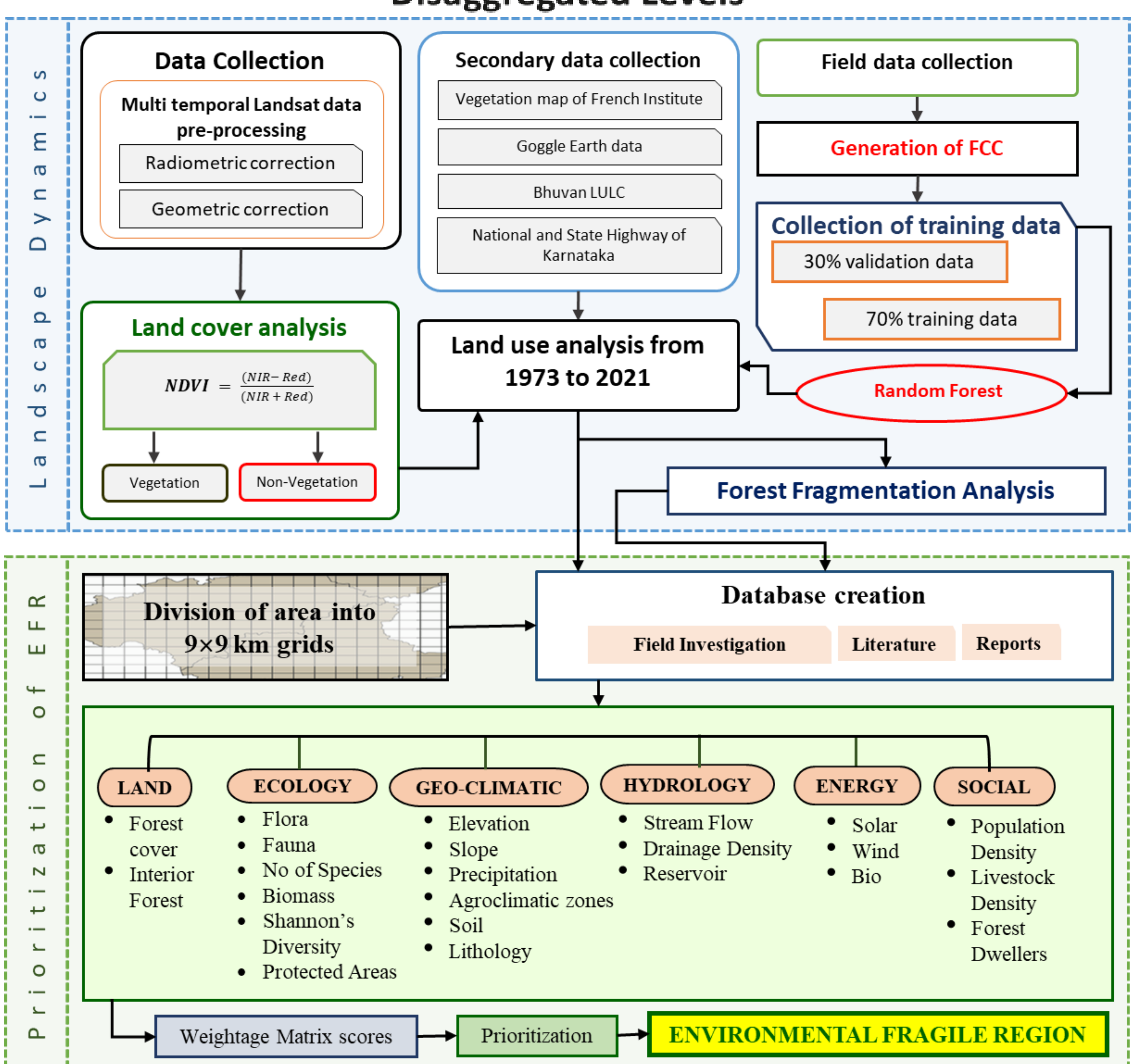
The method adopted for assessing LULC changes and prioritising livelihood lifeline regions (LLR) or ecological fragile regions (EFR)in Chikamagaluru district, Karnataka State, India, at disaggregated levels, is outlined in Figure 2.

2.1.1. Land use Land cover (LULC) dynamic

Land cover analyses involving delineation of the district into vegetation and non-vegetation, through computation of the Normalized Difference Vegetation Index (NDVI).

Land use dynamics were computed using temporal remote sensing data (1973 to 2021) through RFC, a supervised machine learning algorithm in the Google Earth Engine platform[5]. Remote sensing data was analyzed by (i) pre-processing of RS data to maintain geometrical and radiometric consistency, (ii) generation of false color composite (FCC) using NIR, Red, and Green spectral bands of Landsat data, which helps in identifying

Figure 2: Protocol for Analyses of Landscape Dynamics and Prioritization of LLR/EFR at Disaggregated Levels



Source: Authors' Compilation

[5]Retrived from : https://earth.google.com

heterogeneous patches in the landscape, (iii) digitizing training polygons in FCC (corresponding to heterogeneous patches spread across and covering at least 15 per cent of the district and supplemented with digitation from the Google Earth image. 70 per cent of the training polygons were used in the supervised classifier RFC), and (iv) validation of classification considering 30 per cent of training polygons

Random Forest Classifier (RFC) is a supervised machine learning algorithm that classifies data into various LU considering several decision trees on various subsets of the given dataset and takes the average value to improve the predictive accuracy of that dataset (Breiman 1996, Breiman, 2001). RFC is designed to handle the prediction from each tree, and predict the final output based on the majority votes of predictions. The land use information is cross-verified with the collateral data such as (i) the vegetation map of South India of the French Institute[6], (ii) vegetation maps from Karnataka Forest Department[7], and (iii) the Survey of India (SoI) topographic maps[8].

LU change (per cent) for each category was calculated considering base year (1973) and current year (2021) data as per equation 1.

2.1.1. Prioritization of LLR/EFRs

EFR or LLR refers to vulnerable areas with high sensitivity and fragility based on the environmental aspect, where anthropogenic activities can cause large-scale disturbances in the natural habitats, affecting the ecosystem processes. The district was divided into 5'X5' grids (9 km X 9 km) equivalent to a grid in the Survey of India topographic map of 1: 50000 scale to calculate the Environmental Fragile Regions (EFRs) at disaggregated levels. Grid-based (disaggregated level) mapping is a standardized approach to collecting spatial data that efficiently compiles large datasets where the output can be consistent and comprehensible. Each grid was assigned values according to its landscape dynamics, ecological, bio-geo-climatic, hydrological, locally available energy resources (renewable), and social characteristics data, which were compiled from field surveys and supplemented with the information from published scientific literature, published

Equation 1

$$\text{Change Rate} = \left(\frac{\text{Land use area of current year} - \text{Land use area of base year}}{\text{Current year} - \text{base year}}\right) * 100 \quad \ldots..(1)$$

[6]Retrived from : https://www.ifpindia.org/bookstore/fmsi-mp6/

[7]Retrieved from : https://aranya.gov.in/aranyacms/images/Maps/Mosaic/Forest%20Type.pdf

[8]Retrieved from : https://www.surveyofindia.gov.in/

datasets (Karnataka Forest Department), forest administrative reports, district statistics (district at a glance), etc. The study region is delineated based on a cumulative weightage metric score at disaggregated levels based on multi-disciplines knowledge (Termorshuizen and Opdam, 2009).

Landscape dynamics essentially provide the extent of temporal land uses and condition of the forest (contiguity of forests - interior forests, etc.). Ecology consists of flora and fauna, biomass, carbon sequestration, no of species, Shannon's diversity, and protected areas under reserve forests, conservation areas, sacred groves, etc. Geo-climatic parameters refer to the various geological and climatic parameters such as rainfall, elevation, slope, soil, agro climatic zones, and lithology. Hydrological parameters include drainage density, stream flow, and reservoir presence. The prospect of renewable energy like solar, wind, and bioenergy has also been considered. The social aspects included population density, the presence of forest dwellers, and livestock density. Finally, a weightage matrix was used to generate weights for each variable of various themes, considering the relative significance of themes (equation 2).

An indicator defines each criterion mapped to a value normalized from 10 to 1. The value 10 corresponds to a significantly higher priority for conservation. The value 7, 5, and 3 corresponds to high, moderate, and low levels of conservation. The approach is based on the standard protocol or framework (Beinat, 1997) for weighing ecologically fragile regions, as it provides an objective and transparent system for combining multiple data sets together. The weightages, based on an individual representation and illustrated extensively on GIS techniques, stand out as the most effective method. For this study, the weights are assigned as per earlier research (Table 1, Ramachandra *et al.*, 2018).

Equation 2

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

where,
n is the number of variables,
W_i is the weight associated with criterion I, and
V_i is the associated variable value.

The aggregated weightage for each grid is generated and grouped based on mean and standard deviation to determine the various levels of fragility. EFR 1 (or LLR 1) represents ecologically highly fragile, requiring strict conservation measures, EFR 2 (LLR 2) is less fragile than EFR 1, except degradation of some forest patches. EFR 3 (LLR 3) represents a moderate conservation region, and EFR 4 (LLR 4) represents less fragility. Identifying EFR/LLR at disaggregated levels would help conserve ecologically fragile regions and implement location-specific developmental activities required for the welfare of local residents.

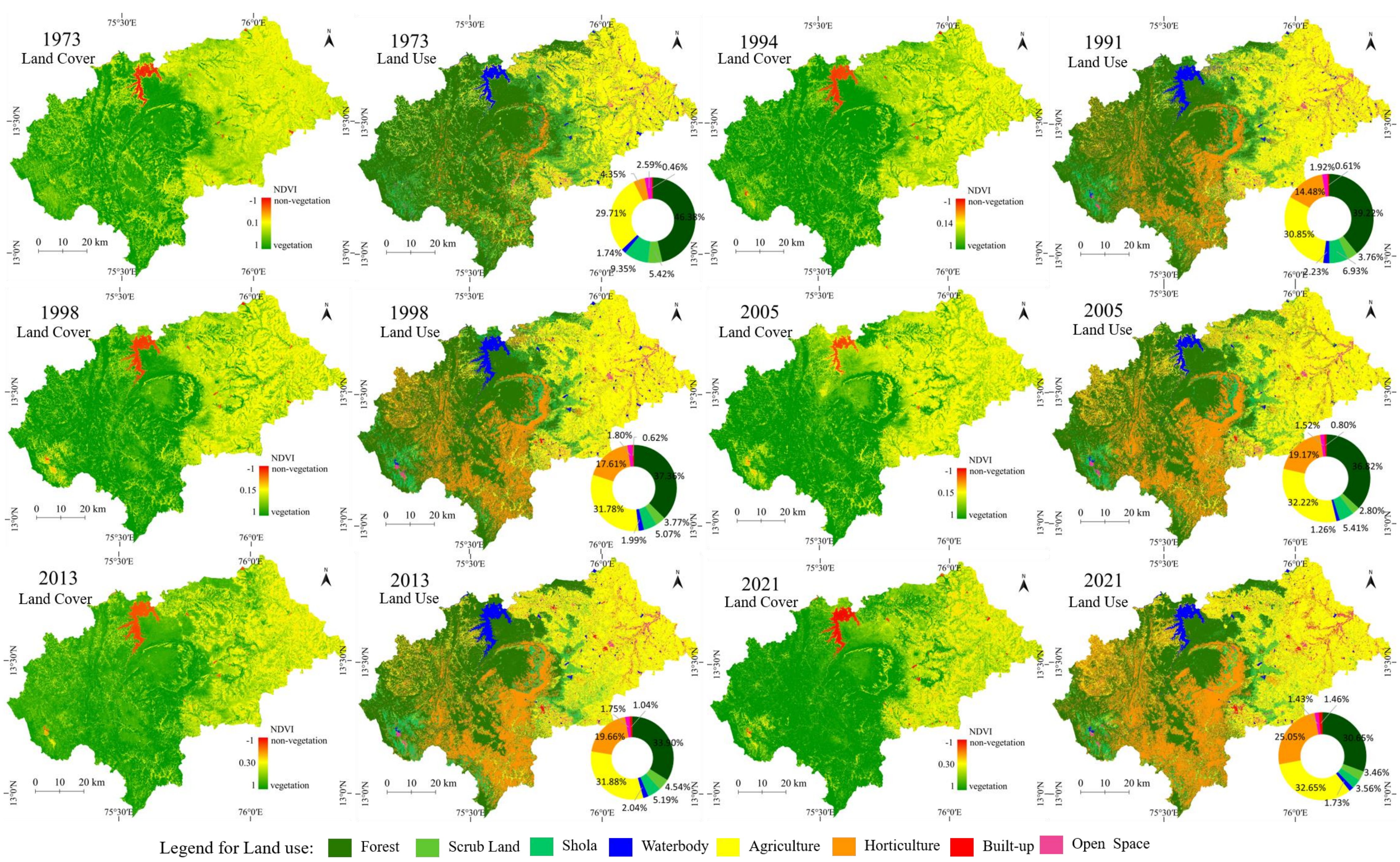
3. Results

3.1. Land Use Land Cover Analysis

Temporal LULC analyses were carried out using remote sensing (Landsat series) data from 1973 to 2021 through RFC. Figure 3 depicts land cover and land use in Chikamagaluru, with the Western Ghats region having higher forest cover. The district has witnessed large-scale LU transitions, evident with the decline of forests from 46.38% (1973) to 30.65% (2021), or from LC showing a decline in vegetation cover from 65.5% (1973) to 62.73% (2021). Large tracts of forests were lost due to developmental activities such as constructing dams and reservoirs, land conversion for built-up areas, agriculture (croplands and horticulture), etc.

Table 1 lists category-wise LU dynamics, which highlights an increase in the built-up cover from 0.46% (1973) to 1.46% (2021),

Figure 3: LULC of Chikamagaluru from 1973 to 2021



Source: Authors' Compilation

Table 1: Land uses of Chikamagaluru from 1973 to 2021

		1973	1991	1998	2005	2013	2021	Change
Forest	sq. km	3345.44	2828.66	2695.07	2656.15	2445.31	2210.96	-2363.5
	%	46.38	39.22	37.36	36.82	33.90	30.65	-32.77
Shola forest	sq. km	390.77	271.17	272.04	201.81	327.32	249.61	-294.09
	%	5.42	3.76	3.77	2.80	4.54	3.46	-4.08
Scrub land	sq. km	674.65	499.93	365.35	390.32	374.29	256.98	-870.14
	%	9.35	6.93	5.07	5.41	5.19	3.56	-12.06
Waterbody	sq. km	125.84	160.93	143.28	90.67	146.94	124.48	-2.83
	%	1.74	2.23	1.99	1.26	2.04	1.73	-0.04
Agriculture	sq. km	2143.02	2225.07	2292.52	2324.31	2299.71	2355.09	441.81
	%	29.71	30.85	31.78	32.22	31.88	32.65	6.13
Horticulture	sq. km	313.43	1044.68	1270.18	1382.50	1418.43	1807.16	3111.93
	%	4.35	14.48	17.61	19.17	19.66	25.05	43.14
Open space	sq. km	187.04	138.61	130.09	109.65	125.91	103.27	-174.52
	%	2.59	1.92	1.80	1.52	1.75	1.43	-2.42
Built-up	sq. km	32.83	43.95	44.49	57.61	75.09	105.47	151.33
	%	0.46	0.61	0.62	0.80	1.04	1.46	2.10

agriculture from 29.71% (1973) to 32.65% (2021), and horticulture from 4.35% (1973) to 25.05% (2021). The decline in the spatial extent of forests, and scrub lands highlights the need for sustainable LU policies to arrest land degradation and deforestation. The natural forests show a decline, evident from the decrease in evergreen forests from 800.14 sq. km (1973) to 706.38 sq. km (2021), shola forest 390.77 sq. km (1973) to 249.61 sq. km (2021), moist deciduous forests from 1960.01 sq. km (1973) to 1139.64 sq. km (2021), dry deciduous forests from 457.41 sq. km (1973) to 368.03 sq. km (2021) and scrub forest from 674.65 sq. km (1973) to 56.98 sq. km (2021). The Bhadra wildlife sanctuary and Kudremukh National Park have the densest forests in the district. Large-scale monoculture plantations of eucalyptus, rubber, acacia, teak, and areca nuts have increased by replacing the forest areas. These abrupt changes have resulted in the imbalance of ecosystems, affecting the hydrologic regime and availability of natural resources.

Table 2: Accuracy of LU classification

Accuracy Assessment	evergreen	moist deciduous	dry deciduous	scrub	shola forest	waterbody	open space	cropland	fallow land	horticulture	built-up	rocky surface	Kappa statistics	Overall Accuracy
Commission	24.4	16.6	14	32	44	0	26	22	16	22	33	43	0.857	90.212
Omission	29.4	22.5	23	32	52	6	25	26	13	13	66	22		

An accuracy assessment of LU classification was done through the computation of category-wise accuracies and Kappa statistics. Table 2 lists the category-wise accuracies, which indicate that the overall accuracy and kappa statistics show 90.21% and 0.85, respectively.

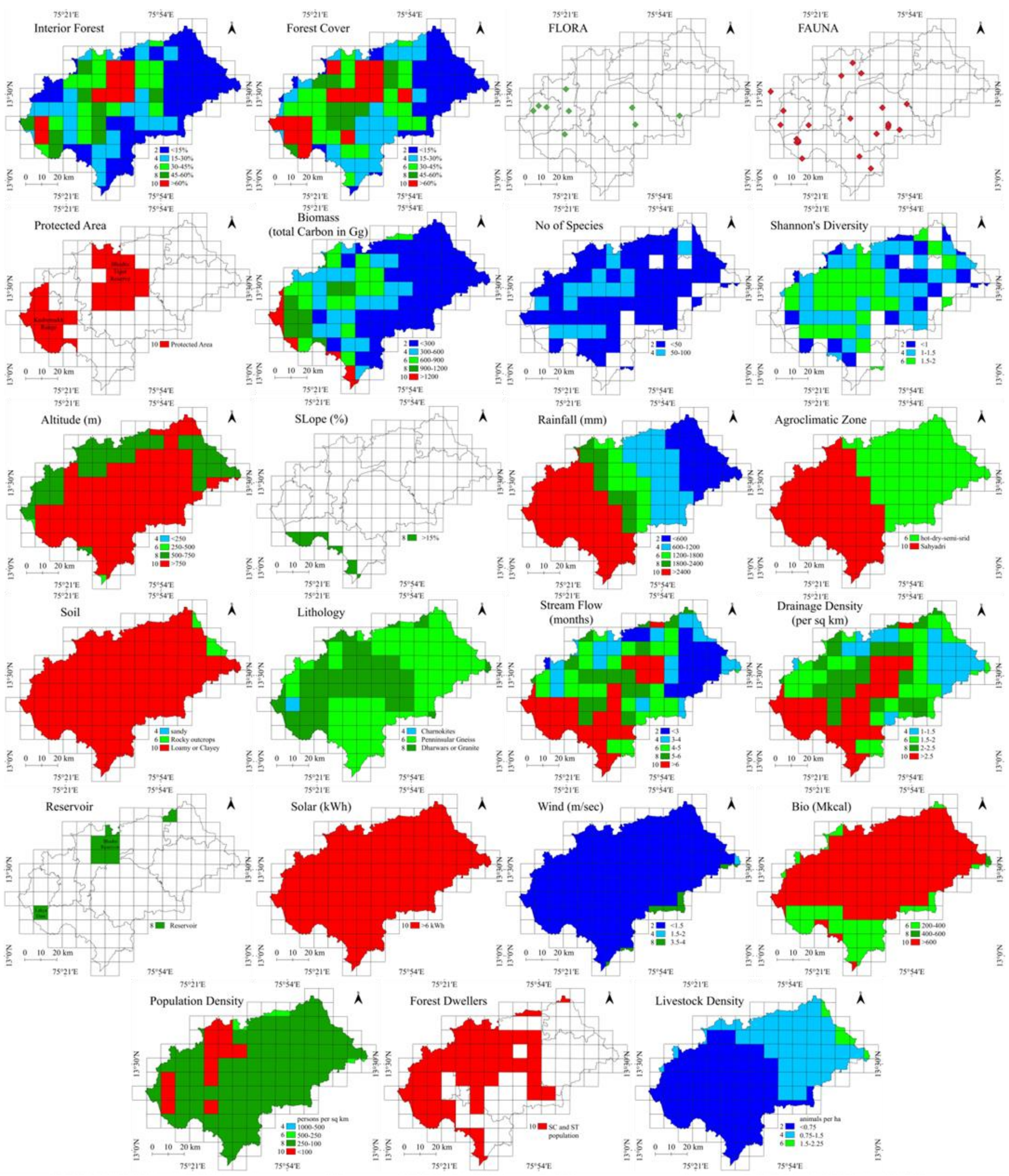
3.2. Ecological Fragile Regions (EFR)

Attribute data of ecology, geo-climate, land, energy potential, hydrology and social aspects were compiled (Figure 4), and weights were assigned and aggregated grid-wise to delineate the EFR/LLR at disaggregated levels.

Chikamagaluru district has a dense evergreen forest at the Kudremukh forest range in the western part and a deciduous forest in the middle section, including Churchegudda Reserve Forest, and Kalesapura Reserve Forests. The maidan region in the eastern part of the district has a forest cover of <30 %. Intact contiguous (interior forests) forests are in Narasimharajapura and Sringeri taluk.

The ecology of Chikamagaluru district was assessed from the data of flora, fauna, biomass and carbon, abundance of species, Shannon's diversity, the status of conservation reserves, etc. The spatial distribution of endemic flora and fauna compiled from the field through transect - quadrats-based vegetation and fauna sampling. The presence of numerous endemic species of flora and fauna highlights of the ecological significance of the district. The density of species and Shannon's diversity are higher in the forest areas of the district. The biomass concentration is higher in the evergreen forests and has >1200 Gg total carbon, while deciduous forests have 300-900 Gg total carbon. Bhadra tiger reserve and Kudremukh forest range are the protected areas in the district.

Figure 4: Weights of Bio-Geo-Climate-Social Variables, Assigned Grid-Wise, Chikamagaluru District



Source: Authors' Compilation

The district has an average elevation of >750 m, and some parts in the east and north have 250-500m elevation. The slope is less than 15% in the whole district except in the Kudremukh Range in Mudigere taluk. The district has a decreasing rainfall pattern from west to east. The Western Ghat section receives an annual rainfall of >2400 mm, the middle part of the district with forest cover receives 1200-2400 mm, the middle part without forest cover receives 600-1200 mm, and the eastern part receives <600 mm of rain. The district has two agroclimatic zones - the Western Ghats or Sahyadri in the west and hot-dry-semi-arid in the east. The eastern and southwestern part of the district comprises Peninsular Gneiss, and the higher elevated regions are composed of Dharwars or Granite area. Loamy or clayey soil is found in the whole district.

Chikamagaluru district has Tunga, and Bhadra rivers in the western hills and Vedavathi River in the east. The streams in the forest region have >6 months of water availability, and rivers in the plain region have <3 months of water. Similarly, forested hilly areas have >2.5 per sq. km drainage density, and the plain area has 0.5-1 per sq. km drainage density. The Bhadra reservoir in this district is one of the biggest reservoirs in Karnataka.

The whole district has more than 6 kWh of solar energy potential. Also, the entire district has less than 1.5 m/sec wind speed throughout the year. Bioenergy potential (Ramachandra and Gunasekaran, 2019) is >600 MKcal in the district except in the Western Ghats region.

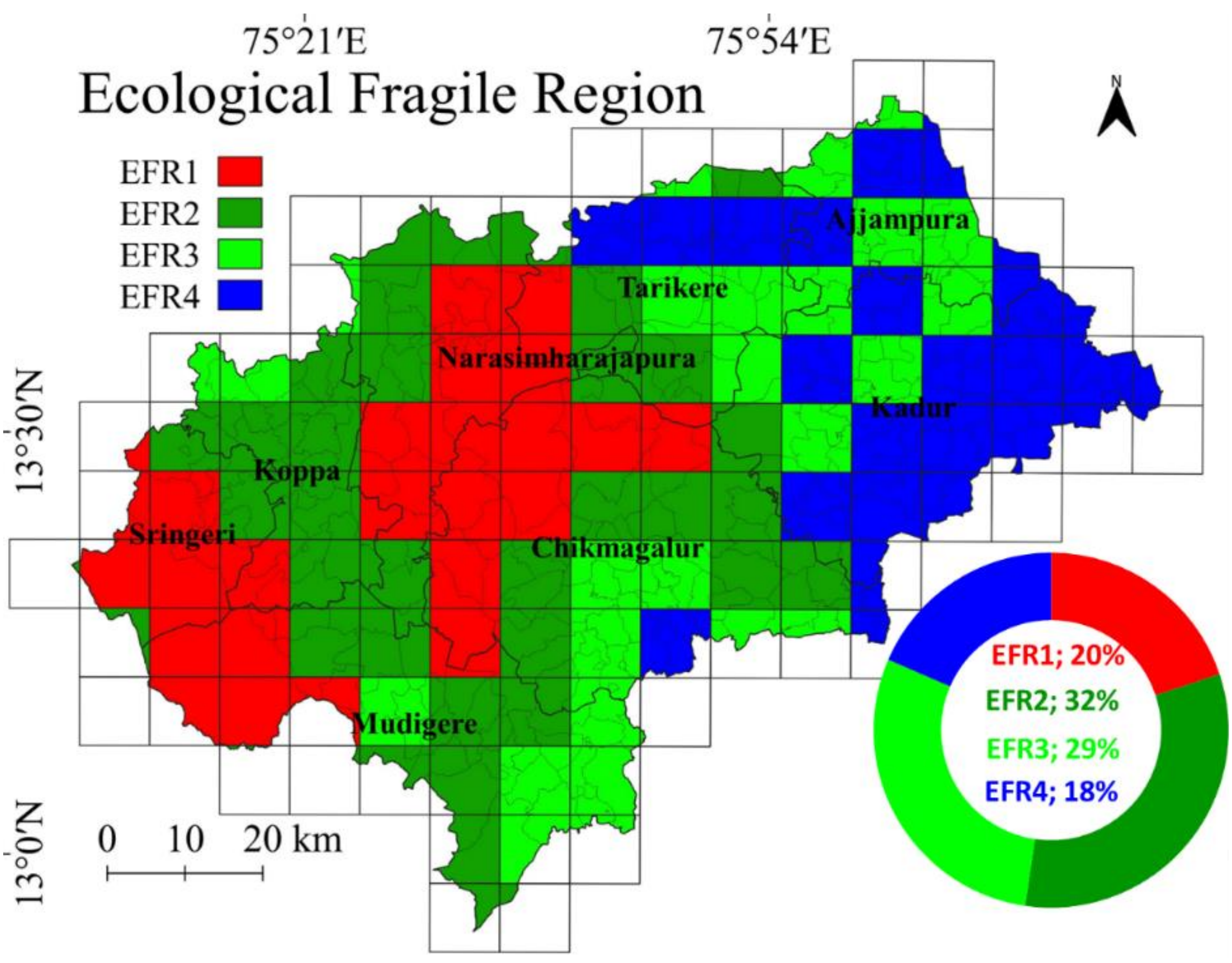
The population density is 250-100 persons per sq. km in the whole district except Narasimharajapura and Sringeri taluk, where the population density is <100 persons per sq. km. Livestock density is 2.25-3 animals per ha in the eastern part and 1.5-2.25 animals per ha in the western part. The presence of forest dwellers is identified at Narasimharajapura, Koppa, and Sringeri taluk.

The aggregated weights (Figure 4) were analysed (frequency distribution), and grids were prioritized based on the relative score to delineate Ecological Fragile Regions (EFRs) or Livelihood Lifeline Regions (LLR).

Chikamagaluru district has been classified into four level of ecological fragility where each level is interconnected with other. Results reveal that 25 grids are EFR1, 38 are EFR2, 30 are EFR3, and 28 are EFR4 (Figure5).

EFR1 represents a zone of highest conservation and requires stringent conservation norms without further degradation. The protected areas and evergreen forests are under EFR1 zone. EFR2 has the potential to become EFR1 provided with strict regulations and improvement of forests. A small change in EFR2 can have more adverse effects on EFR1, so it is recommended to impose a complete ban on the over-exploitation of forest resources. The study highlights the critical role of active stakeholder participation, particularly involving local communities, in the conservation of forests. The delineation of Environmental Fragile Regions (EFRs) at a granular level has been identified as a valuable tool for policy formulation for effectively managing land resources in the Chikamagaluru region. The study stresses the importance of protecting Livelihood Lifeline Regions, spanning from EFR1 to EFR3 to sustain the livelihoods of local people while ensuring the preservation of natural resources. The research findings are expected to contribute to policy development for

Figure 5: Grid-Based and Gram Panchayet Based Ecological Fragile Regions of Chikamagaluru



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implementing sustainable development practices. The goal is to enhance livelihood options for local communities while minimizing further degradation of ecosystems in the region. Planting native endemic species would maintain the balance and ensure the sustenance of water (throughout a year), while improving biodiversity and pollination services (higher yield) to sustain the livelihood of local people.

4. Conclusion

Ecological Fragile Regions (EFRs) Livelihood lifeline regions (LLR) are delineated at disaggregated levels in the Chikamagaluru district of Central Western

Ghats using temporal LU information based on machine learning algorithm with bio-geo-climatic, hydrologic, ecological and social variables.

LULC analysis showed a continued decline of 2363.5 sq. km of forest cover from 1973 to 2021, with increased agricultural and horticultural lands. Built-up areas have also increased by 151.33 sq. km with increased industrial and infrastructure development.

The prioritization of Ecological Fragile Regions at disaggregated levels revealed that highly sensitive EFR1, covers 20% of the district. The delineation of EFRs at disaggregated levels helps in policy formulation to manage land resources and suggesting landslides mitigated measures for in Chikamagaluru (Ramachandra et al., 2020). Livelihood lifeline regions (EFR1 to EFR 3) are to be protected to sustain livelihood of local people with the sustenance of natural resources. The outcome of the research would aid in policy formulations toward implementing sustainable development practices to enhance livelihood options with the minimisation of further degradation of ecosystems.

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