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Insights into the linkages of forest structure dynamics with ecosystem services

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Large-scale land cover changes leading to land degradation and deforestation in fragile ecosystems such as the Western Ghats have impaired ecosystem services, evident from the conversion of perennial water bodies to seasonal, which necessitates an understanding of forest structure dynamics with ecosystem services to evolve appropriate location-specific mitigation measures to arrest land degradation. The current study evaluates the extent and condition of forest ecosystems in Goa of the Central Western Ghats, a biodiversity hotspot. Land use dynamics is assessed through a supervised hierarchical classifier based on the Random Forest Machine Learning Algorithm, revealing that total forest cover declined by 3.75% during the post-1990s due to market forces associated with globalization. Likely land uses predicated through the CA-Markov-based Analytic Hierarchy Process (AHP) highlight a decline in evergreen forest cover of 10.98%. The carbon sequestration potential of forests in Goa assessed through the InVEST model highlights the storage of 56,131.16 Gg of carbon, which accounts for 373.47 billion INR (4.49 billion USD). The total ecosystem supply value (TESV) for forest ecosystems was computed by aggregating the provisioning, regulating, and cultural services, which accounts for 481.76 billion INR per year. TESV helps in accounting for the degradation cost of ecosystems towards the development of green GDP (Gross Domestic Product). Prioritization of Ecologically Sensitive Regions (ESR) considering bio-geo-climatic, ecological, and social characteristics at disaggregated levels reveals that 54.41% of the region is highly sensitive (ESR1 and ESR2). The outcome of the research offers invaluable insights for the formulation of strategic natural resource management approaches.

Inventorying, mapping, and monitoring of ecosystems

Changes in the climate, evident from the increase in temperature and erratic rainfall regimes, have been posing serious challenges to the sustenance of natural resources. The impact extends to individual species, influencing their interactions with other organisms and their habitats[1], altering the structure and functioning of ecosystems, which impacts goods and services[2]. A crucial aspect lies in understanding the direction and magnitude of ecological responses, enabling human communities to predict these changes and adapt proactively[3,4]. This entails inventorying, mapping, and monitoring ecosystems at regular intervals to update natural resource management plans. Additionally, these assessments play a crucial role in evaluating the effectiveness of adaptation actions. These insights contribute to a better understanding of the implications of climate change, enabling informed decision-making and strategic planning for sustainable and resilient ecosystems.

Land degradation

India has been experiencing desertification in most states and Union territories, and about 97.85 million hectares (29.77%) were impacted by land degradation due to the loss of vegetation cover and subsequent topsoil erosion accounting for 11.01% of degradation in the country in 2018-19, majorly contributed by Rajasthan, Maharashtra, Gujarat, Jammu & Kashmir, Karnataka, Jharkhand, Odisha, Madhya Pradesh, and Telangana States[5]. The most

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significant process of desertification or land degradation in the Goa State is evident from escalating (37.32% in 2011-13 and 35.74% in 2003- 05) degradation[6].

Goa, Central Western Ghats: global biodiversity hotspot

The Central Western Ghats landscape, spanning across Karnataka, Goa, and Maharashtra states, is endowed with exceptional ecological significance, evident from rich biodiversity, perennial rivers, Myristica swamps (with a higher proportion of critically endangered and endangered endemic biotic species), prominent geological features, captivating beauty, rich cultural heritage locations (sacred groves), etc[7]. Goa state, with its exceptionally rich diversity of flora and fauna, hosts a diverse array of species across various habitats, including forests, coastal areas, and marine ecosystems. Notably, Goa harbors about 7% of the endemic flowering plant species found in the Western Ghats[8]. The region is home to over 3,000 species of plants and flowering trees, including several IUCN Red-listed species such as *Myristica fatua var. magnifica*, *Semecarpus kathalekanensis*, and *Syzygium travancoricum*[9]. The mangrove flora in this region comprises 15 distinct types distributed across 10 genera and 7 families dominated by *Rhizophora mucronata*, *Sonneratia alba*, and *Avicennia officinalis*[10]. The fauna includes about 50 mammal species, such as tigers, foxes, wild boars, and guars, along with over 473 bird species. Among these, 11 species are endemic to the Western Ghats, and 19 are threatened species[11]. Additionally, Goa's biodiversity encompasses a variety of reptiles, including 23 snake species, and other reptiles such as crocodiles, lizards, and turtles, particularly in mangrove and coastal areas (Goa Tourism). The marine ecosystem is equally diverse, with over 224 fish species, numerous crustaceans like gastropods (86 species), bivalves (19 species), shrimps (17 species), crabs (51 species), lobsters, and hermit crabs, and a diverse array of mollusks[12–14].

Forest ecosystems

Forests are essential ecosystems, covering approximately 30% of the earth's surface[15]. The forest ecosystem, with interconnected communities of microorganisms, plants, animals, soils, water, and climate, interacts with each other in a biologically and ecologically integrated manner[16–18]. The spatial extent of forests, including tree cover in India, is 82.74 million hectares, 25.17% of the geographical area[19]. Quantifying the spatial extent and condition of forest ecosystems provides valuable insights into strategic planning to ensure the sustainability of natural resources[20]. Alterations in the extent or conditions of forests due to unplanned human activities have far-reaching impacts on ecosystem services, which are crucial for human well-being[21]. Forest fragmentation is the process involving the fragmentation of contiguous forests into smaller and isolated patches, with alterations in the hydrologic regime, microclimate, enhancing predation, increasing fire susceptibility, higher instances of human-animal conflicts, the decline in plant and animal communities, dispersing seeds, and pollinating services impacting the sustenance of natural resources[22–26]. Additionally, fragmentation collectively disrupts vital ecological processes, decreases carbon sequestration capability, enhances carbon emissions, and exacerbates the negative consequences[27,28].

Ecosystem services

Forests contribute significantly to ecosystem services, offering extensive support directly or indirectly to both nature and human well-being. They provide various provisioning services, such as food, medicine, timber, water, litter, and latex. Additionally, forests offer regulating services (carbon sequestration, climate change mitigation, air quality monitoring, pollination, flood control, and soil productivity) as well as cultural services (recreational services, aesthetic services)[15,29,30]. Carbon sequestration is the pivotal service provided by forest ecosystems to regulate global warming and make ecosystems more resilient to climate change[31–33]. Quantifying carbon emissions and sinks is crucial for informed decisions with effective and sustainable forest management strategies. Global forests sequester 359 billion tonnes of carbon, highlighting the pivotal role in maintaining carbon balance[34,35]. The carbon stock in Indian forest ecosystems amounts to 7,204 million tonnes[19], highlighting the need for appropriate forest management practices[36]. Natural capital accounting and valuation of ecosystem services (NCAVES) will aid in ascertaining the economic and social significance of natural ecosystems[37] through quantification of provisioning, regulating, and cultural services and provide insights into the cost of environmental degradation and associated market failures in the current economic accounting[38,39]. NCAVES is crucial for guiding policy decisions toward promoting sustainable resource management, as it enables the comparison of ecosystem services with other economic commodities[40–42]. Recent research underscores the importance of adopting a more holistic approach to value natural assets, highlighting their capacity to support prudent decision-making and conservation initiatives[39].

Ecologically sensitive regions (ESR)

Ecological sensitivity refers to the eternal and irreparable loss of extant life forms or significant impairment to the natural processes of evolution and speciation with the alterations in the ecological integrity of a region[43]. Alterations in the structure of forest ecosystems due to overexploitation of resources, the introduction of invasive species, pollution, climate change, etc., will have detrimental consequences on the biological, hydrological, and ecological functions, leading to the depletion of ecosystem services, which poses a significant threat to economic activity and human well-being[44–46]. Land degradations induced by changes in land use (LU) due to unplanned developmental activities[22] have had detrimental effects, leading to a decline in biodiversity and disruptions in the hydrological system, thereby compromising the sustenance of natural resources[15,47–51]. The comprehensive knowledge of the ecological fragility of a region is quintessential for evolving strategies for conserving the area, which entails identifying factors responsible for ecological sensitiveness, including landscape dynamics, and visualizing future transitions to mitigate the problems of haphazard and uncontrolled development approaches. Mapping of ecologically sensitive regions (ESRs) at disaggregated levels by considering the relative significance of landscape (ecosystem extent and condition), ecological, bio-geo-climatic, hydrological, energy, environmental

and social characteristics is essential for sustainable planning toward the conservation of the Western Ghats, the hottest hotspot of biodiversity[43].

Assessment of landscape dynamics using Spatial data through machine learning algorithms

Advancements in geoinformatics with the availability of multi-resolution spatial data (remote sensing data) and machine learning algorithms have gained significant attention due to their robustness and reduced computational time with complex and large datasets compared to traditional methods[52,53]. Integration of ensemble learning algorithms (ML) for the classification of multi-resolution spatial data acquired through space-borne sensors (such as Landsat, Sentinel, etc.) has enhanced the accuracy of LU classification, which is crucial for environmental monitoring through understanding the landscape dynamics for informed decisions of sustainable land management and policy interventions[54,55]. Commonly used ensemble learning algorithms include Random Forest (R.F.), Support Vector Machines (SVM) and Artificial Neural Networks (ANN), in LU classification[56–59] and earlier studies have demonstrated that among non-parametric supervised classifiers, R.F. performs better in the classification of LU for undulating terrain such as the Western Ghats using multispectral moderate resolution data[60,61]. R.F. is computationally efficient when dealing with large datasets containing more parameters and fewer biases than other ML classifiers, which require extensive training on large amounts of labeled data and significant computational resources[62,63]. Also, RF provides intrinsic feature importance metrics, which are beneficial for understanding the contribution of individual features in classification[64–66].

Prediction of likely land uses

Inventorying, mapping, change analyses, modeling, and visualization of landscape dynamics provide empirical evidence of the consequences of spatial changes[50,67,68]. Land use modeling for visualization of likely land uses would provide vital insights for implementing sustainable development strategies and preserving biological and cultural diversities[68–70]. Predictive statistical and geospatial models for landscape dynamics being employed are spatial dynamics models, spatial Markov chains (MC), Cellular automata (CA), multi-criteria decision-making (MCDM), etc. In this context, agent-based modeling (ABM) has been widely used for land use modeling, considering diverse characteristics of agents and the heterogeneous nature of landscapes within a temporal scale and geographical space in a spatially explicit and multi-scale manner with the incorporation of social and environmental processes in decision-making at disaggregated levels[71,72]. Multi-criteria evaluation (MCE) for land use planning involves assessing various alternatives by considering multiple factors, including environmental impacts, economic viability, and social implications. MCE techniques facilitate complex decision-making processes through the simultaneous evaluation of multiple objectives and constraints[73]. Integration of MCE through a range of factors, which is assigned a weight based on its relative importance, would help in determining the optimal development conditions[74,75]. Factors considered are (i) driving agents with spatial attributes with the potential to have a negative or positive impact and (ii) constraints[76,77]. The Analytic Hierarchy Process (AHP) in MCE uses pair-wise comparisons (as a means of measurement) and relies on the expertise and judgments of individuals to establish priority scales and assess the consistency of importance[78–80].

AHP[81–84] enables the creation of a hierarchical structure in the decision-making process, incorporating both qualitative and quantitative factors while allowing the users to determine the weights of the factors[83,85]. AHP offers a framework for identifying and rectifying inconsistencies while judging the relative importance of factors[86], which aid in selecting the most suitable option for predicting likely land-use changes and effectively represents individual decision-making with temporal and spatial dynamics[87–89].

Forest structure dynamics in the Goa state of Central Western Ghats were assessed through temporal land uses to understand the impact of (i) the prevalent practice of shifting cultivation (slash and burn practice) till the annexation of Goa to the Indian Union (1961), (ii) mining in core forest areas during the post-independence period, and (iii) unplanned developmental activities subsequent to globalization and relaxing markets (1990s), which led to the spurt in the anthropogenic activities involving large scale infrastructure projects, industrialization, etc. Studies pertaining to the assessment of the forest structure dynamics with the factors affecting the fragmentation, which impacts integrity and biodiversity in Goa, are scanty. There is limited research on natural capital accounting and valuation of ecosystem services, despite Goa being endowed with mangroves and terrestrial forests with rich biodiversity and the crucial role of ecosystems in sustaining natural resources, which necessitated comprehensive interdisciplinary research integrating ecological, economic, and social perspectives to support sustainable management of Goa's diverse ecosystems. The current study investigates (i) forest structure dynamics using temporal remote sensing data (of 1973 to 2022) in Goa state, Central Western Ghats by employing a supervised hierarchical classification based on the Random Forest Machine Learning Algorithm, (ii) the condition of forests through computation of fragmentation metrics, (iii) predicts and geo-visualizes likely land uses in 2038 through MCE and the AHP by considering agents of urban development (major roads, minor roads, industrial estates, railways, proposed layouts) and factors contributing to the degradation of natural resources, which will help to evolve strategies for prudent natural resources management as per the Sustainability Development Goals (SDG) as per the 2030 agenda for Sustainable Development, (iv) evaluation of the carbon storage potential of the forest ecosystem, (v) prioritization of Ecologically Sensitive Regions (ESR) at disaggregated levels, and (vi) valuation of forest ecosystem services across various levels of ecological sensitivity.

Results

Land cover

Normalized Difference Vegetation Index (NDVI) provided land cover, presented in Fig. 1, which aided as a key indicator of the spatial extent of vegetation. Supplementary Table S1 provides temporal land cover details, which reveal that in 1973, vegetation occupied 2347.43 sq. km (63.41%) and witnessed changes subsequently, and the
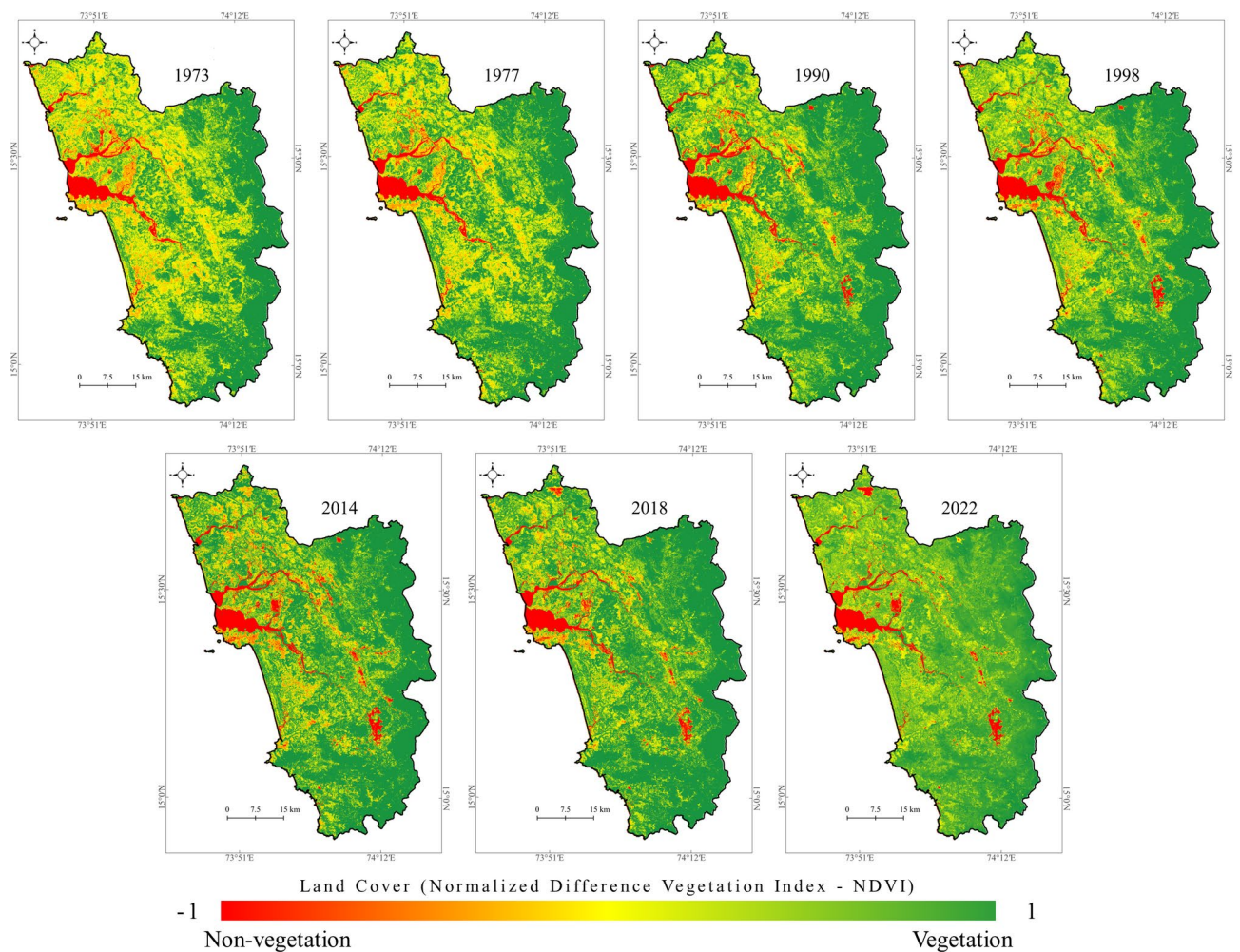
Fig. 1. Land cover dynamics in Goa, Central Western Ghats. Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

highest cover was observed in 1990 (2474.76 sq. km, 66.90%). The land cover changes are indicative of land use changes with anthropogenic influences.
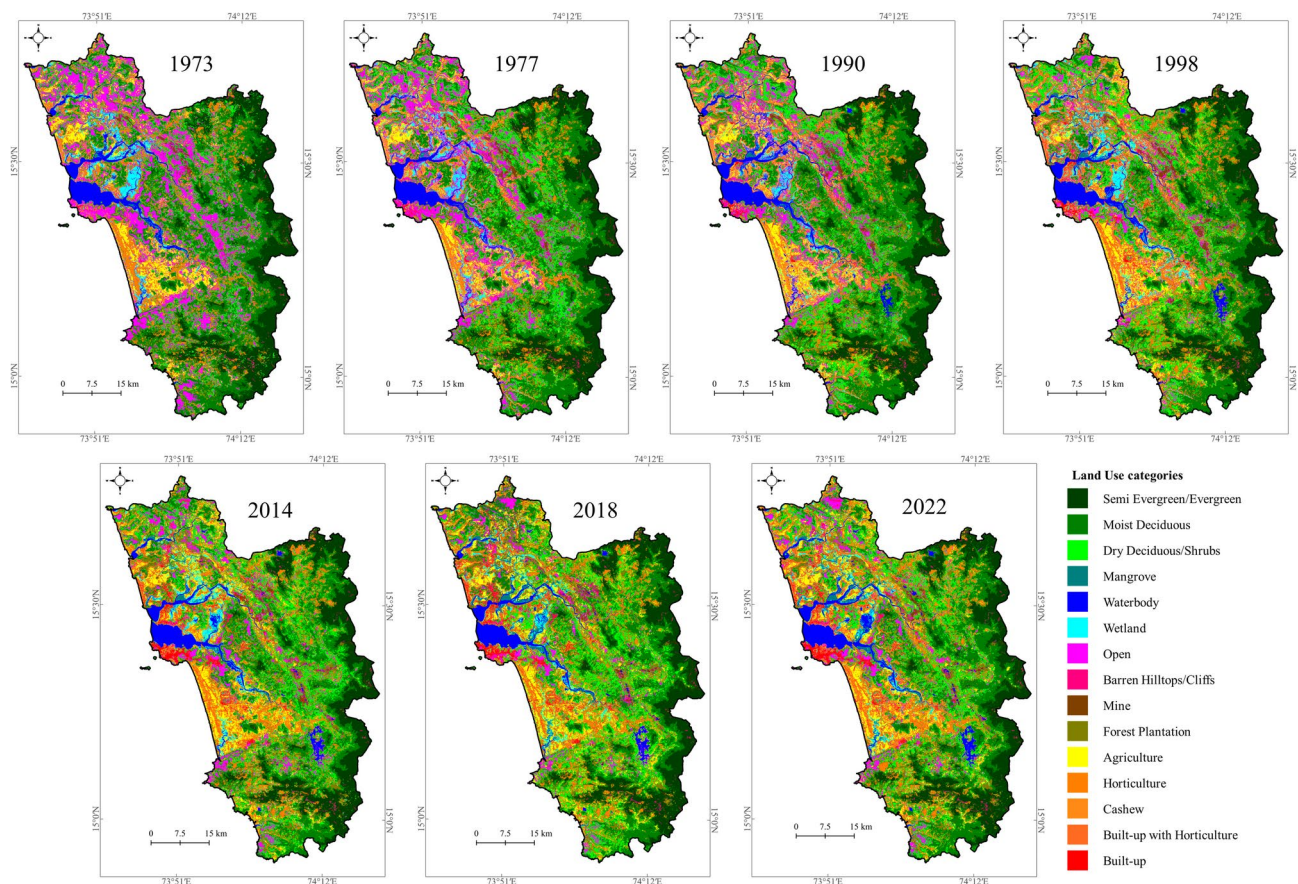
Land use

The land use dynamics assessed over the last five decades (1973–2022) using remote sensing data, given in Fig. 2, reveal that the extent of evergreen forests increased from 495.12 sq. km (13.37%) in 1973 to 520.34 sq. km (14.06%) in 1998, due to the regeneration of evergreen species with stringent forest protection measures (Supplementary Table S2). However, a decline in evergreen forests during the post-globalization period (1990s) is evident from the spatial extent of 497.31 sq. km (13.43%) in 2022. Moist deciduous forest cover declined from 1029.43 sq. km (27.81%) in 1977 to 838.04 sq. km (22.64%) in 2022. Dry deciduous and shrubland areas increased notably, from 477.03 sq. km (12.89%) in 1973 to 616.99 sq. km (16.67%) in 2022, which suggests degradation of forest ecosystems with a shift in vegetation composition towards more arid or semi-arid ecosystems.

Open spaces experienced a substantial reduction from 711.19 sq. km (19.21%) in 1973 to 207.1 sq. km (5.59%) in 2022 due to urban expansions with the consistent growth in built-up areas from 22.2 sq. km (0.6%) in 1973 to 180.94 sq. km (4.89%) in 2022. Urbanization with the decline of native vegetation cover exacerbates hydrological processes, leading to increased runoff and reduced water retention[25,90]. The loss of vegetation cover contributes to increased soil erosion and alters water quality, as more sediment and pollutants enter water bodies. Unplanned developmental activities have contributed to rapid urbanization leading to sprawl with the expansion of major cities such as Panaji, Mormugao, Ponda, and Mapusa and industrial areas like Verna, which has profound impacts with fragmentation of ecosystems, resulting in biodiversity losses and erosion of essential ecosystem functions[23]. This process leads to significant declines in species richness and genetic diversity, with smaller and more isolated forest fragments experiencing the greatest biodiversity loss due to reduced habitat size and increased isolation[91].

Supplementary Figure S1 highlights the trends in land use transitions. The agricultural landscape expanded, with croplands peaking at 333.5 sq. km (9.01%) in 2018, and horticultural areas steadily increased to 416.39 sq. km (11.25%) in 2022 from 337.63 sq. km (9.12%) in 1973. Cashew plantations witnessed a steep increase in the

Fig. 2. Land use dynamics in Goa. Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

last five decades, covering 4.26% of the Goa landscape. Mining activities were at the peak in 1998, covering 41.47 sq. km (1.12%). Monoculture plantation of exotic species like *Acacia auriculiformis*, *Tectona grandis*, *Eucalyptus globulus*, *Casuarina equisetifolia L.*, *Hevea brasiliensis*, and others increased from 0.89% (1973) to 2.43% (2022). Supplementary Table S2 provides land use transitions, highlighting the need for land cover monitoring to address emerging environmental challenges and foster landscape resilience through sustainable land use practices.

Land use modeling

Prediction of likely land uses was made in two scenarios: (i) a Business-as-usual (BAU) or natural increase scenario, and (ii) an agent-based simulation of land use, Analytical Hierarchical Process (AHP) CA-Markov method using Multi-Criteria Evaluation (MCE). The modeling outcome is validated by comparing the actual land uses of 2022 with the simulated land uses of 2022. In the case of the BAU scenario, the accuracy is $K_{no} = 0.8376$, $K_{location} = 0.8344$, $K_{locationStrata} = 0.8344$, and $K_{standard} = 0.794$. While in AHP-based modeling, the accuracy is $K_{no} = 0.8417$, $K_{location} = 0.8344$, $K_{locationStrata} = 0.8344$, and $K_{standard} = 0.7998$, which highlights agreement between actual and simulated land uses. Hence, this approach was adopted for predicting likely land uses in 2038. In both scenarios, the Built-up increases, suggesting urbanization or infrastructure development, and the percentage of native forest decreases, indicating further degradation in the forest ecosystems (Fig. 3).

The predicted land uses listed in Supplementary Table S3 reveal that the spatial extent of evergreen forests is expected to decline to 10.67% (BAU) and 10.98% (AHP), and moist deciduous land cover remains relatively stable at 22.64% from 2022 to 2038 in BAU scenario, while AHP scenario indicates a decline to 19.74% (2038). Dry deciduous and shrubs increase under the BAU scenario to 20.52% (in 2038) from 16.67% (2022), indicating a shift towards drier vegetation types, while the AHP scenario shows a minimal change, and the spatial extent would be 16.64%. Mangrove forests and wetland ecosystems show an increasing trend in BAU (spatial extent of 1.69% and 2.41%, respectively) and a decreasing trend in the AHP scenario (1.06% and 1.85% respectively) compared to 1.38% and 2.36% respectively in 2022. Waterbodies are likely to decline in both BAU (to 3.30%) and AHP scenarios (4.19%) from 4.77% (2022). On the other hand, open land cover shows a decreasing trend in both scenarios (Current 5.59%, BAU 5.14%, AHP 4.82%), reflecting increasing urbanization or infrastructure development. Agricultural land is projected to expand in BAU (9.34%) from 2022 (7.42%) but decline in the AHP scenario (6.65%) due to the conversion of agricultural lands into horticultural land, paved surfaces, etc. Horticulture shows a substantial increase in the AHP scenario (spatial extent of 13.69%) compared to BAU
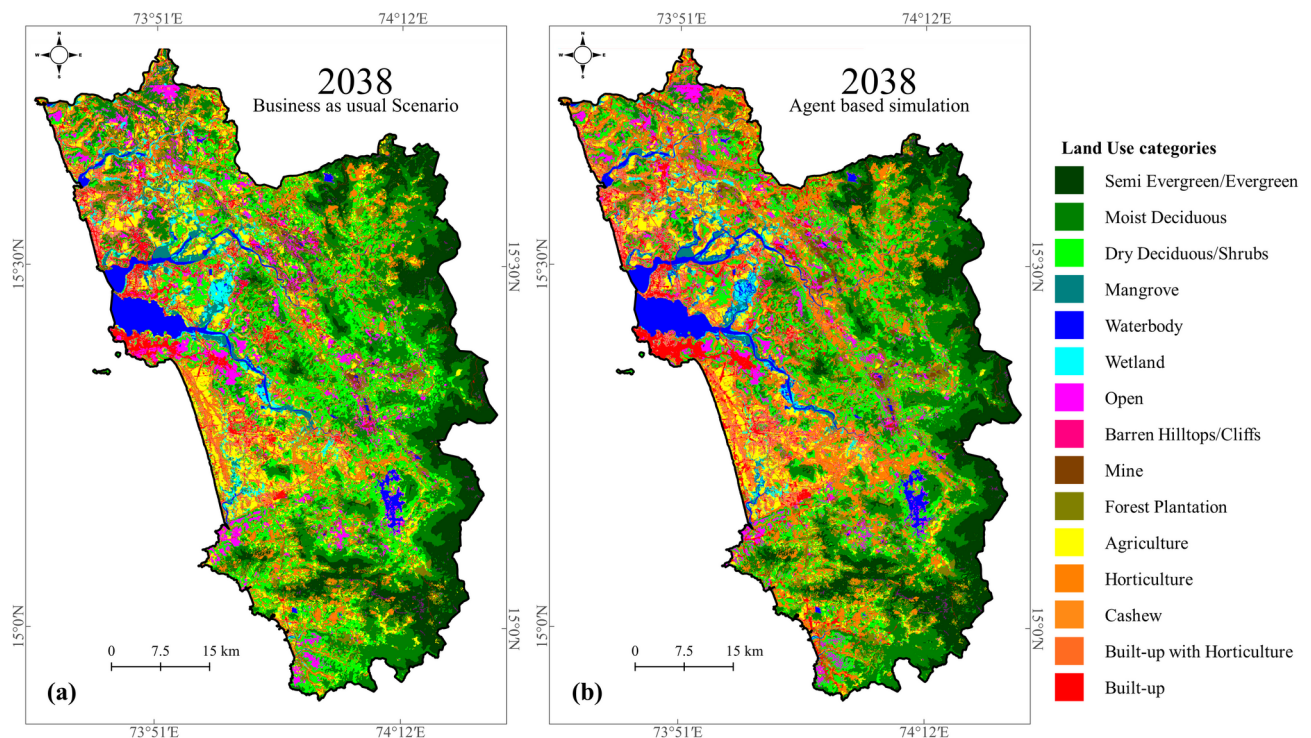
Fig. 3. Predicted land uses of 2038 in (a) Business-as-usual Scenario and (b) Agent-based scenario. Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

(8.32%). The agriculture and allied sectors contribute less than 5% to the state's GDP, but their share in the Gross Value Added (GVA) at current prices is substantial, amounting to INR 55,06,000[92].

Urbanization is expected to intensify in both scenarios, with a notable increase under AHP (6.31%) compared to BAU (5.79%), and current spatial extent of 4.89%). The area under Built-up with horticulture also shows a significant rise in both scenarios. The area under mining is expected to increase from 0.61% (2022) to 0.7% (2038) in BAU and 0.84% in the AHP scenario. The plantation area of exotic species shows a noteworthy increase to 5.23% in the AHP scenario compared to 2.56% in BAU from 2.43% in 2022. The analysis of land use dynamics for 2038 under BAU and AHP scenarios, presented in Supplementary Table S3, highlights that these changes would pose challenges in balancing economic activities with environmental sustainability. The AHP scenario, characterized by multi-criteria evaluation, presents more robust land use estimates than BAU scenario.
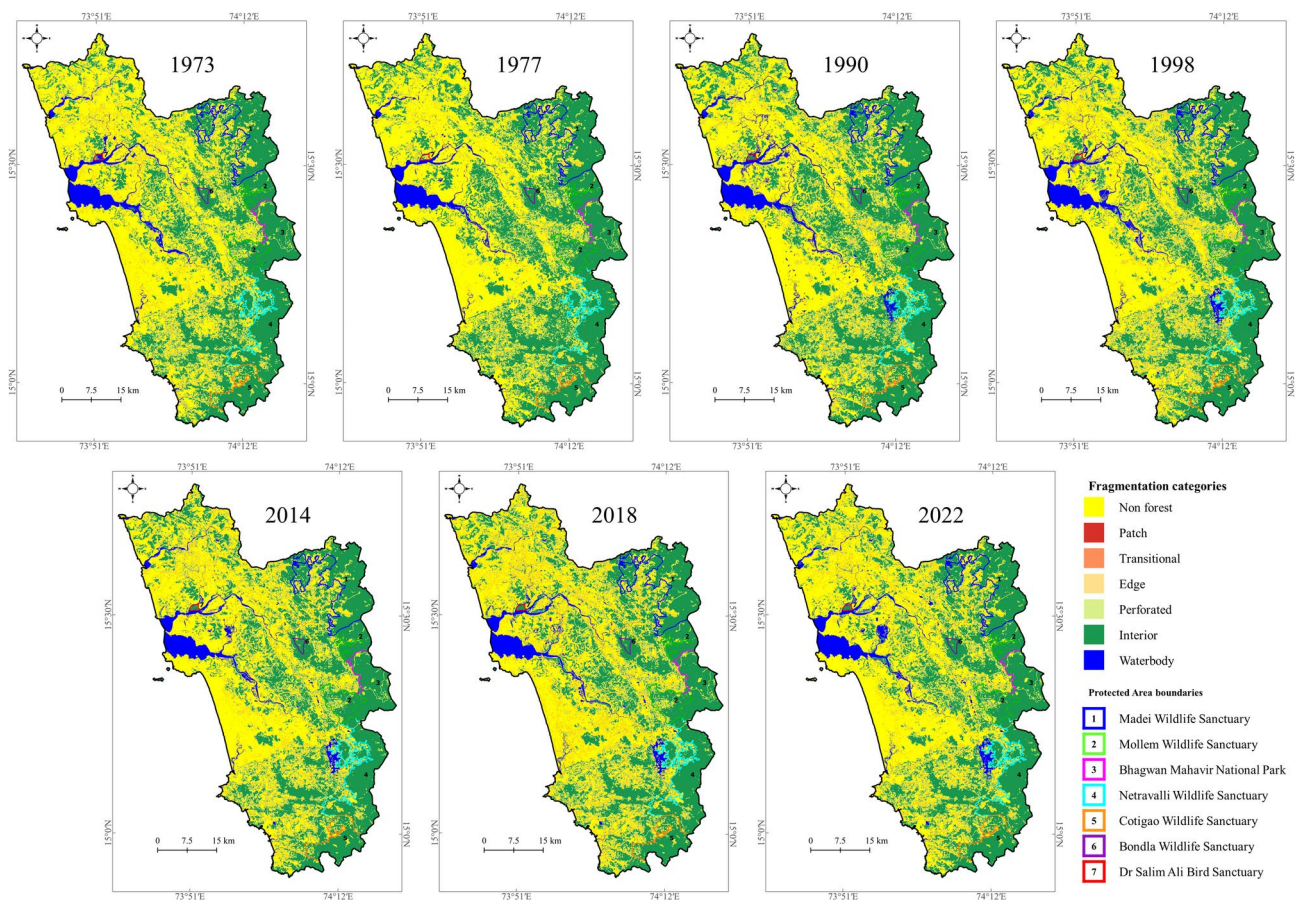
Condition of forest ecosystems

The condition of forest ecosystems assessed through fragmentation metrics (Fig. 4, Ecological significance in Supplementary Table S4) and results are listed in Supplementary Table S5, which highlights interior forest of 1398.38 sq. km (42.45%) in 1973, increased to 1571.47 sq. km (42.45%) in 1977 due to forest regeneration with the stringent forest conservation measures. However, degradation was noticed after 1977, as the interior forest decreased to 1375.06 sq. km (37.14%) in 2022 (Fig. 4). Meanwhile, the non-forest area decreased from 1590.53 sq. km (1973) to 1410.84 sq. km (1990) and then increased to 1590.22 sq. km (2022). The fragmentation of forests restricts animal movement, leading to inbreeding with gene extirpation and, eventually, the extinction of endemic species. Additionally, their isolation diminishes adaptability to environmental changes, which enhances vulnerability to diseases[93]. The loss of biodiversity also erodes ecosystem services (such as pollination, pest control, etc.) which are crucial for maintaining healthy ecosystems[94].

Supplementary Figure S2 depicts the dynamics of forest fragmentation from 1973 to 2022. Figure 5 illustrates intact forests (interior), and various levels of fragmentation (such as patch, perforated, edge, transition, etc.). The principal agents of fragmentation of forests include anthropogenic activities of agricultural and horticultural (including coconut, cashew, and other horticulture), mining and waste dumping, construction of buildings, expansion of roads and power lines through forested areas, and large-scale plantations of exotic monoculture species like *Acacia auriculiformis*, etc. Monoculture plantations have detrimental effects on the overall resilience of the ecosystem evident from the reduced infiltration of precipitation, decline of pollinators, soil micro-organisms, etc[25,95]. The absence of diverse plant species disrupts ecological interactions, potentially impairing the ecosystem's ability to withstand environmental stresses and maintain essential ecological processes[95,96].

Carbon sequestration

Carbon sequestration in forest ecosystems is accounted for through field data collection and the compilation of information from published literature[30,39,97], which are listed in Supplementary Table S6. Supplementary Figure

Fig. 4. Assessment of the condition of the Forest ecosystem of Goa.Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

S3 depicts the spatial variability of carbon, which highlights that very dense forested areas are endowed with higher biomass (44012.40 Gg). Moderately dense and degraded forests represent 2320.09 Gg and 7051.61 Gg of carbon. The total quantum of carbon sequestered is 53384.11 Gg in the forest ecosystems (based on 2022 land use) (Fig. 6). The ecosystem supply value of carbon sequestration service is calculated by considering the social cost of carbon per ton as US$ 80 using the GDP deflator[39,98]. The carbon sequestration from forests is quantified through the InVEST model (https://naturalcapitalproject.stanford.edu/software/invest), which shows that the carbon sequestration ranges from 292.84, 15.44, and 46.92 billion INR for very dense, moderately dense, and degraded forest ecosystems.

Figure 6 highlights the spatial variability of mangroves (51.16 sq. km), which store carbon of 2747.05 Gigagrams (Gg). Notably, the carbon sequestration service of forest ecosystems amounts to 18.28 billion INR, highlighting the role of mangrove ecosystems in sustaining livelihood while mitigating changes in the climate. The carbon sequestration values of very dense, moderately dense, and degraded mangrove ecosystems are highlighted in Supplementary Figure S4.

Prioritization of ecologically sensitive regions (ESR)

Ecologically Sensitive Regions (ESR) in Goa have been prioritized at disaggregated levels for the decentralized governance of fragile ecosystems through insights into ecological fragility by considering landscape (ecosystem extent and condition), ecological, geo-climatic, hydrological, energy availability, and social characteristics. Table 1 illustrates that 33.82% and 20.59% of the region are under ESR1 and ESR2, which depicts the highest ecologically sensitive zones. ESRs with attribute information can be geo-visualized virtually in WGSDSS - Western Ghats Spatial Decision Support System (https://wgbis.ces.iisc.ac.in/sdss/wgsdss/index.php)[13]. ESR1 and ESR2 are ecologically highly fragile, and these regions are to be protected without any anthropogenic developmental activities ESR3 and ESR4 cover 16.18% and 29.41% (Fig. 7), where sustainable development should be practiced with prudent management while protecting critical natural resources.

Valuation of ecosystem services (VES)

Ecosystem services have been quantified as per the UN-SEEA framework[39,99]. Table 1 lists the provisioning services, regulating services (including Carbon sequestration), cultural services and total ecosystem supply value (TESV) of the forest ecosystem. The total ecosystem supply value (TESV) of forest ecosystems in Goa amounts
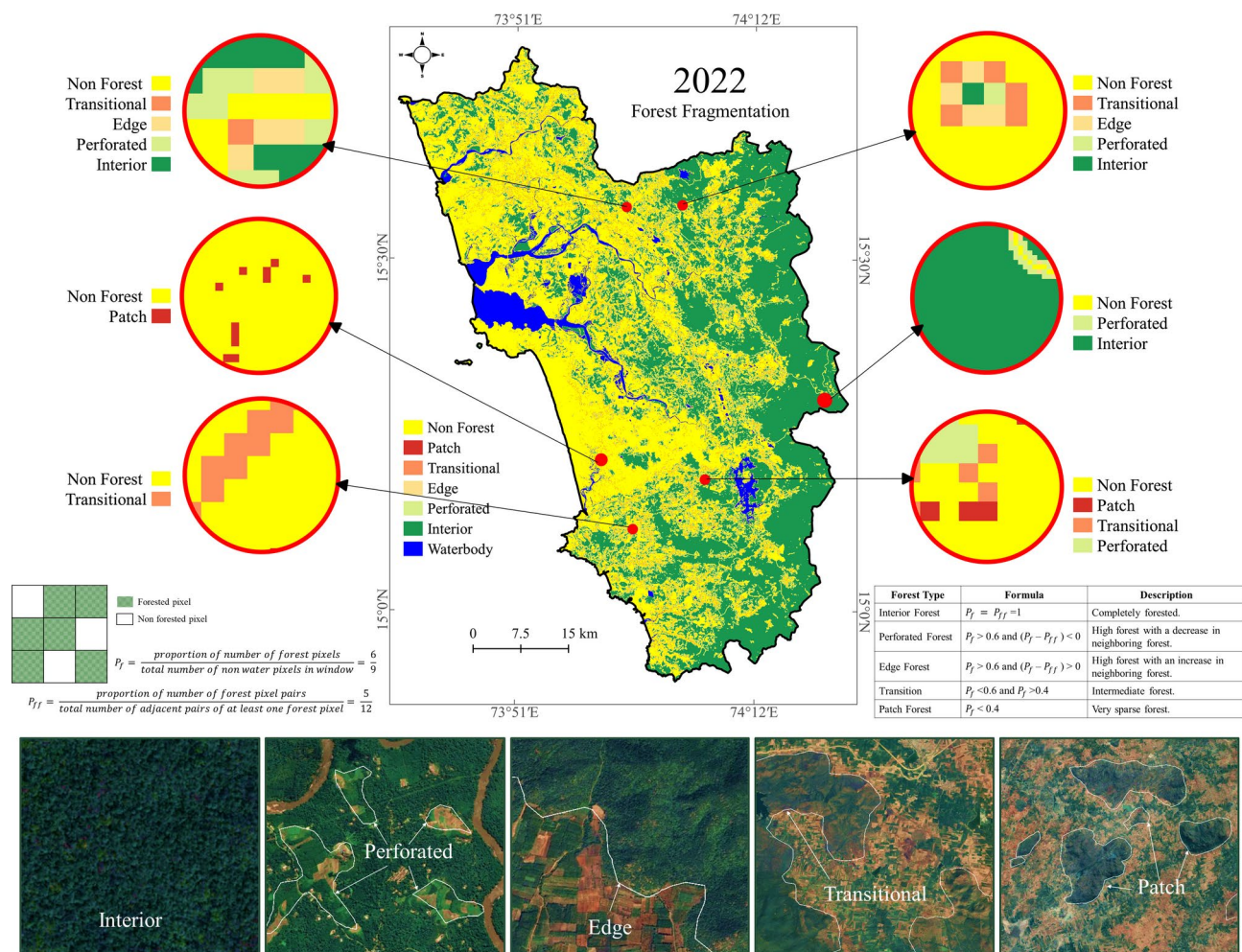
Fig. 5. Condition of forest ecosystems (highlighting various levels of fragmentation). Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].
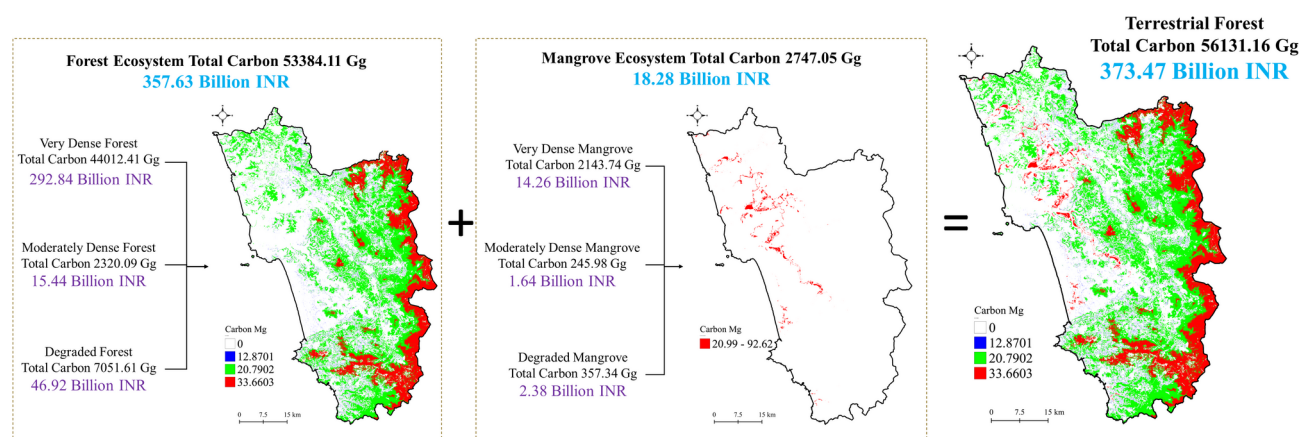
Fig. 6. Carbon sequestration services of terrestrial forest ecosystems in Goa. Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

Details	Ecological sensitiveness				
	ESR1	ESR2	ESR3	ESR4	Total
Spatial extent of Forest ecosystem (ha)	90988.81	57514.94	20070.60	22133.89	**190708.24**
Ecosystem services					
Provisioning Million ₹	25742.48	16548.29	6040.15	6753.03	55083.95
Regulating Million ₹	219764.82	108028.27	38371.87	40076.59	406241.55
Cultural Million ₹	9550.45	6139.41	2240.89	2505.37	20436.11
Total Ecosystem Supply Value (TESV)					
TESV Million ₹	255057.75	130715.97	46652.91	49334.98	481761.61
TESV Billion ₹	255.06	130.72	46.65	49.33	**481.76**

Table 1. Quantification of ecosystem services of forest ecosystem (based on eco-sensitiveness) of Goa. Bold indicates significant values.
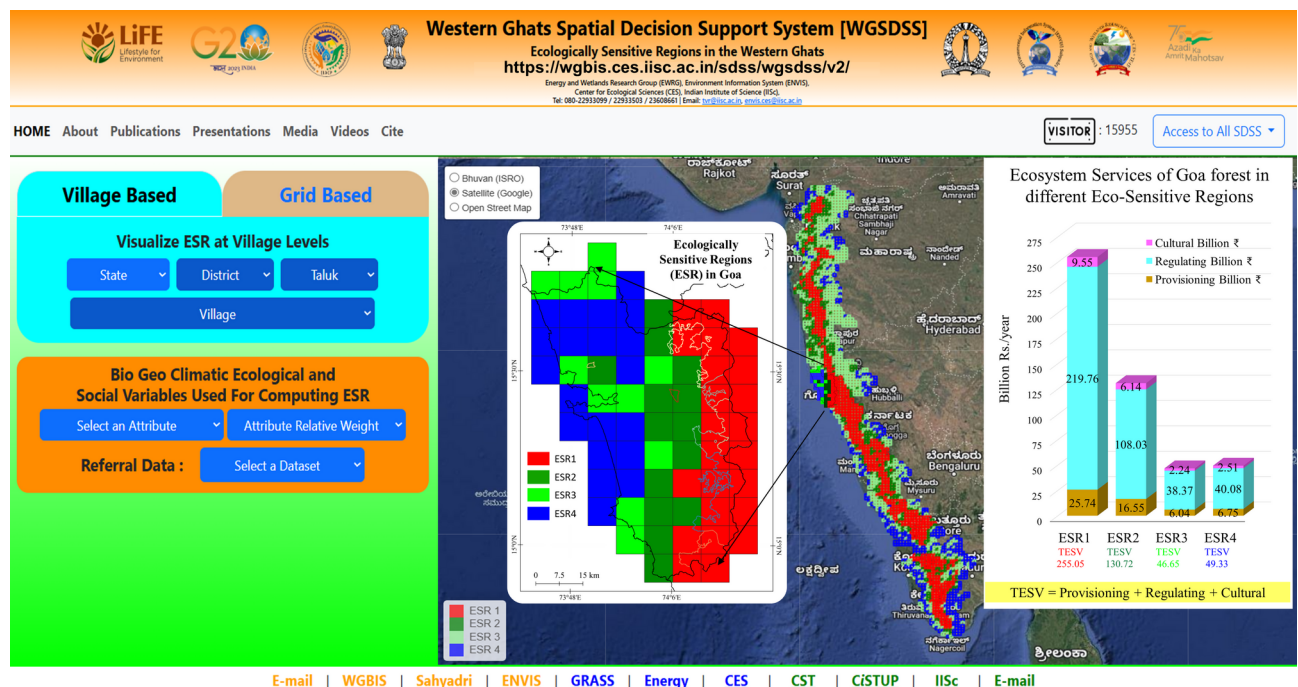
Fig. 7. Visualization of eco-sensitive regions at disaggregated levels through the Western Ghats Spatial Decision Support System (WGSDSS - https://wgbis.ces.iisc.ac.in/sdss/wgsdss/v2/).

to 481.76 billion INR (2022). Provisioning services constitute 12%, regulating services 84%, and cultural services 4% of TESV (Fig. 7).

Discussion

Forest ecosystems in Goa provide diverse services vital for human well-being and economic prosperity, and valuing these services is crucial for prudent management through informed decision-making. TESV accounts for 481.76 billion INR/year (in 2022), with regulating services constituting a substantial 84%, which highlights the role of ecosystems in maintaining environmental health while mitigating changes in the climate. Values of the forest ecosystem services accounted for Goa, Central Western Ghats are comparable to earlier studies—(i) 456.47 billion INR /year from forests of neighboring Uttara Kannada district[95], (ii) a decline of TESV from 2,841 billion INR/year (2005) to 1,835 billion INR/ year (2019), highlights the implications of 35% decline in the forest ecosystems[39], (iii) the total economic value of Himachal Pradesh forests at 1066 billion INR per year[38], (iv) value of ecosystem services of Arunachal Pradesh State tropical forests to be 1,518 billion INR per year[41], (v) valuation of ecosystem services provided by several tiger reserves in India[40], reveal significant annual flow benefits: Corbet (US$ 227 million/year), Kanha (US$ 253 million/year), Kaziranga (US$ 150 million/year), Periyar (US$ 271 million/year), Ranthambore (US$ 128 million/year), and Sundarbans (US$ 197 million/year) (vi) the recreational value of Rajaji National Park to be 248.63 million INR/year[37].

Valuing the economic benefits of carbon sequestration provides insights for conservation through sustainable land management practices to mitigate escalating GHG footprint[100,101]. Local and regional assessments of

carbon sequestration would aid in the conservation and support of community livelihoods through informed decision-making for sustaining ecological processes[102]. The total tree carbon density for Central India varies from 48.97 to 214.97 Mg C per hectare[104]. Forest ecosystems of Goa store 56131.16 Gg of carbon, which accounts for 373.47 billion INR ($ 4.49 billion), considering $80 per ton as the social cost of carbon[39]. Similarly, carbon stored in forest ecosystems of the Western Ghats is INR 100 billion, based on a carbon trading price of INR 2142 (US$30) per tonne[30].

Large-scale land-use changes leading to land degradation and deforestation have significantly impacted the ecological functioning of forest ecosystems contributing to climate change[24,95]. Assessment of land-use dynamics reveals a 3.75% decline with globalization in the 1990s, with rapid unplanned urbanization to cater to the burgeoning population needs, infrastructure, and market demand. Goa witnessed increased forest cover (the 1970s and 1980s) with the ban on shifting cultivation after independence (1961). The Draft National Forest Policy 2018[104] stipulated one-third of forest cover to address national needs with conservation, for addressing soil erosion, forest degradation (caused by shifting cultivation), etc. The Policy emphasizes the need to maintain ecological balance to ensure environmental stability and arrest the degradation of forests. The prohibition of shifting cultivation and establishing wildlife conservation areas, national parks, and biosphere reserves supported the regrowth or regeneration of native vegetation.

Many villages of Goa have witnessed a significant decline in agricultural productivity due to environmental degradation and lowered fertility of the Khazan wetlands[105]. Understanding the drivers of land-use change at disaggregated levels would aid in prioritizing critical ecosystems for conservation. Unlike conventional prediction models, Agent-Based Models (ABM) harness dynamic simulations of actual systems, providing effective tools for forecasting future performance and taking proactive measures to manage risks. Agent-based models focus on abstract, microsocial models and uncover causal mechanisms, including climate policy analysis[106,107].

Intense mining activities had a detrimental impact on the local communities, primarily through land dispossession, lowered yield due to dust pollution, and failing health of the local population with widespread environmental damage[108,109]. Mining activities in Goa were restricted in October 2012 due to environmental concerns. Subsequently, in February 2018, the apex Court delivered a definitive judgment, declaring all mining leases in Goa are illegal because of violations of various environmental and mining regulations, including the MMDR Act, the Forest (Conservation) Act, and the Environment (Protection) Act.

Goa has undergone a significant change in the spatial extent of mangroves[110], with the abandonment of Khazan farming, and along Chapora, Mandovi, Cumbarjua, and Sal Rivers, mangroves have witnessed a remarkable resurgence. The increase in the spatial extent of mangrove cover from 19.73 sq. km to 51.16 sq. km is due to the sustained conservation and reforestation efforts with initiatives such as the declaration of Chorao Island in the Mandovi Estuary as a bird sanctuary in 1987 and the plan to develop 50 hectares of mangrove plantations annually by the Goa State Social Forestry Division as part of the National Mangrove Plan[111]. The decline in both cultivated areas with increased fallow land coincides with the diminishing interest of farmers in agricultural pursuits, attributed to low productivity and rising uncertainty in precipitation patterns[112].

Forest ecosystems are vital to sustain the balance in the global carbon cycle considering escalating anthropogenically induced rise in greenhouse gas emissions and the decline of carbon sequestration capability present a dual threat of loss of ecosystem services and exacerbation of climate change. The extent and condition of forest ecosystems are assessed using temporal remote sensing data through supervised machine learning techniques. The quantification of land use dynamics reflects the urban expansion, which is evident in the consistent increase in built-up areas from 0.6% (22.2 sq. km) in 1973 to 4.89% (180.94 sq. km) in 2022. Large-scale land-use changes leading to the decline of forests during post-1990 were due to globalization and a spurt in market activities with infrastructure development[113].

Assessment of likely land use changes using agent-based modeling indicates that there will be a further decline in evergreen forest cover in both BAU (10.67%) and AHP (10.98%), emphasizing the need for conservation efforts. Invasive species pose a significant threat to biodiversity, acting as potent drivers of ecosystem service disruption and consequently causing profound alterations in socio-economic conditions through diverse mechanisms. Monoculture plantation of exotic species such as *Acacia auriculiformis*, *Tectona grandis*, *Eucalyptus globulus*, *Casuarina equisetifolia L.*, *Hevea brasiliensis*, etc. shows a noteworthy increase in the AHP scenario (5.23%). This assessment, with insights into the ecosystem's sensitivity, vulnerability, and resilience to unforeseen changes, facilitates the development of informed biodiversity protection strategies and offers a critical decision-making framework for sustainable biodiversity protection plans, which safeguards the natural resources with the long-term flow of crucial goods and services for future generations[68].

Ecosystem services contribute to economic welfare in two ways – (i) contributions to the generation of income and well-being and (ii) the prevention of damages that inflict costs on society[39]. These benefits are accounted for in policy appraisal with a broader focus on valuing the benefits provided by ecosystems. Policy options that enhance the natural environment are more likely to be considered, demonstrating that investing in natural capital would make economic sense[99].

Goa state, India, is trying to accelerate economic growth, and there has been tremendous pressure to divert natural systems to other uses. Hence, there is an urgent need to undertake the natural capital accounting and valuation of the ecosystem services, especially intangible benefits (such as regulating services, etc.), provided by ecosystems. The value of all ecosystem services, including the degradation costs, needs to be understood to develop appropriate policies toward ecosystem conservation and sustainable management[114]. Scientific efforts during the past decade have refined the understanding of ecosystem function and demonstrated the links between ecosystem functions and the provision of ecosystem services[39,114–117]. This knowledge needs to be communicated effectively to decision-makers and the public, which will lead to developing policies that adequately consider the trade-offs between the conservation of natural resources and economic growth.

The overall assessment of the ecological services provides information for prioritizing ecosystems for sustainable land-use practices, promoting off-farm incomes to the dependent communities, restoring degraded sites, biodiversity conservation, integrated management of water resources, etc. while promoting community-based prudent management of natural resources. There is a need to enhance awareness of the protection of the environment, especially the maintenance of native forest cover, which is crucial for balanced economic and social progress in the region. Over the last few decades, though environmental legislation, policies, and programs for environmental protection and conservation of natural resources have evolved, these policies and programs have been unevenly implemented. Thus, ecosystem accounting can play a role in two ways. First, ecosystem accounts can help policymakers factor in ecosystem service benefits when making economic policies that impact natural resources and ecosystems. Second, ecosystem accounts, which are regularly compiled, can be used to help monitor the impact of these policies over time and ensure that they are being implemented properly.

Limitations of the current study

(a) Ecosystem services have varying spatial and temporal scales, such as the benefits at local levels (of provisioning services and regulating services such as soil conservation, flood mitigation, water purification, etc.), while climate regulation services are global, and valuation must consider the full geographical extent and long-term impacts of ecosystem changes.
(b) Cultural services, such as recreational and spiritual values, are difficult to monetize due to their subjective nature and can lead to underrepresenting these services in economic valuations despite their significant importance in sustaining local livelihood.
(c) There is considerable complexity in understanding and assessing the underlying links between a policy, its effects on ecosystems and related services, and valuing its impacts in economic terms. Collaboration between those working in policy, science, and economics disciplines is essential in implementing this approach in practice. The critical importance of the links to scientific analysis, which form the basis for valuing ecosystem services, needs be recognized.

Recommendations for policy intervention

Forest ecosystems in Goa State have witnessed change and degradation since their value is poorly understood and not considered in the policy-making process. The assessment of the extent and condition of forest ecosystems at regular intervals, taking advantage of advancements in geoinformatics with artificial intelligence and deep learning algorithms, and the availability of spatial data at regular intervals to estimate the economic value of ecosystems forests and reflect the value of forests in policy decisions.

Forests provide various services classified as provisioning, regulating, and cultural services. Most of these services are underestimated or not estimated and are thus undervalued in policy decisions. Poor understanding of the complex ecological processes and proper estimation of the ecosystem benefits have often led to the destruction of fragile ecosystems. To improve the scenario, a thorough understanding of the complex ecosystem dynamics and its socio-religious association with community life is important from a conservation and management point of view. However, the valuation of regulating services and cultural services is challenging to estimate and thus poses serious challenges to planners and practitioners. Hence, the valuation of the ecosystem services in the income accounting of a region/nation is essential to make plans and policies more sustainable. The accounting of the forest sector in Goa increases the prospects in terms of more investment in the forest sector, reducing the risk of disaster, more business opportunities, curbing biodiversity loss, biodiversity conservation, ensuring food and ecological balance, etc.

The ecosystem services computed for Goa State also support the viability of markets for ecosystem services. The development of such markets requires additional institutional reforms, such as changes with respect to property rights and reforms in land and labor markets. Hence, ecosystem services need to be internalized in decision-making, strengthening the economic case for conserving forests in all states in India and developing countries, as there is great pressure to relax forest laws and divert forests to non-forest uses. The main policy challenge is to promote conservation and develop such markets so that those bearing the cost of conservation are adequately compensated. This will also support local communities in their efforts to sustainably manage forest resources, recognizing their traditional practices and knowledge. There is an urgent policy need for more comprehensive assessments of the natural capital of ecosystems, which will aid in comparing these aggregate values with the opportunity cost of this land. Policymakers need such information to gain support for conservation funding, engage local communities, and develop market-based instruments for conservation. This necessitates accounting for the natural capital found in the forest ecosystems (among others) and incorporating their economic worth added to the measurement of the wealth of a region. Ecosystem services accounting for Goa state have a large potential to be used for payment for ecosystem services schemes. The Supreme Court of India (2006)[118] directed the national government to set up compensatory payments for converting forest land to non-forest uses and use these payments to improve India's forest cover.

Materials and methods
Study area

Goa, with a spatial extent of 3702 sq. km comprising two districts, North Goa and South Goa (Fig. 8) is the 25th State of the Union states of India on the west coast of India, located between 15° 48' 00"N 74° 20' 13" E and 14° 43' 54" N 73° 40' 33"E. Several major rivers traverse the region, including the Mandovi, Zuari, Terekhol, Chapora, Sal, Talpona, Galgibag, and Betul. The Mountain region of Goa is situated east of South Goa and is covered in dense forest. The climate of Goa is hot and experiences rainfall in June, July, August, and September. Mainly plantations of cashews, Coconut, Mangoes, Areca palm, Kokum, and Jack fruit are predominant in
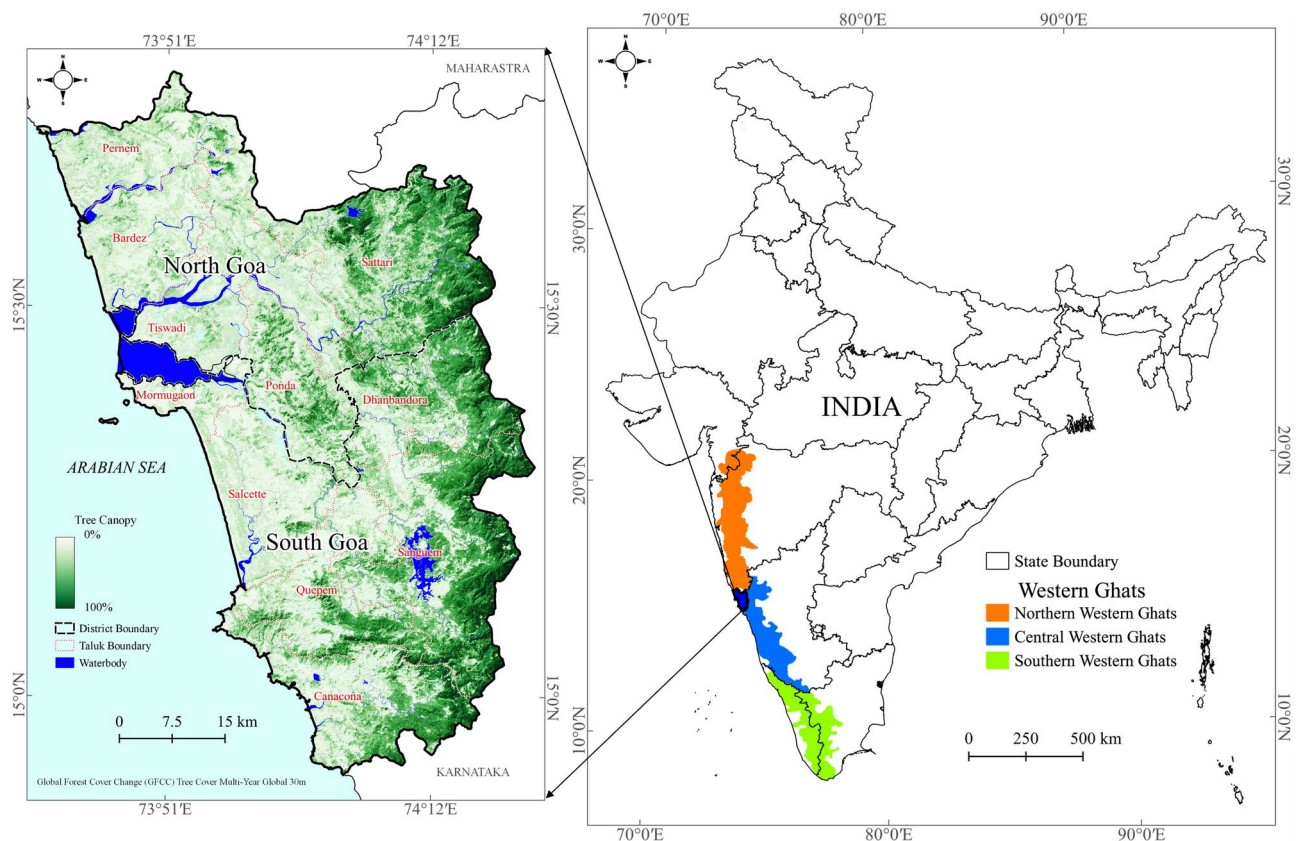
Fig. 8. Study area—Goa State, Central Western Ghats, India. Created using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

Goa. Goa possesses abundant mineral resources, including iron ore, manganese, ferromanganese, bauxite, and silica sand. The iron and manganese mining industries are crucial for the economy. Rivers serve as a means of transportation, and inland waterways are exceptionally vital for transporting mineral ores from mining sites such as Costi, Kirpal, Netravalim, Rivona, Ducorcond, and Kuddegal in the Sanguem taluka to the Mormugao harbor for export. As per India State of Forest Report (ISFR) 2023, the spatial extent of the forest cover of Goa is 2,265.72 sq. km[19], and diversity is due to the variation in altitude, aspect, soil characters, slope, etc. Forests provide essential products: bamboo, fuelwood, non-timber forest produce (NTFP), etc. As per the classification of forest types in India[119], the forests of Goa include (i) estuarine vegetation consisting of mangrove species, (ii) stranded vegetation along the coastal belts, (iii) plateau vegetation is confined especially to the low altitude (open scrub jungle, moist mixed deciduous forests, secondary moist mixed deciduous forests, subtropical hill forests), and (iv) Semi-evergreen and evergreen forests (Semi-evergreen forests, Lateritic Semi-evergreen forests, Evergreen forests). Conservation of the unique biodiversity of the State has been implemented through protected areas of six Wildlife Sanctuaries and one National Park.

Data

Table 2 lists details of the temporal remote sensing data (1973 to 2022), ancillary data, and field data. The remote sensing data utilized for land cover dynamics assessment are Landsat MSS, Landsat TM, Landsat OLI, and Google Earth (http://earth.google.com). Ancillary data included cadastral revenue maps (1:6000), the Survey of India (SOI: https://surveyofindia.gov.in/) topographic maps (1:50,000 and 1:250,000 scales), forest categories of 2019, and Forest Survey map of India (FSI) for mining area of 1970 from the Forest Survey map of India (FSI: https://fsi.nic.in/)[109], land use maps (2005-06, 2011-12, 2015-16) from National Remote Sensing Center (NRSC: https://nrsc.gov.in), land use (2021) from Environmental Systems Research Institute (ESRI: https://www.esri.com/), land use (1985, 1995, 2005) from Indian Biodiversity Information System (IBIS: https://www.indianbiodiversity.org/), Dynamic World Land use (2022) (https://dynamicworld.app/)[120], and a vegetation map of South India at a scale of 1:250,000 from the French Institute (1984) (https://www.ifpindia.org/)[121]. Reserve Forest Area (RFA) boundaries representing different forest types were collected from the forest department, Goa[122]. Forest plantation details were compiled from the North Goa Forest Working Plan (2013-14) to (2022-23), the South Goa Forest Working Plan (2011-12) to (2020-21) of the Forest Department of Goa[122].

Data	Year	Source	Data type	Temporal resolution	Spatial resolution
Remote sensing data					
Landsat Multispectral Sensor (MSS)	1973, 1977	U.S. Geological Survey https://earthexplorer.usgs.gov/	Raster	16 days	30 m
Landsat Thematic Mapper (TM)	1990, 1993, 1998, 2001	U.S. Geological Survey https://earthexplorer.usgs.gov/	Raster	16 days	31 m
Landsat Operational Land Imagery (OLI)	2014, 2022	U.S. Geological Survey https://earthexplorer.usgs.gov/	Raster	16 days	32 m
Cartosat Digital Elevation Model (Carto-DEM)	2015	U.S. Geological Survey https://earthexplorer.usgs.gov/	Raster	–	1 m
Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM)	2014	U.S. Geological Survey https://earthexplorer.usgs.gov/	Raster	–	30 m
Collateral data					
Survey of India Toposheet	2005-06	surveyofindia.gov.in	Raster	–	1:50000
Survey of India Toposheet	1964-66	surveyofindia.gov.in	Raster	–	1:250000
French Institute Vegetation Map of South India	1984	[121]	Raster	–	1:250000
Forest Survey of India (FSI) Forest category	2019	[122]	Raster	–	23.5 m
Forest Survey of India (FSI) mining area	1970	[122]	Raster	–	
Google Satellite	1985–2023	Google Earth https://earth.google.com/	Raster	–	0.1–5 m
National Remote Sensing Centre (NRSC) Land Use	2005-06, 2011-12, 2015-16	Bhuvan https://bhuvan.nrsc.gov.in/home/index.php	Raster	–	1:50,000
Environmental Systems Research Institute (ESRI) Land Use	2021	Esri Land Cover https://livingatlas.arcgis.com/landcover/	Raster	–	10 m
Indian Biodiversity Information System Land Use	1985, 1995, 2005	Indian Biodiversity Information System https://www.indianbiodiversity.org/	Raster	–	100 m
Dynamic World Land Use	2022	[120]	Raster	–	10 m

Table 2. Data used to assess the forest structure dynamics.

Method

Figure 9 outlines the method adopted for assessing ecosystem extent and condition, quantification of ecosystem services, and geo-visualization of eco-sensitive regions in Goa for prudent management of natural resources to ensure the sustenance of people's livelihood.

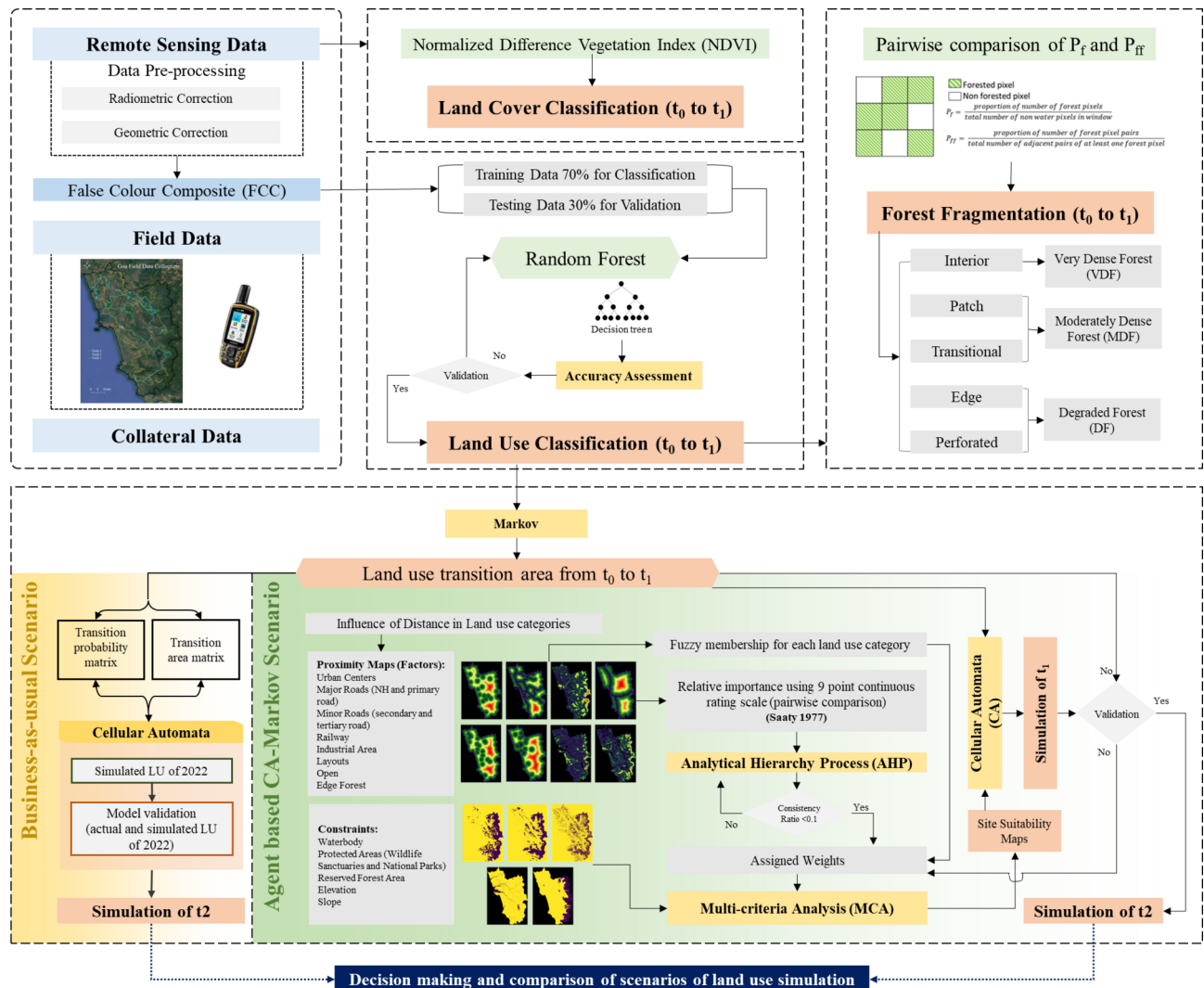### Assessment of land cover and land use dynamics—extent of forest ecosystems

Assessment of land use dynamics entailed (i) acquisition of remote sensing data (1973 to 2022, downloaded from the public archive (https://earthexplorer.usgs.gov/), (ii) data preprocessing (to rectify geometric and radiometric errors), (iii) land use type-wise training data with attribute information compilation, (iv) classification of remote sensing data using the supervised non-parametric classifier (Random Forest algorithm) for deriving land use information, (v) validation of classification (through accuracy assessment), (vi) compilation ancillary data from the government sources, etc., and digitization of encroachments using forest administrative boundaries.

Ground control points (GCPs) were digitized from the geo-referenced topographic maps and scanned paper maps to rectify remote sensing data. The vegetation map of South India (1984) was used to digitize forest types required to classify the remote sensing data. Other ancillary data included land cover maps, administration boundary data, and transportation data (road network). Attribute data corresponding to the training polygons were collected from the field using pre-calibrated hand-held GPS (Global Positioning System - Garmin GPS units).

Remote sensing data were geo-referenced, rectified, and cropped to correspond to the study region. Remote sensing data from 1973 to 1977 were resampled to 30 m × 30 m to match the resolution of post-1990 data. To ensure consistency across the time series analysis (1973–2022), Landsat data with a uniform spatial resolution of 30 m was utilized. False Color Composite (FCC) using the green, red, and near-infrared (NIR) bands of remote sensing data were generated, which aided in identifying heterogeneous patches. Training polygons corresponding to heterogenous patches were digitized, covering 15% of the study area and uniformly distributed across the study area. The coordinates of these training polygons were transferred to pre-calibrated GPS, and attribute data (land use types) corresponding to training polygons were collected from the field. 70% of the data was used as training data, and the remaining 30% was used for the validation or accuracy assessment.

Random forest (R.F.), an ensemble of tree-type machine learning classifier[123], was used for the land use classification. R.F. has the capability to handle both classification and regression tasks, accommodating categorical and continuous variables[123,124]. R.F. algorithm creates multiple decision trees (CART), based on the training data through bagging or bootstrap aggregation[54,125]. Incorporating the bootstrap component in R.F.

Fig. 9. Assessment of landscape dynamics and prediction of likely land use changes using CA-Markov with AHP method.

entails parameterizing each tree using a randomly sampled subset of observations from the training data, where sampling is done with replacement, which helps in reducing the multicollinearity among the trees[126]. R.F. is a combination of classifiers where each classifier contributes to the classification by voting for the most popular class as input (x). Finally, the assignation of the class is based on the majority votes of the decision trees.

R.F. classifier requires optimization of mainly two hyperparameters to generate a prediction model. The desired number of classification trees (*ntrees*) and the number of prediction variables (*mtry*) are used at each node to grow the tree. 'm' number of random predictive variables are employed to classify a new dataset, and each dataset example is classified by n trees determined by the user[126,127]. Consequently, for each example final assigned class value corresponds to the most frequent value among the total (n) generated trees. Additionally, as the number of trees increases, the generalization error consistently converges and is not sensitive to noise or over-training on R.F. Conversely, reducing the number of predictive variables (*mtry*) makes each tree in the model less influential but also diminishes the correlation between trees, leading to improved model accuracy. Thus, optimizing the parameters *ntrees* and *mtry* becomes essential to minimize the generalization error[54]. R.F. can handle thousands of input variables and estimate the importance of individual variables in the classification.

Initially, the K-means cluster method was utilized to group LU categories into clusters based on the spectral signature. The clusters were then identified by comparing them with the high-spatial-resolution remote sensing data (Google Earth, https://earth.google.com) and field data to categorize them into specific land use classes. Finally, a hierarchical classification scheme was employed to classify land use classes.

Similarities in spectral characteristics and the distinguishability of classes were the criteria considered for hierarchical classification. The hierarchical classification process consisted of two levels. Level 1 considered hierarchically: (i) classification of water and non-water classes, (ii) identification of vegetation and non-vegetation classes from the non-water class, (iii) vegetation class were further classified into forest and non-forest, (iii) classification of the forest class into evergreen and non- evergreen classes, (iv) further division of the

non- evergreen class into moist deciduous and dry deciduous/shrubs, (v) similarly, non- forest class was further divided into horticulture and agriculture. Level 2 followed the hierarchical approach of (i) separating the open land and fallow agriculture land classes from non-vegetation classes and (ii) mosaicking crop and fallow lands.

Accuracy assessment: Validation of the classification of remote sensing data is done through the computation of the confusion matrix and Kappa statistics. The confusion matrix compares the correlation between the reference data (training data) and the classification results, revealing areas of agreement and discrepancy. From the information within the error matrix, various classification accuracy measures computed are omission error, commission error, overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient, each providing unique insights into the quality of the classification.

Condition of forest ecosystems (assessment through fragmentation metrics)

The condition of the forest ecosystem is assessed at the pixel level through the computation of fragmentation metrics: P_f is the ratio of forested pixels to the total number of non-water pixels within a defined analysis window. P_{ff} is the proportion of adjacent pixel pairs (considering only cardinal directions) that include at least one forested pixel, where both pixels are classified as forested[95,128]. These metrics provide valuable insights into the spatial distribution, structure, and connectivity of forest patches within the landscape[129–132] and were categorized as interior, patch, edge, perforated, and transitional forest by categorization of pixels based on the type of fragmentation as (i) interior forest ($P_f = P_{ff}$=1), (ii) perforated forest (for pixels with $P_f > 0.6$ and ($P_f - P_{ff}$) < 0), (iii) Edge forest ($P_f > 0.6$ and ($P_f - P_{ff}$) > 0), (iv) Transition (pixels with $P_f < 0.6$ and $P_f > 0.4$), and (v) Patch forest (with pixels $P_f < 0.4$)[59].

Based on the condition considering the level of fragmentation, forest ecosystems were categorized as (i) Very Dense Forest (VDF), corresponding to intact interior zones; (ii) Moderately Dense Forest (MDF), consisting of patch and transitional forests; and (iii) Degraded Forest (DF), comprising edge and perforated forest areas.

The temporal land use analyses were carried out through the random forest (R.F.) classifier in the cloud-based platform Google Earth Engine (GEE) [https://earthengine.google.com/]. Forest fragmentation analysis and spatial land use statistics were subsequently derived using the open-source software QGIS 3.10 [https://www.qgis.org/] and GRASS GIS 7.8.2 [https://wgbis.ces.iisc.ac.in/grass/].

Prediction of likely land uses using CA-Markov

The current study has used the CA-Markov model to assess likely land use in the landscape. The Markov chain model considers the transition probabilities between different land-use classes over time for predicting likely land uses by considering the transition probabilities of land-use classes[60]. The transition probability matrix [P] and transition area matrix [A] are as per Eqs. (1 and 2).

$$P = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \cdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \tag{1}$$

where P_{ij} is the probability of ith land use converting into jth class during the transition period and n is the number of land use classes.

$$A = \begin{bmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \cdots \\ A_{n1} & \cdots & A_{nn} \end{bmatrix} \tag{2}$$

where A_{ij} is the area of ith LU transition into jth LU class.

CA-Markov model integrates cellular automata (CA), Markov chain (MC), multi-criteria (MCA), and multi-objective land allocation (MOLA) to predict or simulate land uses. CA model explicitly considers these spatial interactions by defining rules that govern the transition of land-use states based on the states of neighboring cells (Eq. 3). This allows for the modeling of spatial patterns and propagation of land uses.

$$S(t, t+1) = f(S(t), N) \tag{3}$$

where S is the set discrete cellular states, N is the Cellular field, f is the transformation rule, and t and t + 1 indicate the different time instances.

The model simulates the temporal land-use patterns by updating the land-use states based on the defined rules. CA Markov model provides insights into the likely future trajectories of land uses by considering the effect of natural, societal, and economic factors while allowing for the exploration of different scenarios[132].

Analytic hierarchy process (AHP): Several modeling approaches for multi-criteria analysis in decision-making are Artificial Neural Networks (ANN), CA, CA-Markov, and AHP. The problem is structured as a hierarchy in AHP, and the process involves conducting pair-wise comparisons to determine the relative importance of each factor concerning pixel suitability for the specific activity and derive weights based on the expert's judgment[68,133]. The weights assigned to the variables in the model are determined using the Analytic Hierarchy Process (AHP). AHP considers the consistency of the decision-making process by assessing the consistency index of the individual comparison matrix[134]. In pair-wise comparison, matric, two factors are considered at a time. In evaluating preferences factors i and j are prioritized as, I = equal preference (both 'i' and 'j' factors are equally influential in decision making), II = slightly preferred (considered i = > j, 'i' is somewhat more important than factor 'j'), III = significantly prefer (i > j, substantial impact of 'i' on 'j'), IV = strongly preferred ('i' have

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 3. Random index (R.I.), according to Saaty[77].
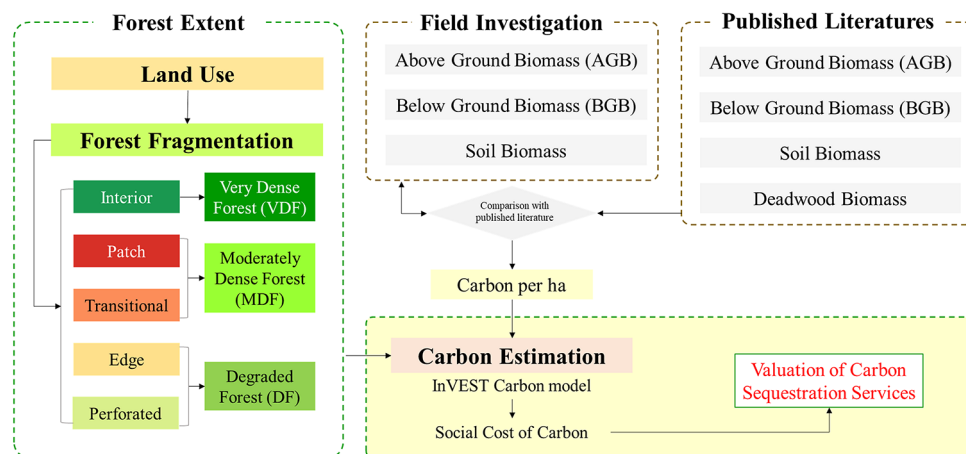
Fig. 10. Valuation of carbon services (considering the condition of forest ecosystems).

strong advantage over 'j'), and V = extremely preferred ('i' is overwhelmingly advantage over 'j'). The consistency index depends on the principal eigenvector (λ_{max}), which is equal to the product between each component of the priority vector and the column totals[77,113].

To validate or to measure the level of consistency of the pair-wise comparison matrix, the consistency ratio (C.R.) was calculated using the given Eq. (4):

$$CR = \frac{CI}{RI} \qquad (4)$$

Where, CI is the consistency index (Eq. 5), and R.I. is the Random Index.

The Random Index suggested by Saaty has been used for the computation of C.R., which is represented in Table 3.

$$CI = \frac{(\lambda_{max} - n)}{n - 1} \qquad (5)$$

where, λ_{max} is the maximum Eigen value, and it is calculated by Eq. (6), P is the pair-wise comparison matrix, v represents the matrix eigenvector, and n is the number of elements compared.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(P.v)_i}{n.v_i} \qquad (6)$$

The acceptable consistency ratio (C.R.) of pair-wise comparisons should be less than 0.10. If the C.R. is not in the acceptable range, then the pair-wise comparison needs to be corrected. Consequently, a change in the comparison matrix will change the weights assigned to the individual factors.

The current study employs the IDRISI Selva 17.02 software (https://idrisi-selva.software.informer.com/) to model the dynamic trajectories of future change and validate the model. AHP CA offers several advantages over traditional modeling techniques as it incorporates dynamic spatial transitions by considering the influence of distances for each factor on the respective land use (LU), rather than solely focusing on a LU category.

Carbon storage services of forest ecosystems

Forest ecosystems provide a vital service of carbon sequestration, which helps in maintaining balance. Carbon stock in a forest ecosystem is estimated (Fig. 10) using the spatial extent of forests and carbon density (forest type-wise) through InVEST 3.14.3 carbon storage and sequestration model (available at: www.naturalcapitalproject.stanford.edu/software/invest/invest-downloads-data developed as part of the natural capital accounting endeavor). Carbon density is computed based on the field data (sampling across forest types (evergreen, moist deciduous, dry deciduous, etc.) through transect-based quadrat and measurements of girth and height (species-wise), which were used to compute AGB (using species-specific allometric equation).

InVEST, an open-source tool that simulates the carbon cycle, and estimates the total carbon stock by considering four carbon pools: above-ground carbon (C_{above}), below-ground biomass (C_{below}), soil carbon (C_{soil}), and dead organic matter (C_{dead}) as given by Eq. (7)[30,39,97].

$$Carbon storage = \sum_{i=1}^{n} A_j * \left(\left(C_{above} + C_{below} \right)_{vegetation} + C_{soil} + C_{dead} \right)_j \qquad (7)$$

Where, j = 1,2,...n and A_j is the area under each land use type j.

Mangroves are critical ecosystems for mitigating climate change, acting as efficient carbon sinks through their high rates of primary production and organic matter accumulation. Quantifying carbon sequestration in mangroves is crucial for understanding their ecosystem services and informing conservation and management strategies. The current study has assessed the carbon sequestration potential of mangroves in Goa using the InVEST Carbon model, considering the spatial extent of mangroves and carbon density[135–137]. A comprehensive literature review and field investigations were carried out to compile data for quantifying aboveground, belowground, and litter carbon density (Mg C/ha) through allometric equations[135,138,139].

Prioritization of ecologically sensitive regions (ESR)

ESR or ecologically sensitive regions are unique areas with distinct bio-geo-climatic, ecological, and social aspects that are easily affected or damaged by human activities, and need to be conserved to sustain natural resources and support the livelihood of people. Data was compiled from the field and through a comprehensive review of published literature, published datasets, and official reports. The detailed method is as per earlier publications[15,25,30]. The study area has been divided into grids of 5'×5' (9 km × 9 km), which match the grid size of the Survey of India topographic maps of 1: 50,000 scale and values is assigned to each grid based on the relative significance of a variable (Supplementary Table S7). The aggregated weight for each grid is computed, and grids are grouped into 4 groups based on mean and standard deviation of aggregates, which aided in identifying various levels of fragility. ESR1 represents ecologically highly fragile and requires strict conservation measures; ESR2 is as good as ESR1, requiring stringent measures to minimize degradation. ESR3 represents a moderate conservation region, and ESR4 represents less fragility.

A web-based Western Ghats Spatial Decision Support System (WGSDSS) was conceptualized and implemented to visualize the ecologically sensitive regions at disaggregated levels in the Western Ghats (https://wgbis.ces.iisc.ac.in/sdss/wgsdss/index.php). The WGSDSS integrates data (bio-geo-climatic, hydrological, ecological, environmental, and social) with the latest spatial technologies and provides a powerful platform for geospatial data exploration, visualization, and utilization through WMS (web map service) and WFS (web feature services) features.

Valuation of ecosystem services (VES)

Goa State is adjacent and shares its boundary with Uttara Kannada district of Karnataka. Valuation of ecosystem services (VES) considering the spatial extent and condition of forest ecosystems has been done through the benefit transfer method considering estimates of economic value for ecosystem services for Uttara Kannada district[39,42], a neighboring district with similar ecological, environmental, geo-climatic, socio-economic, and cultural factors[97,114–116,140,141]. The valuation of ecosystem services provides valuable insights into the ecological and economic significance of forests for opting for policies to ensure sustainable resource management.

Data availability

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

References

1. Mooney, H. et al. Biodiversity, climate change, and ecosystem services. *Curr. Opin. Environ. Sustain.* **1** (1), 46–54. https://doi.org/10.1016/j.cosust.2009.07.006 (2009).
2. Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W. & Courchamp, F. Impacts of climate change on the future of biodiversity. *Ecol. Lett.* **15** (4), 365–377. https://doi.org/10.1111/j.1461-0248.2011.01736.x (2012).
3. Muluneh, M. G. Impact of climate change on biodiversity and food security: a global perspective—a review Article. *Agric. Food Secur.* **10** (1), 1–25. https://doi.org/10.1186/s40066-021-00318-5 (2021).
4. Prakash, S. Impact of climate change on aquatic ecosystem and its biodiversity: an overview. *Int. J. Biol. Innovations*. **3**, 2. https://doi.org/10.46505/IJBI.2021.3210 (2021).
5. SAC. Desertification and land degradation atlas of India (Assessment and analysis of changes over 15 years based on remote sensing). Space Applications Center, ISRO, Ahmedabad. India (2021, accessed Dec 2023). https://vedas.sac.gov.in/static/atlas/dsm/DLD_Atlas_SAC_2021.pdf.
6. SAC, I. Desertification and land degradation atlas of India (Based on IRS AWiFS data of 2011-13 and 2003-05). Ahmedabad: Space Applications Centre, ISRO, Ahmedabad, India, 219. (2016, accessed Dec 2023). https://www.sac.gov.in/SACSITE/Desertification_Atlas_2016_SAC_ISRO.pdf.
7. Ramachandra, T. V., Subash Chandran, M. D., Joshi, N. V. & Sumesh, D. Exploring Biodiversity and Ecology of Central Western Ghats., Sahyadri Conservation Series 13, ENVIS Technical Report: 39, March 2012, Energy & Wetlands Research Group, Centre for Ecological Sciences, Indian Institute of Science, Bangalore 560 012 (2013).
8. Joshi, V. C. & Janarthanam, M. K. The diversity of life-form type, habitat preference and phenology of the endemics in the Goa region of the Western Ghats, India. *J. Biogeogr.* **31**, 1227–1237 (2004).
9. Prabhugaonkar, A. First report of three red-listed tree species from swampy relics of Goa State, India. *J. Threatened Taxa*. **6**, 5503–5506 (2014).
10. Goa Forest Department. *Mangroves Goa* (2024, accessed Feb 2024). https://www.forest.goa.gov.in/mangroves.
11. Baidya, P. & Bhagat, M. A checklist of the birds of Goa, India. *Indian Birds*. **14** (1), 1–31 (2018).
12. Western Ghats Biodiversity Information System (WGBIS). Centre for ecological sciences, Indian Institute of science, Bangalore (2024, accessed 23 Feb 2024). https://wgbis.ces.iisc.ac.in/.

13. Ramachandra, T. V., Setturu, B., Vinay, S., Chandran, M. D. S. & Aithal, B. H. Abhishek Baghel (2023), Western Ghats Spatial Decision Support System [WGSDSS]. https://wgbis.ces.iisc.ac.in/sdss/wgsdss/ (2023).

14. Biodiversity, E. & Environmental Information System, Environmental Information System (ENVIS), Centre for Ecological Sciences, Indian Institute of Science, Bangalore (2024, accessed 23 Feb 2024). https://wgbis.ces.iisc.ac.in/energy_database.

15. Ramachandra, T. V., Setturu, B. & S., Vinay Assessment of forest transitions and regions of conservation importance in Udupi district. *Karnataka Indian Forester*. **147** (9), 834–847. https://doi.org/10.36808/if/2021/v147i9/164166 (2021).

16. Kimmins, J. P. Old-growth forest: an ancient and stable sylvan equilibrium, or a relatively transitory ecosystem condition that offers people a visual and emotional feast? answer it depends. *Forestry Chron.* **79** (3), 429–440. https://doi.org/10.5558/tfc79429-3 (2003).

17. Betts, M. G. et al. Global forest loss disproportionately erodes biodiversity in intact landscapes. *Nature* **547** (7664), 441–444. https://doi.org/10.1038/nature23285 (2017).

18. , F. A. O. The state of the world's forests 2022. Forest pathways for green recovery and Building inclusive, resilient and sustainable economies. *Rome FAO* (2023, accessed Dec 2023).https://doi.org/10.4060/cb9360en.

19. India State of Forest Report (ISFR). Government of India (2023, accessed Dec 2023). https://fsi.nic.in/forest-report-2023-details.

20. Hansen, A. J., Rotella, J. J., Kraska, M. P. & Brown, D. Spatial patterns of primary productivity in the greater Yellowstone ecosystem. *Landscape Ecol.* **15**, 505–522. https://doi.org/10.1023/A:1008127228878 (2000).

21. Xie, G., Zhang, C., Zhen, L. & Zhang, L. Dynamic changes in the value of China's ecosystem services. *Ecosyst. Serv.* **26**, 146–154. https://doi.org/10.1016/j.ecoser.2017.06.010 (2017).

22. Forman, R. T. & Godron, M. Patches and structural components for a landscape ecology. *BioScience* **31** (10), 733–740. https://doi.org/10.2307/1308780 (1981).

23. Haddad, N. M. et al. Habitat fragmentation and its lasting impact on earth's ecosystems. *Sci. Adv.* **1**(2), e1500052. https://doi.org/10.1126/sciadv.1500052 (2015).

24. Laurance, W. F. Reflections on the tropical deforestation crisis. *Biol. Conserv.* **91** (2–3), 109–117. https://doi.org/10.1016/S0006-3207(99)00088-9 (1999).

25. Ramachandra, T. V., Vinay, S., Bharath, S., Chandran, M. S. & Aithal, B. H. Insights into riverscape dynamics with the hydrological, ecological and social dimensions for water sustenance. *Curr. Sci.* **118** (9), 1379–1393 (2020).

26. Laurance, W. F. et al. Ecosystem decay of Amazonian forest fragments: a 22-year investigation. *Conserv. Biol.* **16** (3), 605–618. https://doi.org/10.1046/j.1523-1739.2002.01025.x (2002).

27. Laurance, W. F. et al. Rain forest fragmentation and the proliferation of successional trees. *Ecology* **87** (2), 469–482. https://doi.org/10.1890/05-0064 (2006).

28. De Frenne, P. et al. Forest microclimates and climate change: Importance, drivers and future research agenda. *Glob. Change Biol.* 27(11), 2279–2297. https://doi.org/10.1111/gcb.15569 (2021).

29. Grammatikopoulou, I. & Vačkářová, D. The value of forest ecosystem services: a meta-analysis at the European scale and application to National ecosystem accounting. *Ecosyst. Serv.* **48**, 101262. https://doi.org/10.1016/j.ecoser.2021.101262 (2021).

30. Ramachandra, T. V. & Bharath, S. Carbon sequestration potential of the forest ecosystems in the Western Ghats, a global biodiversity hotspot. *Nat. Resour. Res.* **29** (4), 2753–2771. https://doi.org/10.1007/s11053-019-09588-0 (2020).

31. Turner, W. R., Oppenheimer, M. & Wilcove, D. S. A force to fight global warming. *Nature* **428**, 278–227. https://doi.org/10.1038/462278a (2009).

32. Anees, S. A. et al. Integration of machine learning and remote sensing for above ground biomass Estimation through Landsat-9 and field data in temperate forests of the Himalayan region. *Ecol. Inf.* **82**, 102732. https://doi.org/10.1016/j.ecoinf.2024.102732 (2024).

33. Mehmood, K. et al. Exploring spatiotemporal dynamics of NDVI and climate-driven responses in ecosystems:Insights for sustainable management and climate resilience. *Ecol. Inf.* **80**, 102532. https://doi.org/10.1016/j.ecoinf.2024.102532 (2024).

34. Hui, D., Deng, Q., Tian, H. & Luo, Y. Climate change and carbon sequestration in forest ecosystems. *Handb. Clim. Change Mitigation Adaptation.* **555**, 594. https://doi.org/10.1007/978-1-4614-6431-0_13-2 (2017).

35. Allen, C. D. et al. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. *Forest Ecol. Manage.* **259**(4), 660–684. https://doi.org/10.1016/j.foreco.2009.09.001 (2010).

36. Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., …Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. Nature,610(7933), 687–692. https://doi.org/10.1038/s41586-022-05224-9.

37. Gupta, A. K., Yadav, V. K. & Bhushan, A. M. R. E. N. D. R. A. Recreational services valuation of Asiatic elephants in developing countries: a case study of Rajaji National park, India. *Indian For.* **141**, 1034–1041 (2015).

38. Verma, M. Economic valuation of forests of Himachal Pradesh. In *Report on economic component of Himachal Pradesh forestry sector review* 7 (2000).

39. Ramachandra, T. V. et al. *Natural Capital Accounting and Valuation of Ecosystem Services* (Ecosystem Services. Springer Nature, 2024).

40. Verma, M. et al. Making the hidden visible: Economic valuation of tiger reserves in India. *Ecosyst. Serv.* **26**, 236–244 (2017).

41. Kumar, S. & Chaudhry, P. Ecosystem services valuation of the forests of Arunachal Pradesh State, India. *Brazilian J. Biol. Sci.* **2** (4), 369–375 (2015).

42. Ramachandra, T. V., Soman, D., Naik, A. D. & Chandran, M. S. Appraisal of forest ecosystems goods and services: challenges and opportunities for conservation. *J. Biodivers.* **8** (1), 12–33 (2017).

43. Ramachandra, T. V., Setturu, B., Chandran, V. S., Baghel, M. S., Aithal, B. H. & A., & Ecologically sensitive regions in the Western Ghats, a biodiversity hotspot. *Indian Forester.* **149**, 1105–1121 (2024).

44. Weiskopf, S. R. et al. Climate change effects on biodiversity, ecosystems,ecosystem services, and natural resource management in the United States. *Sci. Total Env.* **733**, 137782. https://doi.org/10.1016/j.scitotenv.2020.137782 (2020).

45. Pereira, P. et al. Ecosystem services in mountain environments: benefits and threats. *Pirineos* **177**, e068. https://doi.org/10.3989/pirineos.2022.177001 (2022).

46. Kindu, M., Schneider, T., Teketay, D. & Knoke, T. Changes of ecosystem service values in response to land use/land cover dynamics in Munessa–Shashemene landscape of the Ethiopian highlands. *Sci. Total Environ.* **547**, 137–147. https://doi.org/10.1016/j.scitotenv.2015.12.127 (2016).

47. Zhu, L., Song, R., Sun, S., Li, Y. & Hu, K. Land use/land cover change and its impact on ecosystem carbon storage in coastal areas of China from 1980 to 2050. *Ecol. Ind.* **142**, 109178. https://doi.org/10.1016/j.ecolind.2022.109178 (2022).

48. Houghton, R. A. et al. Carbon emissions from land use and land-cover change. *Biogeosciences* **9** (12), 5125–5142. https://doi.org/10.5194/bg-9-5125-2012 (2012).

49. Polasky, S., Nelson, E., Pennington, D. & Johnson, K. A. The impact of land-use change on ecosystem services, biodiversity and returns to landowners: a case study in the state of Minnesota. *Environ. Resource Econ.* **48**, 219–242. https://doi.org/10.1007/s10640-010-9407-0 (2011).

50. Bharath, S., Rajan, K. S. & Ramachandra, T. V. Status and future transition of rapid urbanizing landscape in central Western Ghats - C.A. Based approach, ISPRS ann. Photogramm. *Remote Sens. Spat. Inf. Sci.* **II-8**, 69–75. https://doi.org/10.5194/isprsannals-II-8-69-2014 (2014).

51. Vinay, S., Bharath, S., Bharath, H. A. & Ramachandra, T. V. Hydrologic model with landscape dynamics for drought monitoring. In *Proceeding of: Joint International Workshop of ISPRS WG VIII/1 and WG IV/4 on Geospatial Data for Disaster and Risk Reduction, Hyderabad, November* 21–22 (2013).

52. Zhou, L., Pan, S., Wang, J. & Vasilakos, A. V. Machine learning on big data: opportunities and challenges. *Neurocomputing* **237**, 350–361. https://doi.org/10.1016/j.neucom.2017.01.026 (2017).
53. Sarker, I. H. Machine learning: algorithms, real-world applications and research directions. *SN Comput. Sci.* **2** (3), 160. https://doi.org/10.1007/s42979-021-00592-x (2021).
54. Breiman, L. Bagging predictors. *Mach. Learn.* **24**, 123–140. https://doi.org/10.1007/BF00058655 (1996).
55. Dietterich, T. G. Ensemble methods in machine learning. In International workshop on multiple classifier systems (pp. 1–15). (Springer, 2000). https://doi.org/10.1007/3-540-45014-9_1.
56. Talukdar, S. et al. Land-use land-cover classification by machine learning classifiers for satellite observations—a review. *Remote Sens.* **12** (7), 1135 (2020).
57. Mutale, B. et al. A performance evaluation of random forest, artificial neural network, and support vector machine learning algorithms to predict spatio-temporal land use-land cover dynamics: a case from Lusaka and Colombo. *Front. Environ. Sci.* **12**, 1431645 (2024).
58. Loukika, K. N., Keesara, V. R. & Sridhar, V. Analysis of land use and land cover using machine learning algorithms on Google Earth engine for Munneru river basin, India. *Sustainability* **13** (24), 13758 (2021).
59. Aryal, J., Sitaula, C. & Frery, A. C. Land use and land cover (LULC) performance modeling using machine learning algorithms: a case study of the city of Melbourne, Australia. *Sci. Rep.* **13**(1), 13510 (2023).
60. Ramachandra, T. V., Mondal, T. & Setturu, B. Relative performance evaluation of machine learning algorithms for land use classification using multispectral moderate resolution data. *SN Appl. Sci.* **5**, 274. https://doi.org/10.1007/s42452-023-05496-4 (2023).
61. Ramachandra, T. V., Negi, P. & Setturu, B. Insights from Big Spatial Data through Machine Learning Techniques for Prudent Management of Natural Resources. *J. Resour. Energy Dev.* **19**(1–2),1–18. https://www.researchgate.net/publication/370130497_Insights_from_big_spatial_data_through_machine_learning_techniques_for_prudent_management_of_natural_resources (2022).
62. Dong, L. et al. Very high resolution remote sensing imagery classification using a fusion of random forest and deep learning technique—Subtropical area for example. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **13**, 113–128 (2019).
63. Boston, T., Van Dijk, A., Larraondo, P. R. & Thackway, R. Comparing CNNs and random forests for Landsat image segmentation trained on a large proxy land cover dataset. *Remote Sens.* **14** (14), 3396 (2022).
64. Adugna, T., Xu, W. & Fan, J. Comparison of random forest and support vector machine classifiers for regional land cover mapping using coarse resolution FY-3 C images. *Remote Sens.* **14** (3), 574 (2022).
65. Abdel-Rahman, E. M., Mutanga, O., Adam, E. & Ismail, R. Detecting Sirex Noctilio grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. *ISPRS J. Photogrammetry Remote Sens.* **88**, 48–59 (2014).
66. Shang, X. & Chisholm, L. A. Classification of Australian native forest species using hyperspectral remote sensing and machine-learning classification algorithms. *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.* **7** (6), 2481–2489 (2013).
67. Ramachandra, T. V., Mondal, T., Setturu, B. & Aithal, B. H. Environmental consequences in the neighbourhood of rapid unplanned urbanisation in Bangalore City. *Adv. Environ. Eng. Res.* **4** (4), 052. https://doi.org/10.21926/aeer.2304052 (2023).
68. Setturu, B. & Ramachandra, T. V. Modeling landscape dynamics of policy interventions in Karnataka State, India. *J. Geovisualization Spat. Anal.* **5** (2), 22. https://doi.org/10.1007/s41651-021-00091-w (2021).
69. Verburg, P. H. et al. Beyond land cover change: towards a new generation of land use models. *Curr. Opin. Environ. Sustain.* **38**, 77–85. https://doi.org/10.1016/j.cosust.2019.05.002 (2019).
70. Schuwirth, N. et al. How to make ecological models useful for environmental management. *Ecol. Model.* **411**, 108784. https://doi.org/10.1016/j.ecolmodel.2019.108784 (2019).
71. Castella, J. C., Trung, T. N. & Boissau, S. Participatory simulation of land-use changes in the Northern mountains of Vietnam: the combined use of an agent-based model, a role-playing game, and a geographic information system. *Ecol. Soc.*, **10**(1). (2005). https://www.jstor.org/stable/26267718.
72. Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G. & Gotts, N. M. Agent-based land-use models: a review of applications. *Landscape Ecol.* **22**, 1447–1459. https://doi.org/10.1007/s10980-007-9135-1 (2007).
73. Wanyama, D., Mighty, M., Sim, S. & Koti, F. A Spatial assessment of land suitability for maize farming in Kenya. *Geocarto Int.* **36** (12), 1378–1395. https://doi.org/10.1080/10106049.2019.1648564 (2021).
74. Qiu, B. W., Chi, T. H. & Wang, Q. M. Fruit tree suitability assessment using GIS and multi-criteria evaluation. *Trans. CSAE.* **21** (6), 667–690 (2005).
75. Nijkamp, P., Rietveld, P. & Voogd, H. *Multi-criteria Evaluation in Physical Planning* (Elsevier, 2013).
76. Morales, F. Jr & de Vries, W. T. Establishment of land use suitability mapping criteria using analytic hierarchy process (AHP) with practitioners and beneficiaries. *Land* **10** (3), 235. https://doi.org/10.3390/land10030235 (2021).
77. Saaty, R. W. The analytic hierarchy process—what it is and how it is used. *Math. Modelling.* **9** (3–5), 161–176. https://doi.org/10.1016/0270-0255(87)90473-8 (1987).
78. Pant, S., Kumar, A., Ram, M., Klochkov, Y. & Sharma, H. K. Consistency indices in analytic hierarchy process: a review. *Mathematics* **10** (8), 1206. https://doi.org/10.3390/math10081206 (2022).
79. Saaty, T. L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **1** (1), 83–98. https://doi.org/10.1142/S0219622005001453 (2008).
80. Saaty, T. L. A scaling method for priorities in hierarchical structures. *J. Math. Psychol.* **15** (3), 234–281. https://doi.org/10.1016/0022-2496(77)90033-5 (1977).
81. Dai, F. C., Lee, C. F. & Zhang, X. H. GIS-based geo-environmental evaluation for urban land-use planning: a case study. *Eng. Geol.* **61** (4), 257–271. https://doi.org/10.1016/S0013-7952(01)00028-X (2001).
82. de Araújo, C. C. & Macedo, A. B. Multi-criteria geologic data analysis for mineral favorability mapping: application to a metal sulphide mineralized area, Ribeira Valley metallogenic Province, Brazil. *Nat. Resour. Res.* **11**, 29–43 (2002).
83. Saaty, T. L. *Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process* (RWS, 1994).
84. Marinoni, O. & Hoppe, A. Using the analytical hierarchy process to support sustainable use of geo-resources in metropolitan areas. *J. Syst. Sci. Syst. Eng.* **15**, 154–164. https://doi.org/10.1007/s11518-006-5004-8 (2006).
85. Öztürk, D. & Batuk, F. Analytic hierarchy process for Spatial decision making. *Sigma* **28** (2), 124–137 (2010).
86. Banai-Kashani, R. A new method for site suitability analysis: the analytic hierarchy process. *Environ. Manage.* **13**, 685–693. https://doi.org/10.1007/BF01868308 (1989).
87. Van Laarhoven, P. J. & Pedrycz, W. A fuzzy extension of Saaty's priority theory. *Fuzzy Sets Syst.* **11** (1–3), 229– 224 https://doi.org/10.1016/S0165-0114(83)80082-7 (1983).
88. Buckley, J. J. Fuzzy hierarchical analysis. *Fuzzy Sets Syst.* **17** (3), 233–247. https://doi.org/10.1016/0165-0114(85)90090-9 (1985).
89. Chang, D. Y. Applications of the extent analysis method on fuzzy AHP. *Eur. J. Oper. Res.* **95** (3), 649–655. https://doi.org/10.1016/0377-2217(95)00300-2 (1996).
90. Anees, S. A. et al. Unveiling fractional vegetation cover dynamics: a spatiotemporal analysis using modis ndvi and machine learning. *Environ. Sustain. Indic.* **24**, 100485. https://doi.org/10.1016/j.indic.2024.100485 (2024).
91. de Barros Ruas, R., Costa, L. M. S. & Bered, F. Urbanization driving changes in plant species and communities–A global view. *Global Ecol. Conserv.*, **38**, e02243. (2022).

92. Government of Goa. Economic Survey 2021-22. Government of Goa (2022, accessed Feb 2023). https://www.goa.gov.in/government/publications/.

93. Simkin, R. D., Seto, K. C., McDonald, R. I. & Jetz, W. Biodiversity impacts and conservation implications of urban land expansion projected to 2050. *Proc. Natl. Acad. Sci.* **119** (12), e2117297119 (2022).

94. Wang, W. et al. Urbanization impacts on natural habitat and ecosystem services in the Guangdong-Hong Kong-Macao megacity. *Sustainability* **12** (16), 6675 (2020).

95. Ramachandra, T. V., Setturu, B. & Chandran, S. Geospatial analysis of forest fragmentation in Uttara Kannada district, India. *For. Ecosyst.* **3** (1), 1–15. https://doi.org/10.1186/s40663-016-0069-4 (2016).

96. Eigenbrod, F. et al. The impact of projected increases in urbanization on ecosystem services. *Proc. R. Soc. B: Biol. Sci.* **278**(1722), 3201–3208 (2011).

97. Plummer, M. L. Assessing benefit transfer for the valuation of ecosystem services. *Front. Ecol. Environ.* **7** (1), 38–45. https://doi.org/10.1890/080091 (2009).

98. MoSPI Forests - the Climate Protectors (Chap. 3), Gov of India (2020, accessed Feb 2023). https://mospi.gov.in/documents/213904//649960/1614147361232_b3_ES2_2020.pdf, https://mospi.gov.in/sites/default/files/reports_and_publication/statistical_publication/EnviStats2/b3_ES2_2020.pdf.

99. SEEA EA. *System of Environmental-Economic Accounting—Ecosystem Accounting, Final Draft, Version 5* (Department of Economic and Social Affairs, Statistics Division, 2021).

100. Canu, D. M. et al. Estimating the value of carbon sequestration ecosystem services in the mediterranean Sea: an ecological economics approach. *Glob. Environ. Change.* **32**, 87–95. https://doi.org/10.1016/j.gloenvcha.2015.02.008 (2015).

101. Lorenz, K. Carbon sequestration in forest ecosystems. https://doi.org/10.1007/978-90-481-3266-9 (2010).

102. Anees, S. A. et al. Spatiotemporal dynamics of vegetation cover: integrative machine learning analysis of multispectral imagery and environmental predictors. *Earth Sci. Inf.* **18**(1), 1–23. https://doi.org/10.1007/s12145-024-01673-0 (2025).

103. Dhyani, S. Impact of forest leaf litter harvesting to support traditional agriculture in Western Himalayas. *Trop. Ecol.* **59**, 473–488 (2018). http://216.10.241.130/pdf/open/PDF_59_3/7%20Shalini%20Dhyani.pdf.

104. Draft National Forest Ministry of Environment, Forest and Climate Change & Policy 2018. Government of India (2018, accessed Feb 2023). https://moef.gov.in/uploads/2019/04/Inviting-comments-from-all-concerned-stakeholders-on-Draft-National-Forest-Policy-2018_1.pdf.

105. Sonak, S., Kazi, S., Sonak, M. & Abraham, M. Factors affecting land-use and land-cover changes in the coastal wetlands of Goa. Multiple dimensions of global environmental change (2006).

106. Clarke, K. C. Cellular automata and agent-based models. *Handb. Regional Sci.* https://doi.org/10.1007/978-3-662-60723-7_63 (2021).

107. Savin, I. et al. Agent-based modeling to integrate elements from different disciplines for ambitious climate policy. *Wiley Interdiscip. Rev. Clim. Change* **14**(2), e811. https://doi.org/10.1002/wcc.811 (2023)

108. Silva, S. D., Nielsen, K. B. & Bedi, H. P. Land use planning, dispossession and contestation in Goa, India. *J. Peasant Stud.* **47** (6), 1301–1326. https://doi.org/10.1080/03066150.2020.1822822 (2020).

109. Directorate of Mines and Geology (2023, accessed Dec 2023). https://dmg.goa.gov.in.

110. Misra, A. & P, V. Assessment of the land use/land cover (LU/LC) and Mangrove changes along the Mandovi–Zuari estuarine complex of Goa, India. *Arab. J. Geosci.* **8**, 267–279. https://doi.org/10.1007/s12517-013-1220-y (2015).

111. Nagi, H. M., Rodrigues, R. S., Murali, M. R. & Jagtap, T. G. Using remote sensing and GIS techniques for detecting land cover changes of Mangrove habitats in Goa, India. *Fac. Sci. Bull.* **26**, 21–33 (2014).

112. Morakar, P. R., Jakati, D. M. & Hiremath, C. P. Geographical analysis of climate change effects on land use & land cover: a case study of . *J. Namibian Studies: History Politics Cult.* **33**, 2098–2115. https://doi.org/10.59670/jns.v33i.2312 (2023).

113. Ramachandra, T. V., Setturu, B., Rajan, K. S. & Subash Chandran, M. D. Modelling the forest transition in central Western Ghats, India. *Spat. Inform. Res.* **25**, 117–130. https://doi.org/10.1007/s41324-017-0084-8 (2017).

114. Costanza, R. et al. The value of the world's ecosystem services and natural capital. *Nature* **387**(6630), 253–260. https://doi.org/10.1038/387253a0 (1997).

115. Costanza, R. et al. Changes in the global value of ecosystem services. *Glob. Environ. Change* **26**, 152–158. https://doi.org/10.1016/j.gloenvcha.2014.04.002 (2014).

116. De Groot, R. et al. Global estimates of the value of ecosystems and their services in monetary units. *Ecosyst. Serv.* **1**(1), 50–61. https://doi.org/10.1016/j.ecoser.2012.07.005 (2012).

117. Ninan, K. N. & Kontoleon, A. Valuing forest ecosystem services and disservices—case study of a protected area in India. *Ecosyst. Serv.* **20**(2016), 1–14. https://doi.org/10.1016/j.ecoser.2016.05.001 (2016).

118. Comptroller and Auditor General of India. Report of the Comptroller and Auditor General of India on Compensatory Afforestation in India (Report No. 21 of 2013), Government of India (2013). https://cag.gov.in/uploads/download_audit_report/2013/Union_Compliance_Civil_Compensatory_Afforestation_21_2013.pdf.(accessed on Feb, 2023).

119. Champion, H. G. & Seth, S. K. *A Revised Survey of Forest Types of India, Govt* 404 (of India, 1968).

120. Brown, C. F. et al. Dynamic World, Near real-time global 10 m land use land cover mapping. *Sci. Data* **9**(1), 251 (2022).

121. Pascal, J. P. Explanatory Booklet on the Forest Map of South India. Sheets: Belgaum-Dharwar-Panaji, Shimoga, Mercara-Mysore. In *Institut Français de Pondichéry, 88 p., Travaux de la Section Scientifique et Technique. Hors Série N° 18* (1984).

122. Goa Forest Department. Feb, (2023). https://forest.goa.gov.in/ (accessed on.

123. Breiman, L. Random forests. *Mach. Learn.* **45**, 5–32. https://doi.org/10.1023/A:1010933404324 (2001).

124. Woznicki, S. A., Baynes, J., Panlasigui, S., Mehaffey, M. & Neale, A. Development of a spatially complete floodplain map of the conterminous united States using random forest. *Sci. Total Environ.* **647**, 942–953. https://doi.org/10.1023/A:1010933404324 (2019).

125. Abdi, A. M. Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience Remote Sens.* **57**(1), 1–20. https://doi.org/10.1080/15481603.2019.1650447 (2020).

126. Rodriguez-Galiano, V. F., Chica-Olmo, M., Abarca-Hernandez, F., Atkinson, P. M. & Jeganathan, C. Random forest classification of mediterranean land cover using multi-seasonal imagery and multi-seasonal texture. *Remote Sens. Environ.* **121**, 93–107. https://doi.org/10.1016/j.rse.2011.12.003 (2012a).

127. Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M. & Rigol-Sanchez, J. P. An assessment of the effectiveness of a random forest classifier for Land-cover classification. *ISPRS J. Photogrammetry Remote Sens.* **67**, 93–104. https://doi.org/10.1016/j.isprsjprs.2011.11.002 (2012b).

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

129. Raši, R., Schwarz, M. & Bratislava, L. U. *FOREST EUROPE 2019* (Pilot study: Forest Fragmentation Indicator, 2019).

130. Ramachandra, T. V., Bharath, S. & Bharath, A. H. Insights of forest dynamics for the regional ecological fragility assessment. *J. Indian Soc. Remote Sens.* **48** (8), 1169–1189 (2020).

131. Riitters, K. H. & Coulston, J. W. Hot spots of perforated forest in the Eastern united States. *Environ. Manage.* **35**, 483–492 (2005).

132. Lambin, E. F., Geist, H. J. & Lepers, E. Dynamics of land-use and land-cover change in tropical regions. *Annu. Rev. Environ. Resour.* **28** (1), 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459 (2003).

133. Sang, L., Zhang, C., Yang, J., Zhu, D. & Yun, W. Simulation of land use Spatial pattern of towns and villages based on CA–Markov model. *Math. Comput. Model.* **54** (3–4), 938–943. https://doi.org/10.1016/j.mcm.2010.11.019 (2011).

134. Bunruamkaew, K. & Murayam, Y. Site suitability evaluation for ecotourism using GIS & AHP: a case study of Surat thani Province. *Thail. Procedia-Social Behav. Sci.* **21**, 269–278. https://doi.org/10.1016/j.sbspro.2011.07.024 (2011).
135. Ramachandra, T. V. & Bharath, S. Global warming mitigation through carbon sequestrations in the central Western Ghats. *Remote Sens. Earth Syst. Sci.* **2**, 39–63. https://doi.org/10.1007/s41976-019-0010-z (2019).
136. Komiyama, A., Poungparn, S. & Kato, S. Common allometric equations for estimating the tree weight of mangroves. *J. Trop. Ecol.* **21** (4), 471–477. https://doi.org/10.1017/S0266467405002476 (2005).
137. Harishma, K. M., Sandeep, S. & Sreekumar, V. B. Biomass and carbon stocks in Mangrove ecosystems of Kerala, Southwest Coast of India. *Ecol. Processes.* **9** (1), 1–9. https://doi.org/10.1186/s13717-020-00227-8 (2020).
138. Vinod, K. et al. Biomass and carbon stocks in Mangrove stands of Kadalundi estuarine wetland, south-west Coast of India. *Indian J. Fisheries.* **65** (2), 89–99. https://doi.org/10.21077/ijf.2018.65.2.72473-11 (2018).
139. Mizanur Rahman, M., Nabiul Islam Khan, M., Fazlul Hoque, A. K. & Ahmed, I. Carbon stock in the sundarbans Mangrove forest: Spatial variations in vegetation types and salinity zones. *Wetlands Ecol. Manage.* **23**, 269–283. https://doi.org/10.1007/s11273-014-9379-x (2015).
140. Nyeko, M. GIS and multi-criteria decision analysis for land use resource planning (2012). https://doi.org/10.4236/jgis.2012.44039.
141. Xie, G. D., Zhen, L., Lu, C. X., Xiao, Y. & Chen, C. Expert knowledge based valuation method of ecosystem services in China. *J. Nat. Resour.* **23** (5), 911–919 (2008).

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Author contributions

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