Geospatial and Machine Learning Approaches to Forest Ecological Vulnerability Assessment: A Systematic Scoping Review and Methodological Synthesis

Sasi, M.[1] and Sawant, S. A.[2]*
Division of Geoinformatics, School of Life Sciences, Mysuru, JSS Academy of Higher Education and Research, Mysuru, Karnataka, India
E-mail: msasigmurugesan@gmail.com,[1] ORCID ID: 0009-0004-3574-412X,[1]
ORCID ID: 0000-0002-1452-0774[2]*
Corresponding Author

DOI: https://doi.org/10.52939/ijg.v22i8.5145

Abstract

Forest ecosystems are increasingly vulnerable to climatic variability and anthropogenic pressures, necessitating robust, scalable, and reproducible assessment approaches. Over the past three decades, remote sensing, geographic information systems, and machine learning techniques have been widely applied to evaluate forest ecological vulnerability; however, a consolidated synthesis of computational methods, indicator frameworks, and modelling paradigms remains limited. This study presents a systematic scoping review of global research on forest ecological vulnerability assessment using geospatial and machine learning approaches. Literature published between 1995 and 2024 was retrieved from Scopus, Web of Science, and Google Scholar following a transparent PRISMA-ScR–guided screening protocol, resulting in the inclusion of 136 studies for qualitative synthesis. The review synthesizes vulnerability indicators structured under exposure, sensitivity, and adaptive capacity, and critically examines the methodological evolution from index-based and statistical models to advanced machine learning and hybrid simulation frameworks. Results indicate a growing reliance on ensemble learning, cloud-based platforms, and high-resolution spatial data, alongside persistent methodological limitations related to model validation, spatial scale dependency, interpretability, and transferability. This study provides an integrated methodological synthesis that combines vulnerability indicator frameworks, geospatial modelling approaches, and emerging machine learning paradigms to identify key methodological trends and research gaps in forest ecological vulnerability assessment. Based on the synthesis of reviewed studies, a conceptual methodological framework is proposed to guide future forest ecological vulnerability assessments by integrating indicator classification, geospatial data processing, predictive modelling, and validation strategies. By integrating indicators, modelling approaches, and computational platforms, this review provides a guide for future ecological informatics research toward transparent, reproducible, and decision-oriented forest vulnerability assessments.

Keywords: Ecological Indicators, Forest Vulnerability, Geospatial Modelling, Machine Learning, Remote Sensing

1. Introduction

Global climate change is accelerating due to increasing anthropogenic pressures, posing significant challenges for forest ecosystem stability and resilience. Climate change adaptation is a measure to make the forest ecosystem resilient, acting as a key regulatory body of the global carbon cycle [1] [2] and [3]. Almost one-third of the Earth's land area is covered by forests, which represent diverse ecosystems that are genetically rich and biologically productive, comprising about 80% of the flora and fauna species within their terrestrial territory [4] and [5]. Forests act as an invaluable resource to expand the economy, supporting human survival and the development of ecosystem services [2] and [3]. The 2015 Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC) [3] highlights the critical role of forests in climate change mitigation by functioning as major global carbon sinks and supporting ecosystem resilience. In contrast to this effect, various studies have proven a wide range of changes in the forest ecosystem.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

A gradual trend in forest degradation has been observed in diverse forest ecosystems since the 1960s, due to rapid climate change and anthropogenic interventions, despite their immense ecological importance [6], with a global surface temperature reaching above 1.1 °C (2011 – 2020), post-19th century [7]. A global-scale assessment of tropical dry forests indicates about 97% of them are in a high-risk category, especially Eurasia, due to increased anthropogenic disturbance, differing in regions, i.e., climate change in America, habitat fragmentation, and fire effects in African forests[8].

Further, in the western Mediterranean sub-region of Turkey, the vulnerability of the forest ecosystem has been assessed under climate change and variability concerning land degradation using the Ecological Vulnerability Index (EVI). It revealed that about 24% of the area fell under the highly vulnerable category, due to encroachment through various means of human disturbances[9]. Also, studies have revealed that under the current climatic scenario, 20% of US forest cover would be lost if the disturbance rates doubled, using the Disturbance Distance Index, wherein the southwestern forest is highly vulnerable. It also showcased that, considering future climatic scenarios, the majority of the forest is resilient if the conditions are tackled adequately [10]. Additionally, the study of the Tuchhola forest, in Poland, identifies the typical indicators for monitoring forest fragmentation and high-risk zones, indicating a decrease in forest cover of nearly 33.23 km^2 between 2020-2023 [11].

According to the IPCC Sixth Assessment Report, the mean global temperature has already increased by approximately 1.1 °C above pre-industrial levels during the 2011–2020 period, highlighting the urgency of limiting warming to 1.5 °C as emphasized in the IPCC Special Report on Global Warming of 1.5 °C. To tackle this situation, countries across the globe have developed international agreements, where India submitted its Nationally Determined Contribution (NDC) to the UNFCC in October 2015, for better climate change policies, and monitoring of forest areas across the country [12].

According to reports from the Indian Meteorological Department (IMD, 2020), the annual mean temperature in India has increased by approximately 0.61 °C per century during the period 1900–2019. Forests are a major contributor to household income in many developing countries, accounting for approximately 22–28% of rural livelihoods [13]. Although examples from India are presented to illustrate regional climate change trends, forest vulnerability remains a global concern affecting major forest systems including the Amazon Basin, Congo Basin, and Southeast Asian tropical forests. These ecosystems play a critical role in global carbon cycling and biodiversity conservation. This observed shift in vegetation types of forest ecosystems has been of major concern in the Indian sub-continent. This escalating forest fragmentation is adversely affecting the ecological balance. Due to natural and anthropogenic disturbances, increasing vulnerability critically affects the forest ecology's structure, function, and distribution. If prolonged, this situation risks species extinction or irreversible biodiversity loss in forest ecosystems, surpassing the adaptation measures without effect.

The advent of Remote Sensing (RS) and Geographic Information System (GIS) by the 1970s has made incredible achievements in capturing and monitoring enormous amounts of information about the global ecosystems[14]. It is important to assess the health of the forest ecosystem and its growing changes, to make effective decisions to adapt to the rising climatic conditions. Modelling the hotspots, species behavior, identifying critical habitats, edge effect will help in continuous monitoring and make resilient ecosystem management [15]. The depletion of the forest ecosystem has been addressed since the 1960s, post-industrialization [6]. Technological advancement will help in recognizing these inherent changes, to build a resilient environment, and sustain the resources for the future. A wide range of studies has been addressed from various perspectives, yet the use of advancing technology has indicated the need to improve the research focusing on forest ecological vulnerability studies, on a futuristic note, as most of the studies have addressed the changes in the forest cover, under current climatic conditions.

Despite the expanding body of literature on forest ecological vulnerability, existing reviews predominantly emphasize thematic descriptions of climate impacts, land-use change, or ecosystem degradation, with comparatively limited attention to the computational and methodological foundations of vulnerability modelling. In particular, systematic comparisons of indicator selection strategies, machine learning algorithms, hybrid simulation models, and software ecosystems remain scarce. Furthermore, issues related to model validation, spatial scalability, reproducibility, and transferability across ecological contexts are often underreported. To address these gaps, this study aims to (i) systematically synthesize forest vulnerability indicators within an exposure–sensitivity–adaptive capacity framework, (ii) critically evaluate the evolution of geospatial and machine learning-based modelling approaches, and (iii) identify methodological limitations and future research directions relevant to ecological informatics and spatial decision-support systems.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

2. Methodology

2.1 Review Design

This study adopts a systematic scoping review approach to synthesize and evaluate geospatial and machine learning-based methods used in forest ecological vulnerability assessment. A scoping design was selected to capture the breadth of methodological developments, indicator frameworks, and modelling paradigms across diverse forest ecosystems and geographic contexts. The review process was guided by the PRISMA-ScR framework to ensure transparency in literature identification, screening, and synthesis.

2.2 Data Sources and Search Strategy

A comprehensive literature search was conducted using Scopus and Web of Science as primary databases. Google Scholar was used only as a supplementary search tool to identify additional relevant studies through citation tracing and grey literature screening. Peer-reviewed journal articles, conference proceedings, theses, and authoritative reports published between 1995 and 2024 were considered. Search queries combined primary terms (Figure 1(a), and Figure 1(b)) related to forest vulnerability with geospatial and computational methods, including: (("forest ecological vulnerability" OR "ecosystem vulnerability") AND ("remote sensing" OR GIS OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "neural networks" OR CNN OR "spatial modelling")). In addition, reference lists of selected articles were manually screened to identify relevant studies not captured during the initial search.

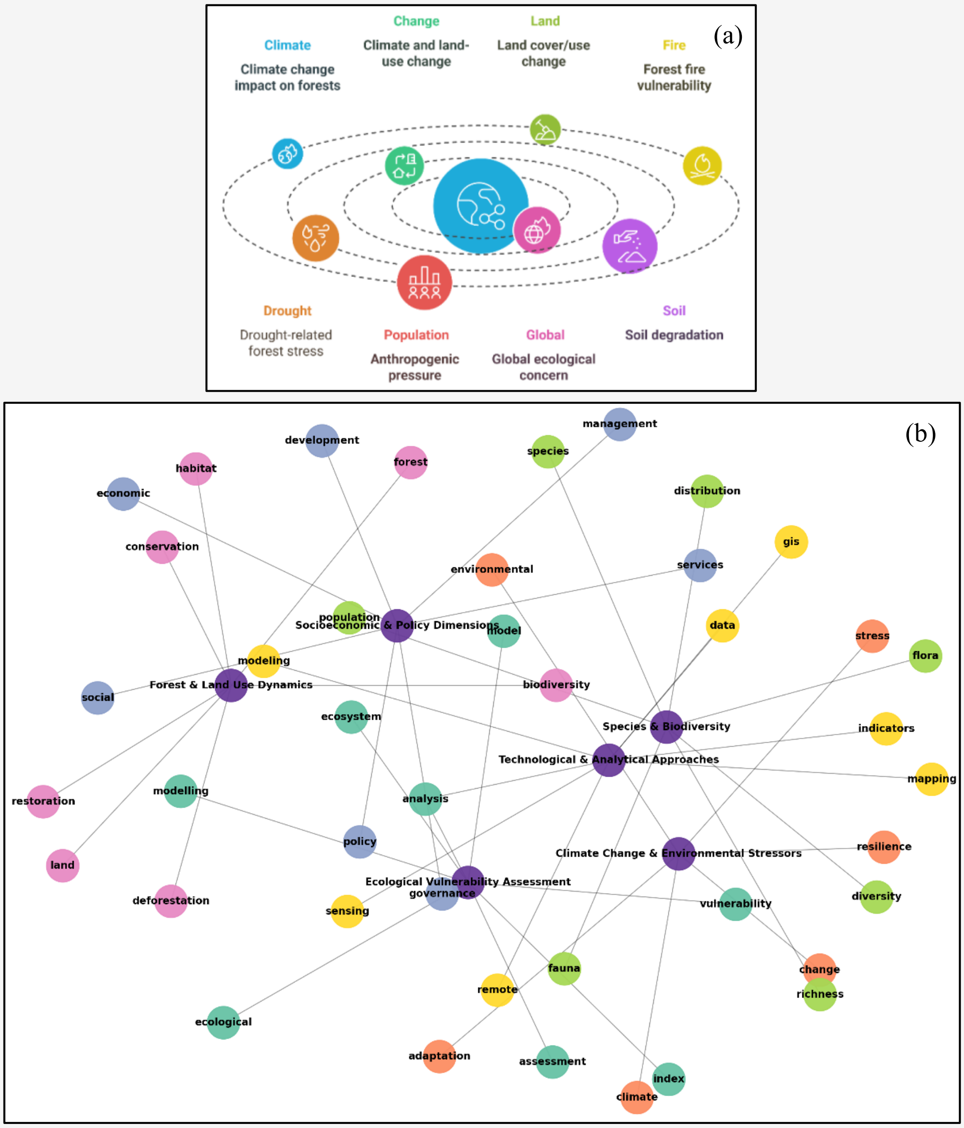

Figure 1: Forest ecological vulnerability: (a) generalized keywords, and (b) enhanced keywords connectivity

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

2.3 Inclusion and Exclusion Criteria

Studies were included if they (i) focused on forest ecosystems, (ii) applied remote sensing, GIS, machine learning, or spatial modelling techniques, and (iii) addressed ecological vulnerability, risk, resilience, or susceptibility. Studies were excluded if they (i) focused on non-forest ecosystems, (ii) lacked a spatial or computational component, or (iii) examined vulnerability solely from socio-economic or policy perspectives without ecological or geospatial analysis.

2.4 Screening and Selection Process

The literature search identified 329 records from Scopus, Web of Science, and Google Scholar, with an additional 18 records obtained through citation searching. After removing 46 duplicate records, 301 studies were screened based on titles and abstracts. Of these, 123 records were excluded due to irrelevance to forest ecosystems or the absence of geospatial or computational components. Full-text assessment was conducted for 178 reports, resulting in the exclusion of 42 studies that lacked a vulnerability framework, spatial modelling component, or sufficient methodological detail. A final set of 136 studies was included in the qualitative synthesis. The screening and selection process is summarized in the PRISMA flow diagram (Figure 2). To ensure methodological transparency and consistency in study selection, the screening and eligibility assessment were conducted following the PRISMA-ScR framework guidelines, which provide structured procedures for identifying, evaluating, and reporting evidence in scoping reviews.

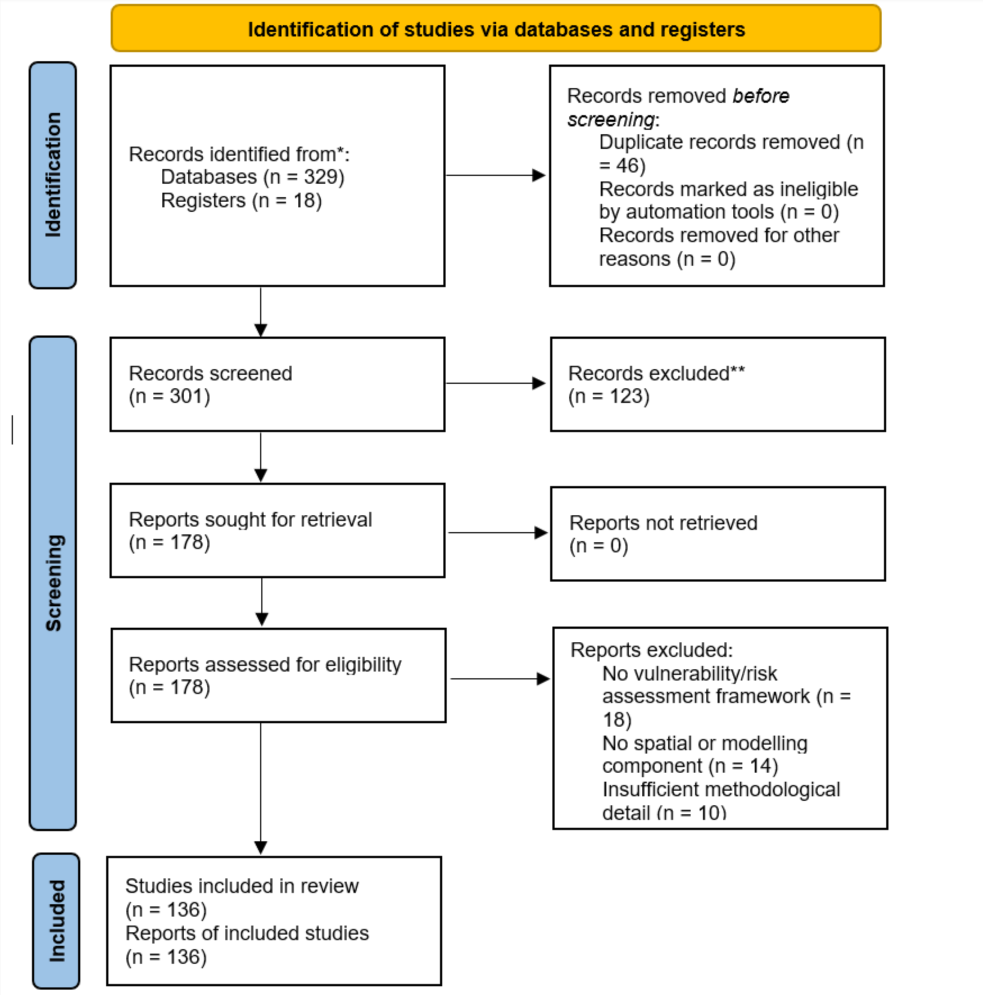

Figure 2: PRISMA flow diagram illustrating the identification, screening, eligibility, and inclusion of studies in the systematic scoping review of forest ecological vulnerability assessment using geospatial and machine learning approaches

2.5 Geographic Origin of Literature Contribution

The global distribution of forest vulnerability articles comprises about 3.07%, including international comparison, and the rest of the countries have a minimal count[16]. Countries like China, India, and the USA contribute to the maximum studies conducted, with 5.50%, 4.85%, and 4.40%. Nigeria contributes about 1.46%, Iran, Pakistan, and Bangladesh contribute about 2.91%. Major studies are conducted on the tropical, subtropical, and temperate countries (Figure 3). With a diverse distribution of forests on a global scale, it is evident that most of the rocky, Himalayan, desertified-temperate, and alpine forest regions have minimal research when it comes to geospatial analysis.

2.6 Thematic and Temporal Distribution of Literature

The thematic coverage of literature on forest ecological vulnerability using RS and GIS (Figures 4 and 5) is broadly classified into ecological vulnerability, change in forest ecology, and ecological risk [17][18][19] and [20], as they have been researched frequently on a diverse forest ecosystem, accounting for 12.15%, 8.10%, and 10.12%. The change analysis helps to understand the impact of climate, human-induced disturbances leading to change, and land use and land cover (LULC) practices, which is a major concern (1999-2024). The rest of the themes are still upcoming, and the count of publications has peaked after 2021, an era of ML, AI, and improved geospatial analysis. The themes are extinction analysis, which focuses on degradation and disturbances in forest ecosystems, either through climate risk or human interference. Adaptation, conservation, evaluation (monitoring/impact), forecasting (trend analysis), sustainability, simulation models (ensemble modelling, susceptibility, comparison), and integrated frameworks [21][22][23][24][25][26][27][28] and [29], which were intensively analyzed after 2010.

3. Strategic Insights and Methodological Reflections

Rather than providing an inventory of individual studies, this section synthesizes dominant methodological patterns, indicator frameworks, and modelling trends that characterize forest ecological vulnerability research using geospatial and machine learning approaches.

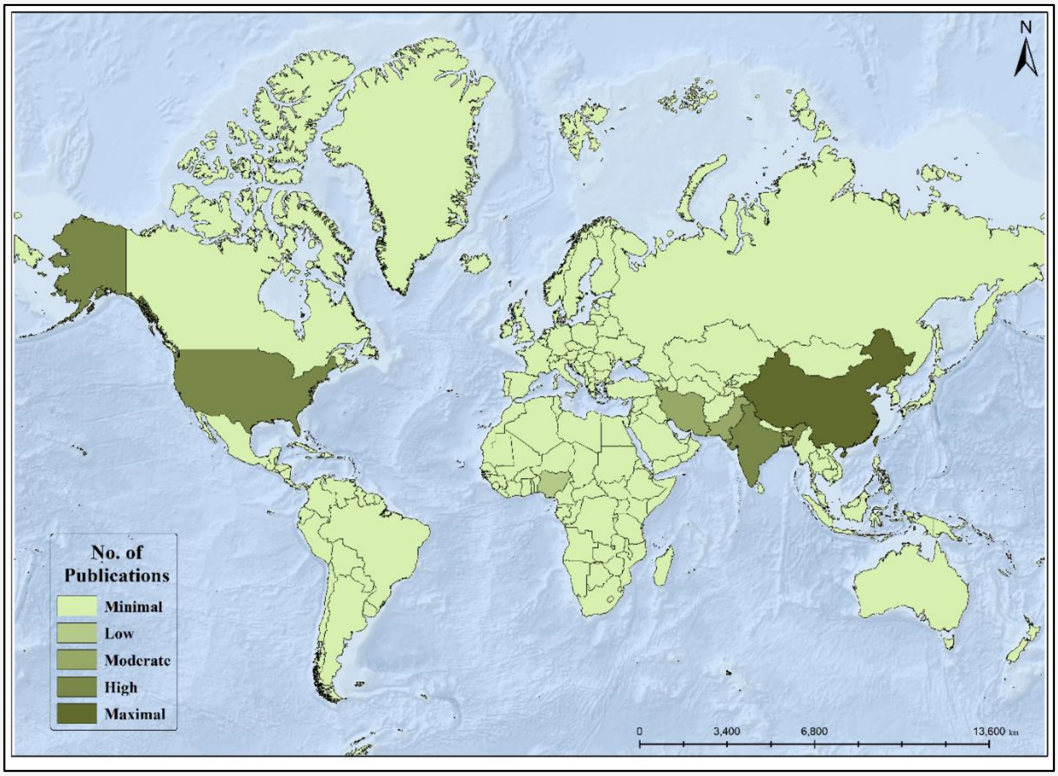

Figure 3: Geographic origin of literature contribution on forest ecological vulnerability modeling using RS and GIS (1995-2024)

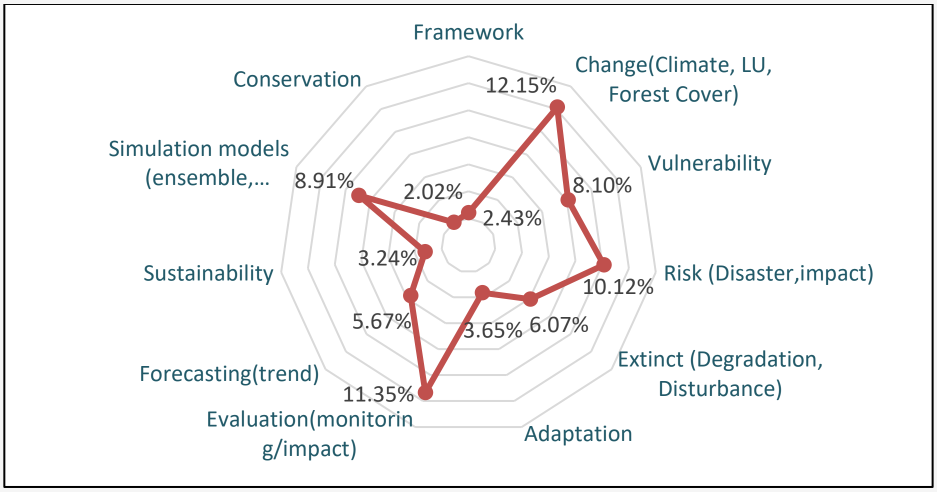

Figure 4: Thematic coverage of literature

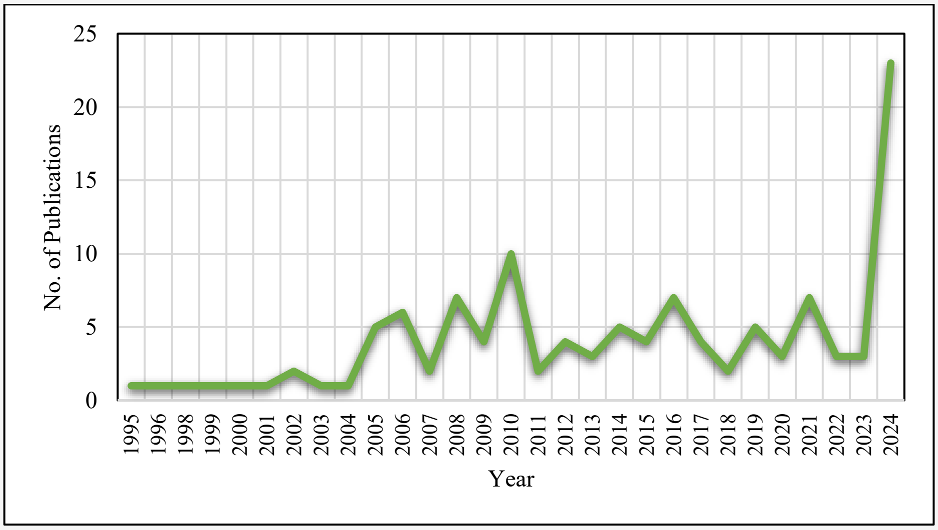

Figure 5: The high time of publication on forest ecological vulnerability using RS & GIS (1995-2024)

3.1 Composite Vulnerability Index Parameters

The initialization of thematic selection of variables by 20th-century researchers has improved the forest ecological vulnerability analysis using geospatial techniques. The parameters have been categorized into 2 groups of frequently used and least used variables. The variables are categorized into climatic, topographic, vegetation, land use, soil, anthropogenic, hydrological, and disturbance variables. Based on the variables' importance, they are broadly categorized as exposure, sensitivity, and adaptive capacity parameters.

3.1.1 Exposure-driven parameters for the vulnerable forest ecosystem

Studies have shown that the forest ecosystem is highly dependent on climatic variability. Since the beginning of the 20th century, climatic variables have been a part of forest ecological studies, which include temperature (mean, annual, average), precipitation (mean, annual, average), relative humidity, drought index, wind speed, and air temperature [24][30][31][32][33] and [34]. Microclimatic variations are dependent on topography. The key variables are elevation (DEM), slope (angle, aspect), and relief [24][27][30][35][36][37][38][39][40][41] and [42]. Vegetation plays a central role in forest ecosystem resilience. Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Net Primary Productivity (NPP) [42][43][44][45][46][47] and [48] are the highly preferred parameters. LULC Change and Urbanization (Landform, Settlement) [39][49][50][51] and [52], the key variables under the land use category play a crucial role in understanding the intensity, the extent of human intervention, and how these disturbances alter the forest's resilience. It should be noted that land use and land cover variables may act as both exposure and sensitivity indicators depending on the modelling framework and study objectives. In exposure-based frameworks, LULC reflects external anthropogenic pressures, whereas in sensitivity frameworks it represents the ecological susceptibility of forest landscapes to disturbance. Forest health and productivity are determined by soil indicators, which include soil type, soil moisture, and soil erosion [19][53][54][55] and [56]. Population density (Human Footprint), deforestation rate [25][35][49][57][58] and [59] are the crucial anthropogenic indicators are driving factors that reduce the adaptive capacity of the forest by intensifying stress, disrupting the ecosystem process. Hydrological factors help in the regeneration of forest health. Distance to rivers, streams, drainage, vegetation, water content, and sea level rise [38][59][60][61][62] and [63] are the factors that highly determine the stress and adaptive capacity of the forest ecosystem. Disturbances such as forest fires and invasive species [49][59][64][65] and [66] reduce biodiversity, influencing the ability to recover from stress. Given the prevalence of these categorical variables in the study, (Table 1) lists the least frequently used exposure indicators, which are used according to the study's needs and regional complexities.

The frequency of indicators across studies suggests that climatic and landscape-based variables remain the dominant drivers of vulnerability modelling, whereas socio-economic indicators are comparatively underrepresented despite their importance in adaptive capacity assessments.

Table 1: Least used exposure indicators

Category	Exposure	Count
Climate	AET, PET, DEF, ESI, PDSI, TVDI, Temperature Condition Index, Air temperature, Water vapor pressure (WVP), Sea level rise, Growing degree days(> 5 °C), Mean temperature of coldest month, Water balance, MAT, TS, MAP, Evapotranspiration (ET), Drought index (AI), Summer days, Frost days, Consecutive days without rain, Rainstorm disaster factors, Precipitation, Temperature, Frost Days, Rainstorm Disaster Factors, annual cumulative precipitation, precipitation seasonality coefficient, average annual temperature, annual range temperature, monthly minimum relative humidity, Temperature seasonality, precipitation seasonality, bioclimatic variables.	4
Topography	profile curvature, landforms, CTI, TWI, Mean elevation, Mean topographical wetness index, Mean radiation, Steep slope (>15), Plan curvature, Relief dissection, Surface cutting depth (SCD), Degree of relief (DR), Relief amplitude, Terrain conditions, Roughness, Surface Cutting Depth, Roughness, mean radiation, geology	3
Vegetation	Flowering Months, Resprouted/Seeders Ratio	2
Land Use	Proximity to croplands, Proximity of agricultural land, Slope farmland proportion, Imperviousness, Built-up land proportion, Impervious Surface Percentage	4
Soil	Calcareous Rock Presence	1
Anthropogenic	proximity to city areas, Industrial land use, Mines, Livestock/poultry farming, Proximity to market areas, Proximity to residential areas, Human interferences (roads, railways, industry), Female-Headed Households	2
Hydrology	Hydro-eco deficit and surplus, Hydro-period, WPF, Change rate of water depth, Hydro-Meteorology, Turbidity Index, Chlorophyll-a	2
Disturbances	Forest fire inventory, Fuel types, Singularity, Frequency of Landslide Event, Frequency of Earthquake Event, Fire Density, Large wildfire hazard, Disturbances (deforestation, landslides), Civil conflicts, Alien invasive species, Pollutant input	3

Table 2: Least used sensitivity indicators

Category	Sensitivity	Count
Climate	Emberger's Thermic Variant (ETV)	3
Topography	Relief Amplitude	2
Vegetation	EVI, LAI, MSAVI, CI-G, TGI, NDMI, NDRE, SAVI, Vegetation indices, Forest health factors (dNBR, FCF, SVI, VHI, NPP, AGB, BGB), Vegetation water content, Tree biomass, Native trees, Elm trees, Allergenic trees, Tree condition, LULC (forest-related), Forest cover rate, Shading by trees, Structural connectivity, biological abundance index (B5), Dispersal Distances	3
Land Use	Landscape indices (Class area, Number of patches, Edge density, Contagion Index, Shannon's Diversity Index), Nighttime Light Index	2
Soil	Soil series, soil erosion (water), soil moisture, soil fertility, Sand/gravel soil, Rocky soil, Calcareous rock, Quartzite rock, Soil erosion modulus, Percentage area for soil and water loss, Pedology, Potential Rate of Exposed Carbonate Rocks, pH value of Acid rain	1
Anthropogenic	Population density index, Socio-economic factors (Population pressure, Poverty, Unemployment, Housing density), Deforestation, Fertilizer/pesticide application, Access to Health Services.	3
Hydrology	Turbidity Index, RVA, Chlorophyll-a, Total Phosphorus, Secchi-disk Depth, Wetland fragmentation, NDMI	1
Disturbances	Insect- and disease-related tree mortality, Civil Conflict Impact	1

3.1.2 Sensitivity-driven parameters for the vulnerable forest ecosystem

Climatic variables that directly influence the ecosystem processes aid in understanding the forest ecosystem's transition zones and arid regions through bioclimatic variables and Potential Evapotranspiration (PET) [23][39][67] and [68]. Aspect, Topographic Wetness Index (TWI) [39][40][61][69][70][71] and [72] are the terrain factors that influence the region's microclimate, influencing the vegetation patterns. The tolerance capacity of the forest and the ability to withstand ecosystem stress are influenced by forest type and canopy cover (canopy density) [27][29][30][32][45][62][64][71][73] and [74], the major vegetative factors. In rapidly developing regions, land use variables, i.e., fragmentation, distance to roads, settlements, croplands, and city regions [11][38][42][54][60][61][64][75] and [76], determine the human pressure on the forest ecosystem. Soil texture and soil fertility [34] [42] and [73] are the most influential soil characteristics, determining the healthy forest growth. The human dimension of forest ecological vulnerability is captured through anthropogenic variables, Gross Domestic Product (GDP), and education level [61][77] and [78], which indicate effective resource use and policy developments. Hydrological variables, i.e., water stress, drought frequency [31][34][40][41][55][76][79] and [80], play a crucial role in regenerating the forest ecosystem. Natural or human-induced disturbances, such as burned areas and increased landslide frequency [55] and [62]are the most sensitive variables that indicate ecosystem biomass content and habitat health. While the aforementioned indicators are used to analyze sensitivity, other indicators are also used depending on the study's requirements (Table 2).

3.1.3 Adaptive capacity-driven parameters for the vulnerable forest ecosystem

Climatic variables that play a key role in regenerating the forest ecosystem from stress include annual water availability, climate resilience (Wet days' frequency-rain days per month) [78][81][82] and [83]. The adaptive capacity of forests increases with greater water availability, helping in microclimate regulation and biodiversity regeneration. The proximity to water bodies the moisture content, enabling the ecosystem to withstand stress. Ecosystem productivity is seen through tree biomass, native species diversity (tree species, species richness) [25][36][67][83] and [84], indicating the forest's health. Land use factors, protected areas, and forest management policies [66] and [74] help understand how resilient forests are under stress, and how human-induced disturbances modify the ecosystem. The stability of the forest ecosystem comes with the soil conservation practices [34][73][78] and [85] as soil is the foundation for a resilient forest ecosystem.

The socioeconomic activities determine the human dimension of how the forest ecosystem is maintained and restored with better adaptive capacity based on the income and social capital [25][44][55] and [58]. The irrigation infrastructure [40] [86] and [87] reduces the human pressure on forests in the urban fringe zone, enhancing the adaptive capacity. Forest fire is both a natural and human-induced disturbance. The fire adaptive strategies [40][86] and [87] help to mitigate the burnt area, helping the forest ecosystem recover and regenerate. The least-used adaptive capacity indicators, notwithstanding the most-used indicators, are included in (Table 3). Depending on the study region, the main purpose of these indicators is to support policymaking and adaptive actions in the susceptible areas.

3.1.4 Indices for forest ecosystem vulnerability

The forest ecosystem is vulnerable to climatic stressors. Climatic indices such as Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Vegetation Condition Index (VCI), Vegetation Health Index (VHI), and Temperature Vegetation Dryness Index (TVDI) [34] [39] and [88] provide actionable insights on the adaptive capacity of the forest. Topographic Wetness Index (TWI), and Compound Topographic Index (CTI) [38][47][61] and [62] determine forest health and vulnerability, indicating the adaptive capacity of the forest ecosystem. Health, productivity, and structural integrity are explicitly captured through vegetation indices such as the Normalised Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI), the Soil Adjusted Vegetation Index (SAVI), the Leaf Area Index (LAI), and Net Primary Productivity (NPP) [39][43][45][89][90] and [91]. Largest Patch Index (LPI), Patch Density (PD), and Edge Density [75][87] and [92] depict vegetation disturbances, structural changes, and fragmentation of the forest canopy cover. Anthropogenic pressure and climate extremes make the ecosystem vulnerable to increased soil exposure and vegetation loss. This can be captured through the Normalised Difference Bare Soil Index (NDBSI) [88]. To capture the intensity of anthropogenic influences, Normalised Difference Built-up Index (NDBI), and Human Footprint Index (HFI) [27] and [42] play a vital role. The susceptibility and resilience of the forest can be understood through hydrological variables, i.e., Normalised Difference Water Index (NDWI), and Normalised Difference Moisture Index (NDMI), which indicate the health of the forest ecosystem. The intensity and frequency of disturbances like fire can be captured through Differenced Normalised Burnt Ratio (dNBR), and the burned area index [31] and [39], which indicates how sensitive the forests are.

4. Results

4.1 Index-Based and Empirical Techniques – Traditional Approaches

The vulnerability analysis approach can be broadly categorized as participatory scenario analysis, which includes the most widely used evaluation techniques (Table 4) such as expert-driven framework, i.e., Analytical Hierarchical Process (AHP) [36] and [43]. Statistical approaches include Principal Component Analysis (PCA) and regression methods [44] [86] [90] and [92]. The former is a Multi-Criteria Decision Making (MCDA) approach that hierarchically ranks variables. Principal Component Analysis (PCA) is commonly used to reduce dimensionality among variables, while spatial models and indicator-based frameworks, including hotspot analysis (Getis-Ord Gi) [64], are applied to support spatial prediction and decision-making. These traditional, conventional methods have also been integrated with advanced techniques. As the research progresses, complex methodological approaches and new frameworks should be developed, which will help in assessing regional characteristics, providing accurate and credible scientific research [16].

Table 3: Least used adaptive capacity indicators

Category	Adaptive Capacity	Count
Climate	Climate Policy Enforcement	2
Topography	Slope Stabilization Measures	1
Vegetation	CO2 sequestration by trees	1
Land Use	Protected Areas, Protected Forest, Orchards, Irrigated agriculture, Rain-fed agriculture, Land use rate, Land Value, Average land size	3
Soil	Organic Farming Adoption	1
Anthropogenic	GDP density, Road network, Building blocks, gHM, NDBI, Protected landcover, Infrastructure (Drinking water, Sewage system, Waste collection, Phone service), Socio-economic resilience (Education, Healthcare access, Economic diversity)	2
Hydrology	Wetland Restoration Efforts	1
Disturbances	Early Warning Systems	2

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 4: Traditional assessment methods

Characteristic	Participatory scenario analysis	Quantitative indicator-based frameworks
Indicator Aggregation	Fuzzy logic, expert-derived weights	Entropy Weight Method, Fuzzy Expert Systems
Landscape pattern measurements	Change detection, Fragmentation dynamics-edge density metrics	Landscape connectivity /diversity indices
Accuracy assessment	Supervised classification	Field surveys
Environmental assessment	Environmental vulnerability assessment, Biogeophysical quality index (BQI), Climate quality index (CQI)	Drought indices (KBDI, SPEI, Palmer)
Decision Making	Multi-Criteria Decision Making (AHP, CRITIC)	AHP (Analytic Hierarchy Process)
Models	Universal Soil Loss Equation (USLE), Fire effects models (FOFEM, CONSUME)	
Spatial Analysis	Hotspot analysis (Getis-Ord Gi), Spatial Autocorrelation (Moran’s I)	Principal Component Analysis (PCA)
Diversity Index	Shannon diversity index (SHDI)	PCA-hierarchical clustering

Table 5: Machine learning driven simulation models

	Machine Learning Algorithms	Predictive Analytics	Hybrid Models
Models	RF, SVM, ANN, CART, BRT, GLM, GBM, XGBoost, CNN, DNN	CA-Markov, DGVMs, U-Net, CMIP5, CMIP6, Bayesian Networks, LCM	RF-DEA, RF-GWO, Artificial bee colony-ANFIS
Description	A diverse pattern recognition algorithm.	Future forecasting models.	Model integration for enhanced prediction.

4.2 Machine Learning (Ml) and Predictive Analysis Simulation Models

Simulation models are advanced techniques that use machine learning algorithms (Table 5) such as Random Forest (RF) and Support Vector Machine (SVM), both supervised machine learning algorithms, are widely used for land-use and land-cover classification tasks [27] and [93]. Deep learning is a part of ML techniques, where Convolutional Neural Network (CNN) and dynamic simulation models, such as Dynamic Global Vegetation Models (DGVMs) [32] and [94], are used for image analysis and vegetation modelling. Since early 2020, hybrid predictive models have been used, including multiple ML algorithms to develop a multi-modal approach[27] and [95]. This helps to identify the most suitable and scientifically accurate methods for the study. The technological advancements in the current situation will outshine traditional techniques, where multi-model ML approaches have proven to provide substantial benefits, yielding accurate results. Upcoming research should integrate ML approaches to develop integrated frameworks and models, which will act as future replication for advanced ML techniques [96] and [97].

4.3 Geospatial Software in Forest Ecological Vulnerability

The vulnerability modeling uses multiple software, plugins, and tools according to the study objectives (Figure 6). Numerous research studies have been conducted using authentic software, ArcGIS, developed by the Environmental Systems Research Institute (ESRI), which has become a critical RS and GIS analysis software. It provides extensive tools for raster and vector data types and several plugins for higher-order analysis [98] and [99]. Vegetation classification, change detection, and vegetation health monitoring are captured using ERDAS IMAGINE. ENVI, an image-processing software [99] developed by L3Harris. Its advanced image analysis capabilities, such as spectral unmixing, classification, and vegetation indices computation, make it most suitable for forest studies. Open-source software such as QGIS, R (biomod2, ade4, landscape metrics), GEE, and TerrSet (IDRISI) supports advanced spatial analysis and modelling. FRAGSTAT and Maxent are the most prominently used software for their extensive species distribution and fragmentation studies analysis.

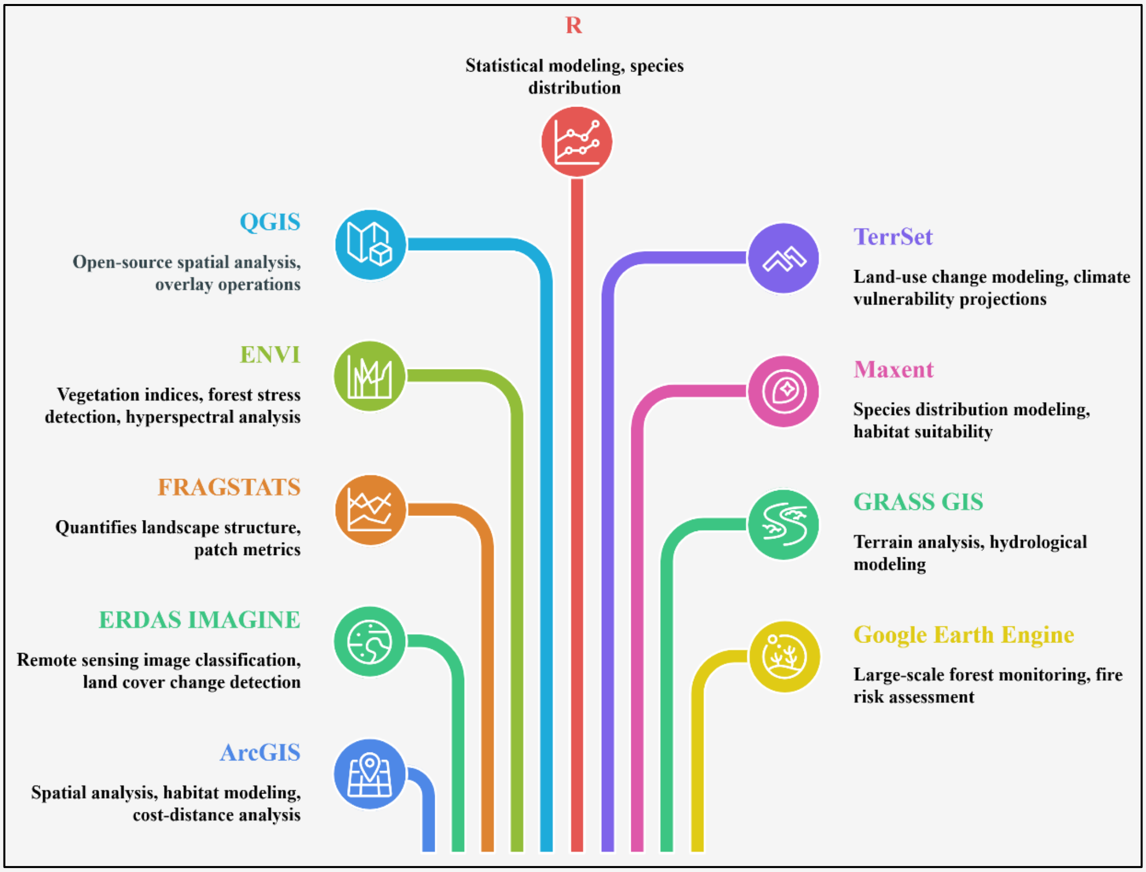

Figure 6: Potential application in forest ecological vulnerability studies

The primary limitation of licensed software is its cost and system compatibility, while open-source software has relatively few tools, either under development, or some plugins are licensed. GEE, a cloud-based platform, has a proven advantage in this case, as it works with coding and provides ready-to-use data from various sources worldwide. Beyond functionality, the choice of geospatial software has implications for computational efficiency and reproducibility. Cloud-based platforms such as Google Earth Engine enable large-scale processing of high-resolution satellite datasets, reducing computational limitations associated with desktop GIS environments. Additionally, open-source tools such as QGIS and R enhance reproducibility by allowing transparent workflows and script-based analysis, which is increasingly encouraged within ecological informatics research. Moving to this platform is highly preferable due to its system compatibility and increased storage capacity [100]. Depending on the tools, integrated techniques, and compatibility, some software that is outdated to an extent, yet offers insights into analysis, is still in use (Table 6) [56][60][64][66][73][84][101][102] and [103].

4.4 Limitations of Machine Learning-Based Vulnerability Modelling

Although machine learning approaches have substantially improved predictive accuracy in forest vulnerability assessments, several limitations persist. Spatial autocorrelation inherent in remotely sensed data often results in overfitting and inflated performance estimates when independent validation is absent. Many studies rely on region-specific training datasets, limiting the transferability of models across ecological contexts. In addition, black-box algorithms such as deep neural networks pose interpretability challenges, reducing transparency for policy and forest management applications. Addressing these limitations requires improved validation strategies, uncertainty quantification, and the integration of explainable artificial intelligence within ecological informatics frameworks.

Table 6: Overview of the least-used software

Software	Relevance to Forest Ecological Vulnerability	Key Limitations
SPLAM	Spatial landscape modeling (niche applications).	Outdated, limited documentation.
Netica (BN software)	Bayesian networks for risk assessment (rare in forest studies).	Complex setup, niche use.
SPLUS	Older statistical software (largely replaced by R).	Outdated, limited GIS integration.
See5	Decision tree modeling (rarely used in modern studies).	Discontinued, replaced by machine learning tools.
gSNAP5.0	Image segmentation (specialized, not widely adopted).	Obsolete, lacks integration with modern GIS.
Geographical Cellular Automata (Geo CA)	Theoretical land-use change modeling	Limited real-world applications.
PRISM	Climate data interpolation (auxiliary role)	Only for climate data, not a full GIS tool.
SPSS	Statistical analysis (rarely used in GIS-based forest studies).	No spatial analysis capabilities.
ClimateWNA	Climate downscaling for ecological studies.	Region-specific, not a full vulnerability tool.
AVIM2	Vegetation modeling (limited adoption).	Niche use, complex parameterization.

5. Discussion

5.1 Methodological Trends in Forest Ecological Vulnerability Assessment

Forest ecological vulnerability assessment has evolved considerably over the last three decades in response to advancements in geospatial data, computational capacity, and modelling techniques. Early studies primarily relied on index-based and expert-driven frameworks, such as weighted overlay and multi-criteria decision-making approaches, which enabled spatial representation of vulnerability but were often constrained by subjectivity in indicator weighting and limited capacity to represent nonlinear ecological processes[104][105] and [106]. The subsequent integration of statistical and empirical models marked a transition toward data-driven vulnerability assessment, allowing dimensionality reduction, variable sensitivity analysis, and improved spatial inference [107] and [108]. More recently, machine learning and hybrid simulation models have emerged as dominant approaches, reflecting a broader shift toward predictive, scenario-based, and computationally intensive vulnerability modelling[109][110] and [111]. The increasing use of ensemble learning, cloud-based platforms such as Google Earth Engine, and high-resolution multisource datasets highlights a growing emphasis on scalability and automation in ecological informatics workflows[99] and [100]. Collectively, these developments indicate a paradigm shift from static vulnerability mapping toward dynamic and model-driven assessment frameworks.

To strengthen the methodological synthesis, a comparative evaluation of vulnerability modelling approaches is essential. Traditional index-based frameworks such as AHP and PCA provide transparent indicator weighting and straightforward interpretability but are limited in representing nonlinear ecological relationships. In contrast, machine learning models such as Random Forest and Gradient Boosting demonstrate higher predictive capability when dealing with complex spatial datasets but often lack interpretability. Hybrid approaches combining geospatial modelling with ensemble machine learning provide improved predictive performance while enabling multi-source data integration. Therefore, future vulnerability assessments should balance interpretability, scalability, and predictive accuracy when selecting modelling frameworks.

5.2 Persistent Methodological and Conceptual Gaps

Despite methodological advancements, several persistent gaps continue to limit the robustness and applicability of forest ecological vulnerability assessments. One of the most critical issues is the limited use of rigorous model validation strategies. Many studies report high predictive accuracy without adequately accounting for spatial autocorrelation,

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

overfitting, or independent validation, leading to potentially inflated model performance estimates [112] and [113]. Cross-regional or multi-site validation remains rare, constraining the transferability of vulnerability models across different forest types and biogeographic contexts. Scale dependency represents another unresolved challenge. The majority of studies are conducted at local or regional scales, yet their findings are often implicitly generalized to broader landscapes or policy contexts [107] and [114]. This mismatch between analytical scale and inference scale limits the comparability of vulnerability assessments and undermines their applicability for large-scale forest management and planning. In addition, indicator selection is frequently driven by data availability rather than ecological relevance, resulting in redundancy among exposure, sensitivity, and adaptive capacity variables and limited sensitivity testing [106] and [115]. From a computational perspective, the increasing reliance on black-box machine learning algorithms introduces interpretability challenges. While predictive performance has improved, the ecological meaning of model outputs is often unclear, reducing their usability for decision-making and policy formulation [110] and [116]. Furthermore, reproducibility remains uneven due to the continued dependence on proprietary software and incomplete reporting of modelling workflows, parameterization, and data preprocessing steps [99].

5.3 Implications for Future Ecological Informatics Research

Addressing these limitations requires a strategic reorientation of forest ecological vulnerability research toward reproducible, interpretable, and scale-aware ecological informatics frameworks. Based on the synthesis of reviewed literature, a methodological roadmap for forest ecological vulnerability assessment can be proposed (Figure 7). The framework involves five key stages: (1) indicator identification within exposure, sensitivity, and adaptive capacity dimensions; (2) spatial data acquisition using remote sensing and geospatial datasets; (3) indicator normalization and weighting using statistical or MCDA approaches; (4) vulnerability modelling using machine learning or hybrid predictive frameworks; and (5) validation and uncertainty analysis using spatial cross-validation and multi-region testing. This roadmap provides a structured workflow for future vulnerability modelling studies. Future studies should prioritize robust validation strategies, including spatial cross-validation and multi-region testing, to enhance model generalizability and reliability [112] and [113]. Integrating uncertainty quantification and explainable machine learning techniques can further improve transparency while retaining predictive capability [117].

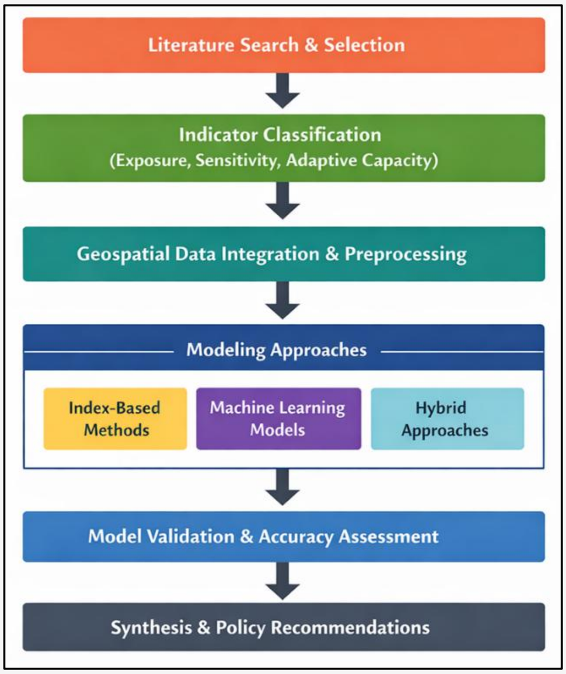

Figure 7: Methodological synthesis framework for forest ecological vulnerability assessment based on the systematic review of geospatial and machine learning approaches

At a conceptual level, vulnerability assessment frameworks should move beyond indicator aggregation toward causal and process-based modelling that explicitly links climatic drivers, ecological responses, and anthropogenic pressures [78] and [3]. The increasing availability of cloud-based and open-source platforms provides opportunities to improve reproducibility and enable comparative analyses across regions and forest types [100]. Embedding vulnerability models within spatial decision-support systems can further enhance their relevance for adaptive forest management, conservation planning, and climate resilience policy [108] and [118]. This methodological synthesis highlights the need for integrated geospatial–AI frameworks capable of linking ecological processes, spatial dynamics, and climate-driven disturbances to support adaptive forest management strategies. Overall, future ecological informatics research should aim to balance computational sophistication with ecological interpretability, ensuring that forest ecological vulnerability assessments are not only predictive but also transparent, transferable, and actionable.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

6. Conclusion

This review provides a systematic synthesis of forest ecological vulnerability research to understand the dynamics, structure, function, and drivers influencing forest ecosystem vulnerability under climatic and anthropogenic pressures. This review synthesizes findings from 136 peer-reviewed studies identified through a PRISMA-ScR guided screening process. This review synthesizes the structured use of vulnerability indicators, methodological frameworks, geospatial software applications, and emerging modelling approaches relevant to forest ecological vulnerability assessment. The conclusions drawn are that the thematic perspective of forest vulnerability assessment has shifted from traditional change, risk, and disturbance analysis to modelled frameworks. Major studies are conducted in tropical, subtropical, and temperate countries, with the contribution of China, India, and the USA with 5.50%, 4.85%, and 4.40%. Studies were conducted to understand the exposure, sensitivity, and adaptive capacity of the forest ecosystem, which has been reflected through the variable and index selection confined to various thematic relevance, according to the study's purpose.

Advanced predictions, trend analysis, and vulnerability modelling have been highly preferred. Index-based analysis, which includes vegetation, climatic, and socio-economic indices, is used to assess the exposure, sensitivity, and adaptive capacity to assess the resilience of the forest ecosystem. Traditional methodological approaches have been shifted to ensembled approaches integrating AI and ML models, with an integrated ensemble approach to understand advanced vulnerable scenarios. Key insights for future research are, study the causative factors for vulnerability to understand the exposure, sensitivity and adaptive capacity of the forest ecosystem, conduct studies on ecoregions, and bridge them into a large study site to understand major conflicts, analysis on forest types, to know the fragmentation, structural resilience, functional aspects, which will give insights into the quantitative decline of carbon counts, moisture content, and health of the ecosystem. This can also be related to the invasive species and how they are inhabiting the ecosystem, done through comparative studies. Wetland ecosystems are affected by climate change and human activities. Studies should indicate changes in the wetlands, the quality of the landscape, where models and frameworks can be developed, to make scientific decisions for conservation practices. Despite providing a comprehensive synthesis, this review has limitations, including reliance on English-language literature and the absence of quantitative meta-analysis due to methodological heterogeneity. Nevertheless, the findings identify clear research priorities, including ensemble and hybrid modelling, cross-scale validation, uncertainty-aware vulnerability assessment, and the integration of explainable machine learning. Advancing these directions will enhance the reliability, scalability, and decision relevance of forest ecological vulnerability assessments within ecological informatics.

References

[1] Nitoslawski, S. A., Wong-Stevens, K., Steenberg, J. W. N., Witherspoon, K., Nesbitt, L. and Konijnendijk van den Bosch, C. C., (2021). The Digital Forest: Mapping A Decade of Knowledge on Technological Applications for Forest Ecosystems. *Earth's Future,* Vol. 9(8). https://doi.org/10.1029/2021EF002123.

[2] Yadav, N., Rakholia, S. and Yosef, R., (2024). Decision Support Systems in Forestry and Tree-Planting Practices and the Prioritization of Ecosystem Services: A Review. *Land,* Vol. 13(2). https://doi.org/10.3390/land13020230.

[3] Liu, H., Li, X., Zhang, M., Wang, X. and Zhang, Y., (2021). A Review of Forest Ecosystem Vulnerability and Resilience: Implications for the Rocky Desertification Control. *Sustainability,* Vol. 13(21). https://doi.org/10.3390/su132111849.

[4] Gupta, R. and Sharma, L. K., (2019). The Process-Based Forest Growth Model 3-PG For Use in Forest Management: A Review. *Ecological Modelling,* Vol. 397; 55–69. https://doi.org/10.1016/j.ecolmodel.2019.01.007.

[5] Thakur, S., Negi, V. S., Dhyani, R., Satish, K. V. and Bhatt, I. D., (2021). Vulnerability Assessments of Mountain Forest Ecosystems: A Global Synthesis. *Trees, Forests and People,* Vol. 6. https://doi.org/10.1016/j.tfp.2021.100156.

[6] Das, U. and Behera, B., (2024). Geospatial Assessment of Ecological Vulnerability of Fragile Eastern Duars Forest Integrating GIS-Based AHP, CRITIC and AHP-TOPSIS Models. *Geomatics, Natural Hazards and Risk,* Vol. 15(1). https://doi.org/10.1080/19475705.2024.2330529.

[7] Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., Barrett, K. and Blanco, G., (2023). Climate Change 2023: Synthesis Report. *Intergovernmental Panel on Climate Change.* https://doi.org/10.59327/IPCC/AR6-9789291691647.001

[8] Miles, L., Newton, A. C., DeFries, R. S., Ravilious, C., May, I., Blyth, S., Kapos, V. and Gordon, J. E., (2006). A Global Overview of the Conservation Status of Tropical Dry Forests. *Journal of Biogeography,* Vol. 33(3); 491–505. https://doi.org/10.1111/j.1365-2699.2005.01424.x

[9] Özcan, O., Musaoğlu, N. and Türkeş, M., (2018). Assessing Vulnerability of a Forest Ecosystem to Climate Change and Variability in the Western Mediterranean Sub-Region of Turkey. *Journal Of Forestry Research,* Vol. 29(3); 709–725. https://doi.org/10.1007/s11676-017-0505-5.

[10] Dolan, K. A., Hurtt, G. C., Chambers, J. Q., Dubayah, R. O. and Frolking, S., (2017). Disturbance Distance: Quantifying Forests' Vulnerability to Disturbance Under Current and Future Conditions. *Environmental Research Letters,* Vol. 12(11). https://doi.org/10.1088/1748-9326/aa8ea9.

[11] Dutt, S., Batar, A. K., Sulik, S. and Kunz, M., (2024). Forest Ecosystem on the Edge: Mapping Forest Fragmentation Susceptibility in Tuchola Forest, Poland. *Ecological Indicators,* Vol. 161. https://doi.org/10.1016/j.ecolind.2024.111980.

[12] Intergovernmental Panel on Climate Change (IPCC) (2021). *Hotspot Analysis Based on Climate Change Scenario.* [Online]. Available: https://www.ipcc.ch/ [Accessed: Jan. 5, 2025]

[13] Avtar, R., Kumar, P., Oono, A., Saraswat, C., Dorji, S. and Hlaing, Z., (2017). Potential Application of Remote Sensing in Monitoring Ecosystem Services of Forests, Mangroves and Urban Areas. *Geocarto International,* Vol. 32(7); 709–723. https://doi.org/10.1080/10106049.2016.1206974.

[14] Risna, R. A., Prasetyo, L. B., Lughadha, E. N., Aidi, M. N., Buchori, D. and Latifah, D., (2023). Forest Resilience Research Using Remote Sensing And GIS: A Systematic Literature Review. *IOP Conference Series: Earth and Environmental Science,* Vol. 1266(1). https://doi.org/10.1088/1755-1315/1266/1/012086

[15] Devi, R. M., Sinha, B., Bisaria, J. and Saran, S., (2018). Multitemporal Analysis of Forest Cover Change Using Remote Sensing and GIS Of Kanha Tiger Reserve, Central India. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* Vol. 42; 211–219. https://doi.org/10.5194/isprs-archives-XLII-5-211-2018.

[16] Hou, K., Li, X., Wang, J. and Zhang, J., (2016). Impact of Land Use and Ecological Vulnerability of Returning Farmland to Forest Policy. *Environmental Science and Pollution Research,* Vol. 23(5); 4670–4680. https://doi.org/10.1007/s11356-015-5679-9.

[17] Shao, H., Sun, X., Wang, H., Zhang, X., Xiang, Z. and Tan, R., (2014). Eco-Environmental Vulnerability Evaluation of Anning River Basin. *Environmental Earth Sciences,* Vol. 72(5); 1555–1568. https://doi.org/10.1007/s12665-014-3060-9.

[18] Zhang, Z., (2024). Evolution of Ecological Damage Probability in Arid Area Based on SPCA. *Frontiers in Artificial Intelligence and Applications,* Vol. 863–871. https://doi.org/10.3233/FAIA231385.

[19] Seidl, R., Rammer, W. and Lexer, M. J. (2011). Adaptation Options to Reduce Climate Change Vulnerability. *Canadian Journal of Forest Research,* Vol. 41(4); 694–706. https://doi.org/10.1139/x10-235.

[20] Ordóñez Barona, C., (2024). Urban Forest Management Plans in Canada. *Landscape and Urban Planning.* Vol. 251. https://doi.org/10.1016/j.landurbplan.2024.105154.

[21] Joshi, P. K., Rawat, A., Narula, S. and Sinha, V., (2012). Assessing Impact of Climate Change on Forest Cover Type Shifts in Western Himalayan Eco-Region. *Journal Of Forestry Research,* Vol. 23(1); 75–80. https://doi.org/10.1007/s11676-012-0235-7.

[22] Newnham, G. J., Siggins, A. S., Blanchi, R. M., Culvenor, D. S., Leonard, J. E. and Mashford, J. S., (2012). Exploiting Three-Dimensional Vegetation Structure to Map Wildland Extent. *Remote Sensing of Environment,* Vol. 123; 155–162. https://doi.org/10.1016/j.rse.2012.02.026.

[23] Steenberg, J. W. N., Millward, A. A., Nowak, D. J., Robinson, P. J. and Ellis, A., (2017). Forecasting Urban Forest Ecosystem Structure, Function, and Vulnerability. *Environmental Management,* Vol. 59(3); 373–392. https://doi.org/10.1007/s00267-016-0782-3.

[24] Seidl, R. and Lexer, M. J., (2013). Forest Management Under Climatic and Social Uncertainty. *Journal of Environmental Management,* Vol. 114; 461–469. https://doi.org/10.1016/j.jenvman.2012.09.028

[25] Sarkar, M. S., (2024). Ensembling Machine Learning Models to Identify Forest Fire Susceptible Zones in Northeast India. *Ecological Informatics,* Vol. 81. https://doi.org/10.1016/j.ecoinf.2024.102598.

[26] Czúcz, B., (2011). Indicator Framework for Climatic Adaptive Capacity of Natural Ecosystems. *Journal of Vegetation Science,* Vol. 22(4); 711–725. https://doi.org/10.1111/j.1654-1103.2011.01251.x.

[27] Steenberg, J. W. N., Millward, A. A. and Nowak, D. J., (2017). Conceptual Framework of Urban Forest Ecosystem Vulnerability. Natural Resources Canada. [Online]. Available: https://www.nrcresearchpress.com [Accessed: Jan. 5, 2025]

[28] Özcan, O., Musaoğlu, N. and Türkeş, M., (2018). Assessing Vulnerability of a Forest Ecosystem to Climate Change and Variability. *Journal of Forestry Research,* Vol. 29(3); 709–725. https://doi.org/10.1007/s11676-017-0505-5.

[29] Mitri, G., Jazi, M. and McWethy, D., (2015). Assessment of Wildfire Risk Using Geographic Object-Based Image Analysis. *Photogrammetric Engineering and Remote Sensing,* Vol. 81(6); 499–506. https://doi.org/10.14358/PERS.81.6.499.

[30] Upgupta, S., Sharma, J., Jayaraman, M., Kumar, V. and Ravindranath, N. H., (2015). Climate Change Impact and Vulnerability Assessment of Forests in Western Himalayan Region. *Climate Risk Management,* Vol. 10; 63–76. https://doi.org/10.1016/j.crm.2015.08.002.

[31] Li, A., Wang, A., Liang, S. and Zhou, W., (2006). Eco-Environmental Vulnerability Evaluation in Mountainous Region Using GIS. *Ecological Modelling,* Vol. 192(1–2); 175–187. https://doi.org/10.1016/j.ecolmodel.2005.07.005.

[32] Luo, D., Caldas, M. M. and Goodin, D. G., (2021). Estimating Environmental Vulnerability Using Machine Learning and Social Data. *Journal of Environmental Management,* Vol. 289. https://doi.org/10.1016/j.jenvman.2021.112502.

[33] Song, G., Chen, Y., Tian, M., Lv, S., Zhang, S. and Liu, S., (2010). Ecological Vulnerability Evaluation in Southwestern China Based on GIS And AHP. *Procedia Environmental Sciences,* Vol. 2; 465–475. https://doi.org/10.1016/j.proenv.2010.10.051.

[34] Pokhriyal, P., (2020). Assessing Forest Cover Vulnerability Using Analytical Hierarchy Process. *Modeling Earth Systems and Environment,* Vol. 6(2); 821–831. https://doi.org/10.1007/s40808-019-00710-y.

[35] Sahoo, S., Dhar, A. and Kar, A. (2016). Environmental Vulnerability Assessment Using Grey Analytical Hierarchy Process. *Environmental Impact Assessment Review,* Vol. 56; 145–154. https://doi.org/10.1016/j.eiar.2015.10.002.

[36] Sahana, M. and Ganaie, T. A., (2017). GIS-Based Landscape Vulnerability Assessment to Forest Fire Susceptibility. *Environmental Earth Sciences,* Vol. 76(20). https://doi.org/10.1007/s12665-017-7008-8.

[37] Singha, C., Swain, K. C., Moghimi, A., Foroughnia, F. and Swain, S. K., (2024). Integrating Geospatial and Machine Learning for Forest Fire Susceptibility Mapping. *Forest Ecology and Management,* Vol. 555. https://doi.org/10.1016/j.foreco.2024.121729.

[38] Achu, A. L., Thomas, J., Aju, C. D., Gopinath, G., Kumar, S. and Reghunath, R., (2021). Machine Learning Modelling of Fire Susceptibility. *Ecological Informatics,* Vol. 64. https://doi.org/10.1016/j.ecoinf.2021.101348.

[39] Parviainen, M., Luoto, M., Ryttäri, T. and Heikkinen, R. K., (2008). Modelling Occurrence of Threatened Plant Species in Taiga Landscapes. *Journal of Biogeography,* Vol. 35(10); 1888–1905. https://doi.org/10.1111/j.1365-2699.2008.01922.x.

[40] Nguyen, A. K., Liou, Y. A., Li, M. H. and Tran, T. A., (2016). Zoning Eco-Environmental Vulnerability for Environmental Management. *Ecological Indicators,* Vol. 69; 100–117. https://doi.org/10.1016/j.ecolind.2016.03.026.

[41] Thammaboribal, P., Triapthti, N., and Lipiloet, S. (2025). Using of Analytical Hierarchy Process (AHP) in Disaster Management: A Review of Flooding and Landslide Susceptibility Mapping. *International Journal of Geoinformatics*, Vol. 21(4); 177–196. https://doi.org/10.52939/ijg.v21i4.4091.

[42] Fischer, A. P. and Frazier, T. G., (2018). Social Vulnerability to Climate Change in Forest Areas. *Annals of the American Association of Geographers,* Vol. 108(3); 658–678. https://doi.org/10.1080/24694452.2017.1387046.

[43] Sahana, M., Sajjad, H. and Ahmed, R., (2015). Assessing Forest Health Using Canopy Density Model. *Modeling Earth Systems and Environment,* Vol. 1(4). https://doi.org/10.1007/s40808-015-0043-0.

[44] Nguyen-Trong, K. and Tran-Xuan, H., (2022). Coastal Forest Cover Change Detection Using CNN. *IAES International Journal of Artificial Intelligence.* Vol. 11(3); 930–938. https://doi.org/10.11591/ijai.v11.i3.pp930-938.

[45] Wylie, B. K., Zhang, L., Bliss, N., Ji, L., Tieszen, L. L. and Jolly, W. M., (2008). Integrating Modelling and Remote Sensing to Identify Ecosystem Anomalies. *International Journal of Digital Earth,* Vol. 1(2); 196–220. https://doi.org/10.1080/17538940802038366.

[46] Gupta, A. K., Nandy, S., Nath, A. J., Mehta, D. and Pandey, R., (2024). Spatial Climate Change Vulnerability Assessment in Himalayas. *Environmental and Sustainability Indicators,* Vol. 22. https://doi.org/10.1016/j.indic.2024.100377.

[47] Joshi, K. P., Adhikari, G., Bhattarai, D., Adhikari, A., and Lamichhane, S. (2024). Forest Fire Vulnerability in Nepal's Chure Region: Investigating Influencing Factors Using Generalized Linear Model. *Heliyon,* Vol. 10(7). https://doi.org/10.1016/j.heliyon.2024.e28525.

[48] Aleksova, B., Milevski, I., Dragićević, S. and Lukić, T., (2024). GIS-Based Integrated Multi-Hazard Vulnerability Assessment in Makedonska Kamenica Municipality. *Atmosphere,* Vol. 15(7). https://doi.org/10.3390/atmos15070774.

[49] Campos, J. A., (2024). Modeling Environmental Vulnerability For 2050 Under Different Scenarios in Doce River Basin. *Water,* Vol. 16(10). https://doi.org/10.3390/w16101459.

[50] Thammaboribal, P., and Tripathi, N. (2024). Predicting Land Use and Land Cover Changes in Pathumthani, Thailand: A Comprehensive Analysis from 2013 to 2023 Using Landsat Satellite Imagery and CA-ANN Algorithm, with Projections for 2028 and 2038. *International Journal of Geoinformatics*, Vol. 20(5); 13–27. https://doi.org/10.52939/ijg.v20i5.3225.

[51] Singh, V., Nema, A. K., Chouksey, A. and Suryawanshi, A., (2024). Assessment of Eco-Environmental Vulnerability Using Remote Sensing and GIS Tools In Maharashtra Region. *International Journal of Environment and Climate Change.* Vol. 14(4); 119–129. https://doi.org/10.9734/ijecc/2024/v14i44103.

[52] Worachairungreung, M., (2024). Logistic Regression and Machine Learning Algorithms for Forest Cover Change Analysis. *Forests,* Vol. 15(6). https://doi.org/10.3390/f15060981.

[53] Nguyen, K. A. and Liou, Y. A., (2019). Global Mapping of Eco-Environmental Vulnerability from Human and Natural Disturbances. *Science of the Total Environment.* Vol. 664; 995–1004. https://doi.org/10.1016/j.scitotenv.2019.01.407

[54] Massie, M. H., Wilson, T. M., Morzillo, A. T. and Henderson, E. B., (2016). Natural Areas as a Basis for Assessing Ecosystem Vulnerability to Climate Change. *Ecosphere,* Vol. 7(11). https://doi.org/10.1002/ecs2.1563.

[55] Chen, Y. and Wang, J., (2020). Ecological Security Early Warning in Central Yunnan Province Using Gray Model. *Ecological Indicators,* Vol. 111. https://doi.org/10.1016/j.ecolind.2019.106000.

[56] Mahendra, A., Widayani, P., and Murti, S. (2025). Monitoring Changes in Ecological Quality of Land Cover Using Landsat-8 OLI Imagery in Semarang City. *International Journal of Geoinformatics*, Vol. 21(8); 67–77. https://doi.org/10.52939/ijg.v21i8.4367.

[57] Omo-Irabor, O. O., Olobaniyi, S. B., Akunna, J., Venus, V., Maina, and J. M. and Paradzayi, C., (2011). Mangrove Vulnerability Modelling Using GIS And Multi-Criteria Analysis. *Environmental Monitoring and Assessment,* Vol. 178(1–4); 39–51. https://doi.org/10.1007/s10661-010-1669-z.

[58] Bera, B., Saha, S. and Bhattacharjee, S., (2020). Forest Cover Dynamics and Deforestation Prediction using Logistic Regression Model. *Trees, Forests and People,* Vol. 2. https://doi.org/10.1016/j.tfp.2020.100034.

[59] Ghorbanzadeh, O., Blaschke, T. Gholamnia, K. and Aryal, J., (2019). Forest Fire Susceptibility and Risk Mapping Using Social and Environmental Variables. *Fire,* Vol. 2(3). https://doi.org/10.3390/fire2030050.

[60] Sahani, N. and Ghosh, T., (2021). Spatial Prediction of Susceptibility Using Logistic Regression and Random Forest Models. *Ecological Informatics,* Vol. 64. https://doi.org/10.1016/j.ecoinf.2021.101352.

[61] Peña-Molina, E., (2024). Fire Vulnerability and Recovery Rates of Mediterranean Pine Forests Using Satellite Time Series. *Remote Sensing,* Vol. 16(10). https://doi.org/10.3390/rs16101718.

[62] Reddy, C. S., Manaswini, G., Satish, K. V., Singh, S., Jha, C. S. and Dadhwal, V. K., (2016). Conservation Priorities of Forest Ecosystems Using Geospatial Techniques. *Ecological Engineering,* Vol. 91; 333–342. https://doi.org/10.1016/j.ecoleng.2016.03.007.

[63] Chuvieco, E., Martínez, S., Román, M. V., Hantson, S. and Pettinari, M. L., (2014). Integration of Ecological and Socio-Economic Factors to Assess Global Wildfire Vulnerability. *Global Ecology and Biogeography,* Vol. 23(2); 245–258. https://doi.org/10.1111/geb.12095.

[64] Nepal, S., Pomara, L. Y., Gould, N. P. and Lee, D. C., (2023). Wildfire Risk Assessment using Bayesian Network Modelling Approach. *Land,* Vol. 12(12). https://doi.org/10.3390/land12122172.

[65] Martes, L., Pfleiderer, P., Köhl, M. and Sillmann, J., (2024). Climate Change Induced Forest Vulnerability Using Earth System Models. *Scientific Reports,* Vol. 14(1). https://doi.org/10.1038/s41598-024-68181-5.

[66] Xu, Y., (2016). Exposure and Sensitivity of Natural Vegetation to Climate Variability in China. *Ecological Indicators,* Vol. 63; 258–272. https://doi.org/10.1016/j.ecolind.2015.12.023

[67] Thakur, S., (2021). Spatial Forest Vulnerability Profile of Major Forest Types in Western Himalaya. *Forest Ecology and Management,* Vol. 497. https://doi.org/10.1016/j.foreco.2021.119527.

[68] Kalantar, B., Ueda, N., Idrees, M. O., Janizadeh, S., Ahmadi, K. and Shabani, F., (2020). Forest Fire Susceptibility Prediction Using Machine Learning Models. *Remote Sensing.* Vol. 12(22). https://doi.org/10.3390/rs12223682.

[69] Wang, F. and Xu, Y. J., (2010). Forest Damage Assessment Related to Ecological Factors at Landscape Scale. *Environmental Monitoring and Assessment,* Vol. 156; 349–364.

[70] Pham, V. T., Do, T. A. T., Tran, H. D. and Do, A. N. T., (2024). Classifying Forest Cover and Mapping Forest Fire Susceptibility in Dak Nong Province, Vietnam Utilizing Remote Sensing and Machine Learning. *Ecological Informatics,* Vol. 79. https://doi.org/10.1016/j.ecoinf.2023.102392.

[71] Wu, S., Dai, E., Huang, M., Shao, X., Li, S. and Tao, B., (2007). Ecosystem Vulnerability of China Under B2 Climate Scenario in the 21st Century. Chinese Science *Bulletin,* Vol. 52(10); 1379–1386. https://doi.org/10.1007/s11434-007-0197-x

[72] Stritih, A., Bebi, P., Rossi, C. and Grêt-Regamey, A. (2021). Addressing Disturbance Risk to Mountain Forest Ecosystem Services. *Journal of Environmental Management,* Vol. 296. https://doi.org/10.10 16/j.jenvman.2021.113188

[73] Zhao, W., Wang, X., Chen, M., Liu, X., Zhao, L. and Zhang, X., (2022). Forest Resource Assets Departure Audit Considering Ecological Sustainable Development: A Case Study. *Land,* Vol. 11(12). https://doi.org/10.3390/land11122156.

[74] Khatun, R., Kabir, M. E., Rahman, M. M., Islam, M. S. and Uddin, M. N., (2021). Integrating Remote Sensing with Swarm Intelligence and Artificial Intelligence for Modelling Wetland Habitat Vulnerability. *Ecological Informatics,* Vol. 64. https://doi.org/10.1016/j.ecoinf.2021.101349.

[75] Gong, C., Yu, S., Joesting, H. and Chen, J., (2013). Determining Socioeconomic Drivers of Urban Forest Fragmentation Using Historical Remote Sensing Data. *Landscape and Urban Planning,* Vol. 117; 57–65. https://doi.org/ 10.1016/j.landurbplan.2013.04.009.

[76] Peng, J., Ma, J., Du, Y., Zhang, L. and Hu, X., (2016). Ecological Suitability Evaluation for Mountainous Area Development Based on Landscape Structure and Function. *Ecological Indicators,* Vol. 61; 500–511. https://doi.org/10.1016/j.ecolind.2015.10.002.

[77] Mitchell, P. J., O'Grady, A. P., Pinkard, E. A., Brodribb, T. J., Blackman, C. J., Duursma, R. A. and Tissue, D. T., (2016). Ecoclimatic Framework for Evaluating Vegetation Resilience to Water Deficit. *Global Change Biology,* Vol. 22(5); 1677–1689. https://doi.org/10.1111/gcb.13177.

[78] Adagbasa, E. G., Adelabu, S. A. and Okello, T. W., (2020). Development of Post-Fire Vegetation Response Model Using GIS and Remote Sensing. *ISPRS Journal of Photogrammetry and Remote Sensing,* Vol. 164; 173–183. https://doi.org/10.1016/j.isprsjprs.2020.04.006.

[79] Kumar, M., (2019). Assessing Vulnerability of Forest Ecosystem in Indian Western Himalayan Region Using Net Primary Productivity Trends. *Biodiversity and Conservation,* Vol. 28(8–9); 2163–2182. https://doi.org/10.1007/s10531-018-1663-2.

[80] Ramachandra, T. V. and Bharath, S., (2020). Carbon Sequestration Potential of Forest Ecosystems in Western Ghats. *Natural Resources Research,* Vol. 29(4); 2753–2771. https://doi.org/10.1007/s11053-019-09588-0

[81] Dobbs, C., Kendal, D. and Nitschke, C. R., (2014). Ecosystem Services and Disservices of Urban Forest. *Ecological Indicators,* Vol. 43; 44–55. https://doi.org/10.1016/j.ecolind.2014.02.007

[82] Blackard, J. A., (2008). Mapping United States Forest Biomass Using Inventory Data. *Remote Sensing of Environment,* Vol. 112(4); 1658–1677. https://doi.org/10.1016/j.rse.2007.08.021

[83] Duguy, B., Alloza, J. A., Röder, A., Vallejo, R. and Pastor, F., (2012). Modelling Ecological Vulnerability to Forest Fires in Mediterranean Ecosystems. *Environmental Management,* Vol. 50(6); 1012–1026. https://doi.org/10.1007/s00267-012-9933-3.

[84] Ortega, M., Saura, S., González-Avila, S., Gómez-Sanz, V. and Elena-Rosselló, R., (2012). Landscape Vulnerability to Wildfires at Forest-Agriculture Interface. A*groforestry Systems,* Vol. 85(3); 331–349. https://doi.org/10.1007/s10457-011-9423-2.

[85] Jagtap, A., Shedge, D., and Mane, P. (2024). Exploring the Effects of Land Use/Land Cover (LULC) Modifications and Land Surface Temperature (LST) in Pune, Maharashtra with Anticipated LULC for 2030. *International Journal of Geoinformatics*, Vol. 20(2); 42–63. https://doi.org/10.52939/ijg.v20i2.3065.

[86] Liu, Y., Xiang, W., Hu, P., Gao, P. and Zhang, A., (2024). Evaluation of Ecological Environment Quality Using Remote Sensing Ecological Index Model. *Remote Sensing,* Vol. 16(18) https://doi.org/10.3390/rs16183485.

[87] Li, H. and Song, W., (2021). Spatiotemporal Distribution and Influencing Factors of Ecosystem Vulnerability on Qinghai-Tibet Plateau. *International Journal of Environmental Research and Public Health,* Vol. 18(12). https://doi.org/10.3390/ijerph18126508.

[88] Zhang, Q., (2022). Dynamic Vulnerability of Ecological Systems to Climate Changes Across Qinghai-Tibet Plateau. *Ecological Indicators,* Vol. 134. https://doi.org/10.1016/j.ecolind.2021.108483.

[89] Chinembiri, T. S., Mutanga, O. and Dube, T., (2024). Predicting Forest Carbon Stock Using Bayesian Geostatistical Modelling Under Climate Warming. *Global Environmental Change Advances,* Vol. 2. https://doi.org/10.1016/j.gecadv.2024.100010.

[90] Bourgoin, C., (2020). Ecological Vulnerability of Forest Landscape to Agricultural Expansion in Vietnam. *International Journal of Applied Earth Observation and Geoinformation,* Vol. 84. https://doi.org/10.1016/j.jag.2019.101958.

[91] Anjos, L. J. S. and Toledo, P. M., (2018). Measuring Resilience and Assessing Vulnerability of Terrestrial Ecosystems in South America. *PLoS ONE,* Vol. 13(3). https://doi.org/10.1371/journal.pone.0194654

[92] Haydar, M., Rafi, A. H., Sadia, H. and Hossain, M. T., (2024). Data Driven Forest Fire Susceptibility Mapping in Bangladesh. *Ecological Indicators,* Vol. 166. https://doi.org/10.1016/j.ecolind.2024.112264

[93] Chen, W., Pourghasemi, H. R., Kornejady, A. and Zhang, N., (2017). Landslide Spatial Modeling Using Ensemble Machine Learning Techniques. *Geoderma,* Vol. 305; 314–327. https://doi.org/10.1016/j.geoderma.2017.06.020.

[94] Barakat, A., Brhaiberh, M., Ettaqy, A., El Jazouli, A. and Ennaji, W., (2023). Machine Learning Based Forest Species Susceptibility Mapping Using Sentinel-2 Data. Bulletin Of Geography: Physical Geography Series. Vol. 25; 63–78. https://doi.org/10.12775/BGEO-2023-0010.

[95] Merry, K., Bettinger, P., Crosby, M. and Boston, K., (2023). Geographic Data Processing: Raster Data. *Geographic Information System Skills for Foresters and Natural Resource Managers.* https://doi.org/10.1016/B978-0-323-90519-0.00009-1.

[96] Ramli, M. and Alias, N., (2024). Multidimensional Vulnerability Mapping Using GIS and Catastrophe Theory. *International Journal of Geoinformatics*, Vol. 20(8); 1–16. https://doi.org/10.52939/ijg.v20i8.3443.

[97] Pérez-Cutillas, P., Pérez-Navarro, A., Conesa-García, C., Zema, D. A. and Amado-Álvarez, J. P., (2023). Systematic Review of Google Earth Engine Applications. *Remote Sensing Applications: Society and Environment,* Vol. 29. https://doi.org/10.1016/j.rsase.2022.100907

[98] Hessburg, P., Smith, B., Salter, R., Ottmar, R. and Alvarado, E., (2000). Recent changes (1930s–1990s) in Spatial Patterns of Interior Northwest Forests, USA. *Forest Ecology and Management - FOREST ECOL MANAGE,* 136. 53-83. 10.1016/S0378-1127(99)00263-7.

[99] Ahmadi, K., Kalantar, B., Saeidi, V., Harandi, E. K. G., Janizadeh, S. and Ueda, N., (2020). Comparison of Machine Learning Methods for Mapping Forest Characteristics Using Sentinel-2 Data. *Remote Sensing,* Vol. 12(18). https://doi.org/10.3390/rs12183019

[100] Chang, B., (2005). Ecological Footprint Analysis Based on Remote Sensing and GIS in Arid Land. *Journal of Geographical Sciences,* Vol. 15(1). https://doi.org/10.1360/gs050106.

[101] Li, A., Wang, A., Liang, S. and Zhou, W., (2006). Eco-Environmental Vulnerability Evaluation in Mountainous Region Using GIS. *Ecological Modelling,* Vol. 192(1–2); 175–187. https://doi.org/10.1016/j.ecolmodel.2005.07.005.

[102] Hou, K., Li, X., Wang, J. and Zhang, J., (2016). Impact of Land Use Policy on Ecological Vulnerability in China. *Environmental Science and Pollution Research,* Vol. 23(5); 4670–4680. https://doi.org/10.1007/s11356-015-5679-9.

[103] Das, U. and Behera, B., (2024). Geospatial Assessment of Ecological Vulnerability using AHP and CRITIC Models. *Geomatics, Natural Hazards and Risk,* Vol. 15(1). https://doi.org/10.1080/19475705.2024.2330529

[104] Peng, J., Ma, J., Du, Y., Zhang, L. and Hu, X., (2016). Ecological Suitability Evaluation for Mountain Development. *Ecological Indicators,* Vol. 61; 500–511. https://doi.org/10.1016/j.ecolind.2015.10.002.

[105] Fischer, A. P. and Frazier, T. G., (2018). Social Vulnerability to Climate Change in Forest Areas. *Annals of the American Association of Geographers,* Vol. 108(3); 658–678. https://doi.org/10.1080/24694452.2017.1387046.

[106] Zhang, F., Liu, X., Zhang, J., Wu, R., Ma, Q. and Chen, Y., (2017). Ecological Vulnerability Assessment Using Multi-Source Data and System Dynamics Model. *Ecological Modelling,* Vol. 349; 41–50. https://doi.org/10.1016/j.ecolmodel.2017.01.016.

[107] Sarkar, S., Manna, H., Roy, S. K., Dolui, M. and Hossain, M., (2024). Remote Sensing Based Ecological Environmental Quality Assessment using Integrated Indicators. *Environmental Monitoring and Assessment,* Vol. 196(7). https://doi.org/10.1007/s10661-024-12793-x.

[108] Nguyen, K. A. and Liou, Y. A., (2019). Global Mapping of Eco-Environmental Vulnerability from Human and Natural Disturbances. *Science of the Total Environment.* Vol. 664; 995–1004. https://doi.org/10.1016/j.scitotenv.2019.01.407.

[109] Luo, D., Caldas, M. M. and Goodin, D. G., (2021). Estimating Environmental Vulnerability Using Machine Learning. *Journal of Environmental Management,* Vol. 289. https://doi.org/10.1016/j.jenvman.2021.112502.

[110] Zeller, K. A., Compton, B. W., Finn, S. P. and Palm, E. C., (2024). Measuring Ecological Connectivity Using Dynamic Resistance Models. *Landscape Ecology,* Vol. 39(5). https://doi.org/10.1007/s10980-024-01890-4.

[111] Liu, S., Liu, R. and Tan, N., (2021). Spatial Flood Risk Framework Using Improved KNN Model. *Sustainability,* Vol. 13(5). https://doi.org/10.3390/su13052859.

[112] Haydar, M., Rafi, A. H., Sadia, H. and Hossain, M. T., (2024). Forest Fire Susceptibility Mapping Using Data Driven Approaches. *Ecological Indicators.* Vol. 166. https://doi.org/10.1016/j.ecolind.2024.112264.

[113] Sarkar, M. S., (2024). Ensembling Machine Learning Models for Forest Fire Susceptibility Mapping. *Ecological Informatics,* Vol. 81. https://doi.org/10.1016/j.ecoinf.2024.102598.

[114] Ordóñez Barona, C., (2024). Urban Forest Management Plans and Social-Ecological Objectives *Analysis. Landscape and Urban Planning,* Vol. 251. https://doi.org/10.1016/j.landurbplan.2024.105154.

[115] Zeller, K. A., Compton, B. W., Finn, S. P., and Palm, E. C., (2024). Measuring Ecological Connectivity Using Dynamic Resistance Models. *Landscape Ecology*. Vol. 39(5). https://doi.org/10.1007/s10980-024-01890-4

[116] Liu, S., Liu, R. and Tan, N., (2021). Spatial Flood Risk Framework Using Improved KNN Model. *Sustainability*, Vol. 13(5). https://doi.org/10.3390/su13052859

[117] Haydar, M., Rafi, A. H., Sadia, H. and Hossain, M. T., (2024). Forest Fire Susceptibility Mapping Using Data Driven Approaches. *Ecological Indicators*, Vol. 166. https://doi.org/10.1016/j.ecolind.2024.112264

[118] Sarkar, M. S., (2024). Ensembling Machine Learning Models for Forest Fire Susceptibility Mapping. *Ecological Informatics*, Vol. 81. https://doi.org/10.1016/j.ecoinf.2024.102598.