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Advances in Spatial Analysis for Land Change Science: A Systematic Review of Geospatial Methodologies

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Abstract

Land Change Science has increasingly relied on spatial analysis methods to monitor, understand, and predict land-use and land-cover change (LULCC). Over the past decade, technological advancements such as high-resolution satellite imagery, machine learning algorithms, and robust GIS platforms have significantly transformed how spatial patterns and environmental transformations are studied. However, there is a lack of a synthesized understanding of how these geospatial methodologies have evolved and been applied across different contexts and regions. This review aims to systematically examine the evolution and application of spatial analysis techniques in land change science, focusing on the tools, models, and analytical approaches used in geospatial studies over the past decade. A systematic literature review (SLR) was conducted using a dataset of 62 peer-reviewed research articles published between 2015 and 2025. The articles were analyzed based on key parameters, including geographic context, spatial analysis methods, software used (e.g., ArcGIS, ERDAS, Google Earth Engine), types of classification models (e.g., CA-Markov, Random Forest, SVM), and theoretical frameworks. The review also considered novelty, limitations, and future research directions highlighted by each study. The review found that CA-Markov modeling, supervised classification, and Random Forest are the most frequently applied spatial analysis techniques. A notable trend is integrating machine learning with remote sensing, particularly through platforms like Google Earth Engine. While ArcGIS remains dominant, open-source tools like QGIS and Python-based APIs are gaining traction. Data availability, spatial resolution, and lack of socio-economic integration often limit studies. Theoretical frameworks, such as Human–Environment Interaction Theory and urban ecological theory, were commonly employed to interpret the findings. Geospatial methodologies in land change science have advanced significantly, enabling more dynamic, scalable, and accurate assessments of environmental change. Future research should focus on integrating socio-economic variables, enhancing ground validation, and developing hybrid models that leverage AI and big data to achieve a more holistic understanding of land system science.

Keywords: Spatial Analysis, Land Use and Land Cover Change (LULCC), Geospatial Modeling, Remote Sensing, CA-Markov Model

1. INTRODUCTION

Over the past two decades, land use and land cover changes in urban and rural areas have become crucial in global geospatial studies. The use of geospatial intelligence, including remote sensing, geographic information systems (GIS), and spatial predictive models such as CA-Markov, MLP, and Random Forest, has broadened the understanding of the dynamics of LULC (land use and land cover) changes in various regions of the world. Studies conducted in South Asia, East Africa, and Latin America, as seen in studies by [1], [2], and [3], demonstrate that demographic pressures, urban growth, and economic transformation are driving significant changes in land use. On the other hand, ecological degradation, such as deforestation and the loss of water bodies, is increasingly evident as a direct result of land conversion to built-up areas or intensive agriculture[4]. Studies in India and Bangladesh have significantly contributed to uncovering the dynamics of rapid urbanization and its impact on surface temperature and ecological balance. For example, [5] and [6] have shown a decline in vegetation of more than 80% over the last two decades, accompanied by an increase in surface temperature (LST) due to the Urban Heat Island (UHI) effect. NDVI and NDBI indices, along with integration with spatial regression analysis, are the primary methods for quantifying these changes[7], [8], [9], [10]. In the Pakistan and Ethiopia regions, [11] and [12] utilized multi-temporal Landsat imagery to map a significant negative correlation between vegetation cover and surface temperature. This emphasizes that changes in the LULC impact not only the spatial-physical aspect, but also the microclimate and environmental health of [13].

Studies focusing on conservation areas such as biosphere reserves, national parks, and lake ecosystems, such as those conducted by [14] in Loktak Lake and [15] in Talra Wildlife Sanctuary, reveal that human pressure through agriculture, tourism, and infrastructure development leads to the loss of natural vegetation and rising local temperatures. NDVI, LST, and regression analysis algorithm-based approaches are widely used to assess the spatial-temporal impact of LULC changes. Decreased vegetation and grassland area strongly correlate with increased temperatures and reduced air and water quality. In this context, research by [8] in Pakistan adds a public health dimension by linking land-use change to declining groundwater quality, due to pollutant infiltration from urban and agricultural activities. Some studies utilize machine learning and deep learning approaches to model projected changes in LULC until 2050 or even 2100. The use of the MLP-Markov model by [16], as well as the integration of Random Forest and CA-Markov by [17] and [18], allows accurate spatial forecasting of the distribution of built-up areas, vegetation, and water bodies. The advantage of this approach lies in its ability to accommodate various input variables such as elevation, road distance, [19]The predicted

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results show a consistent trend: a decrease in natural vegetation and agricultural land and a significant increase in built-up areas, especially in peri-urban areas and watersheds.[20], [21].

Some studies emphasize the ecological and physical aspects, as well as the social dimension and people's perceptions of landscape change. [22] In Chile, for example, a viewshed approach was used to examine the differences between population perceptions and actual spatial data, demonstrating the importance of integrating qualitative and quantitative data in LULC studies. A similar study by [23] In India, weighted spatial regression (GWR) was used to identify factors driving urban expansion, such as proximity to roads, centers of economic activity, and administrative zoning. This shows that land use change cannot be separated from the socio-political and spatial governance context that prevails in each region. In the tropical areas such as Madagascar and the tropical forest regions of Eastern India, research by [24] and [4] emphasizes the importance of high spatial resolution in detecting changes in land cover. Using OBIA (Object-Based Image Analysis) and very high-resolution satellite imagery, such as the Pleiades, results in up to 94% classification accuracy. This technique is particularly effective for complex land cover mosaics, such as mixed agriculture, shrubs, and agroforestry areas. In the urban context, research by [25] in Chennai and [26] in Kosovo shows that coastal and suburban urbanization has increased average surface temperatures by 2.5–3.5°C in the last twenty years.

Not only limited to changes in LULC and surface temperature, several studies have linked these spatial transformations to soil degradation and erosion risk [27]. A study by [28] in Ethiopia used the RUSLE model to map the potential for land loss due to land cover change. The results show that conversion from forests and shrubs to agriculture and vacant land exacerbates erosion, with the rate of land loss doubling in the last three decades.[9], [29], [30]. Similar findings were found in Ethiopia's Chimbel and Rib watersheds, indicating the urgency of more integrated spatial-based conservation interventions. In some cases, using more than a century of historical data opens up insights into the long-term dynamics of the LULC and its relationship to climate and social change. Research by [31] in Bursa, Turkey, which used cadastral maps and aerial photographs from 1858 to 2020, showed different patterns of deforestation and depopulation between regions[31]. This contrast reinforces the idea that the dynamics of the LULC were heavily influenced by spatial policies, population pressures, and changes in political-economic regimes that lasted for decades. Recent research in irrigated areas, such as that conducted by [32] in Sego, Ethiopia, shows that agricultural intensification without good water management can lead to significant soil salinization. Non-saline areas decreased drastically while highly saline regions increased by 5.5% yearly. This shows another dimension of LULC transformation, namely soil quality degradation, which has a long-term impact on food security and land productivity. In contrast, research in tourism areas such as Manali [33] shows that the expansion of built-up areas to steep slopes can increase the risk of landslides and topographic degradation due to the pressures of tourism sector growth.

In general, all of the findings from these 62 articles show consistency in terms of key global trends: significant increases in built-up areas, decline in natural vegetation, fluctuations in water bodies, and ecological degradation accelerated by climate change, urbanization, and non-adaptive land-use policies. The use of cutting-edge geospatial methods significantly contributes to the spatial-temporal and predictive understanding of LULC changes and their impact on various environmental and social aspects. However, there are still several limitations, such as the lack of integration of socioeconomic data, the absence of field validation in some studies, and the dominance of studies in South Asia and East Africa, which opens up space for more in-depth exploration of other regions.

2. RESEARCH METHODOLOGY

Over the past decade, land change science has increasingly relied on spatial analysis to understand complex patterns of land use and land cover change (LULCC). Rapid advancements in remote sensing technologies, geospatial tools, and computational models have driven this reliance. A growing body of research has explored a variety of methodologies, from traditional classification techniques to sophisticated machine learning algorithms, to monitor and predict landscape transformations. However, there remains a need to synthesize how these geospatial methodologies have evolved, the theoretical frameworks they employ, and the challenges they face across diverse ecological, urban, and socio-environmental contexts.

2.1 Evolution of Geospatial Methodologies in Land Change Science

The evolution of geospatial methodologies in land change science has witnessed significant advancements in modeling techniques over the last decade, particularly with the incorporation of Cellular Automata (CA), Markov Chain models, and various hybrid approaches. Central to this evolution is the CA-Markov model, which integrates the spatial modeling capabilities of CA with the temporal predictive strengths of Markov chains, yielding improvements in the accuracy and reliability of predictions of land use and land cover (LULC) changes. The CA-Markov model has gained widespread recognition due to its robustness in simulating complex spatial phenomena. This model combines cellular automata's advantages in capturing spatial patterns' dynamics with the Markov process's capability for future state prediction. For instance, Chu et al. highlight how this model enhances forecasts of land use transformations and effectively simulates variations in land use structures, providing valuable insights, especially in heterogeneous landscapes such as the Three Gorges Reservoir Area in China [34]. Moreover, the model's utility is evident in its application across diverse scenarios, such as urban growth and habitat quality assessments [35], [36].

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In addition to the CA-Markov approach, other methodologies have also been developed or adapted to tackle unique challenges in land use modeling. For example, hybrid methods have emerged, integrating various models to mitigate individual weaknesses. Dang and Kawasaki discuss the significant attention towards methodological integration in land use change models, emphasizing how combining different techniques enriches predictive capabilities and enhances model reliability [37]. The incorporation of machine learning and artificial neural networks with conventional models is also becoming mainstream, as observed in studies focused on urban growth predictions, where models like the WOE-CA and ANN-CA demonstrate high accuracy in forecasting urbanization trends [35], [38]. Geographically weighted regression (GWR) and multi-layer perceptron (MLP) models have also been researched as complementary approaches within land change science. These methodologies provide critical insights into spatial heterogeneity and variable interactions that affect land use patterns. Applications of GWR can help elucidate the local variations in the relationships between land use and its driving socio-economic factors. At the same time, MLP can assist in understanding complex non-linear relationships in land cover dynamics [39]. The potential of hybrid models has been increasingly recognized, as further studies incorporate aspects of agent-based modeling alongside CA-Markov methods to simulate LULC changes while considering socio-economic drivers and environmental constraints [40]. This evolution signifies a substantial shift from traditional static models to dynamic, integrated frameworks that enhance the ecological management discourse by enabling more nuanced and adaptive strategies in response to land use changes.

2.2 Remote Sensing Platforms and Their Applications in LULC Studies

Remote sensing platforms play a pivotal role in the monitoring and understanding land use and land cover (LULC) dynamics across various ecosystems. Among these platforms, Landsat, Sentinel, and Google Earth Engine (GEE) are particularly significant due to their extensive datasets and applications in environmental science. The Landsat program, initiated in 1972, has been instrumental in providing continuous, long-term data about Earth's surface. Its various iterations, including Landsat 5, 7, and 8, have facilitated comprehensive studies of LULC changes. For instance, Landsat imagery has been effectively utilized to detect urban expansion and agricultural changes across multiple regions, such as New Moscow, where researchers reported a substantial increase in urban area due to LULC transitions from 2012 to 2018 [41]. Furthermore, Landsat data have proven effective in global studies comparing land use datasets, enhancing our understanding of anthropogenic impacts on ecosystems [42]. Sentinel-2, part of the European Space Agency's Copernicus program, provides higher resolution imagery compared to its predecessors, making it suitable for more detailed land cover assessments. In a study addressing the capabilities of Sentinel-2, it was found that the platform excelled in identifying built-up areas, demonstrating a complementarity with Landsat imagery for detailed urban studies [43]. This feature aids in monitoring rapid urbanization, thus supporting sustainable development efforts.

The advent of GEE has revolutionized the use of satellite data by providing a cloud-based platform for large-scale data processing and analysis. It enables users to quickly access and analyze vast amounts of temporal data from Landsat and Sentinel satellites [44]. GEE's integration offers a significant advantage for researchers conducting LULC assessments as it allows for efficient processing of historical datasets and extensive applications across various geographic contexts [45]. Different methodologies surrounding the classification and analysis of LULC dynamics using these platforms have emerged. Techniques such as automated classification and change detection have become essential, employing spectral pattern analysis with multi-temporal satellite data for enhanced accuracy [46]. For example, in studies conducted in Assam, India, researchers incorporated remote sensing with Geographic Information System (GIS) techniques to identify land cover changes effectively from 1977 to 2010, showcasing the power of combining various data sources for LULC monitoring [47]. Moreover, the utility of remote sensing in analyzing thermal dynamics associated with LULC change has been highlighted in several studies. Landsat's thermal infrared sensors have been utilized to understand the effects of urban heat island on the island, thus illustrating how land cover changes can impact local climates [48]. This intersection between remote sensing, temperature measurements, and LULC provides insights into environmental changes that directly affect urban livability and ecological sustainability.

2.3 Machine Learning and Artificial Intelligence for Spatial Pattern Detection

Machine Learning (ML) and Artificial Intelligence (AI) techniques have significantly transformed spatial pattern detection, particularly in Land Use and Land Cover (LULC) classification and prediction. Prominent algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Deep Learning models are increasingly favored for their robust performance in accurately classifying complex spatial data. Random Forest is recognized for its ensemble learning capabilities, allowing it to manage high-dimensional feature spaces commonly found in LULC data. It builds multiple decision trees and merges their predictions to improve accuracy and control overfitting [49]. In various studies, Random Forest has shown significant efficacy in handling noisy data, demonstrating high classification performance relative to other algorithms [49], [50]. Notably, the method's ability to estimate feature importance aids in understanding which spectral and spatial features are most relevant for effective classification, which is crucial in environmental monitoring and resource management.

SVMs, celebrated for their robust handling of multi-class classification problems, are particularly advantageous due to their ability to define optimal hyperplanes in high-dimensional spaces. The integration of kernel functions allows SVM to address non-linearity in data, making it suitable for complex datasets typical of hyperspectral imagery [51]. In LULC applications, SVMs have been combined with spectral-spatial approaches to enhance classification accuracy by

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utilizing the spectral characteristics of pixels and their spatial relationships [52]. Furthermore, recent advancements include subspace methods to improve SVM's performance in mixed pixels and noisy environments [51], pushing the boundaries of traditional classification strategies.

Artificial Neural Networks (ANNs) represent another significant tool in spatial pattern recognition. With their capacity to learn from large datasets, ANNs excel in identifying intricate patterns that may not be readily apparent to other algorithms [53]. Research has demonstrated that ANNs can effectively classify land cover types with high precision by learning spatial representations from training data, reflecting their applicability in real-world scenarios [53], [54]. Moreover, the hierarchical nature of deeper neural networks, particularly Convolutional Neural Networks (CNNs), enhances their ability to capture spatial hierarchies from raw spectral data, further improving classification outcomes in LULC tasks [50]. Deep Learning, particularly through CNNs, has emerged as a powerful approach in the field due to its ability to process large volumes of data while automatically extracting hierarchical features. CNNs have been successfully employed in semantic segmentation tasks for LULC classification, demonstrating advantages in capturing complex patterns through layers of feature abstraction [50], [52]. The recent trend towards semantic segmentation using ultra-high-resolution imagery highlights how CNNs can provide granular insights into land features, which is essential for urban planning and environmental analysis [50], [55].

2.4 Theoretical Foundations in Geospatial Land Change Research

The theoretical foundations of geospatial land change research encompass various interconnected frameworks that facilitate understanding the complex interactions between human and environmental systems. Key theories in this field include Human-Environment Interaction, Urban Ecology, Landscape Risk, and Land Systems Science, each contributing unique perspectives and methodologies. Human-Environment Interaction encompasses the dynamic relationships between societal activities and natural systems. Geographic Information Systems (GIS) and Geospatial Data Science have significantly advanced the understanding of these interactions. Innovations in data collection and spatial analysis enable examining how human actions influence the environment and vice versa. For instance, Packard emphasizes that advanced geospatial technologies allow researchers to explore the intricate relationships in human-environment systems, leveraging large datasets and sophisticated analytic tools for a comprehensive understanding [56]. Similarly, Huang illustrates the integration of land use and land cover (LULC) dynamics with water quality monitoring, highlighting the direct impacts of urbanization on local eco-hydrological systems [57]. Collectively, these studies underline the importance of employing geospatial methodologies to decode the nuances of the human effects on environmental landscapes.

Urban Ecology focuses on interactions in urban settings, particularly how urbanization affects biodiversity and ecosystem services. The dual pressures of urban expansion and increasing population densities challenge traditional ecological models, which often fail to account for the unique variables present in urban environments. Research conducted by Sumari et al. on urban expansion through temporal monitoring reveals how geospatial methods can quantify agricultural land loss amidst urban growth, thus illustrating critical patterns of land cover change [58]. Furthermore, Dixit et al. discuss establishing demographic and environmental geospatial surveillance platforms to integrate various analyses that support better urban planning and resource management [59]. These studies emphasize the need for urban ecology to adopt geospatial analysis to manage urban complexities effectively. Landscape Risk theory analyzes the potential consequences of land-use changes on ecological and societal well-being. This framework aids in assessing vulnerabilities inherent in landscapes, informing conservation strategies and sustainable land management practices. The combination of remote sensing and GIS allows for a spatial examination of risks related to land-use changes, as demonstrated by Rwanga and Ndambuki, who assess land cover classification accuracy through remote sensing techniques, enhancing the understanding of landscape dynamics [60]. Moreover, the work of Verburg et al. highlights how understanding land systems provides insight into sustainability challenges faced by socio-ecological systems, particularly in terms of recognizing trade-offs involved in land-use decisions [61]. These insights are vital for developing strategies that mitigate landscape risks while balancing human needs and ecological integrity.

Land Systems Science (LSS) integrates multiple disciplines to explore how land system changes impact environmental and socio-economic contexts. As articulated by Gosnell et al., LSS emphasizes the importance of combining remote sensing data with social science methodologies to understand the governance of land use and forest resources [62]. This integrative approach allows researchers to unravel complex feedback loops between human activities and ecological responses, facilitating multiple-scale policy assessments. Furthermore, foundational theories in this realm focus on biophysical aspects and account for socio-cultural dynamics that influence land decision-making processes. Thus, LSS serves as a pivotal framework for understanding the interplay between human systems and land-use patterns, fostering adaptive management strategies in response to environmental changes.

2.5 Challenges in Spatial Analysis for LULCC Research

Spatial analysis for land use and land cover change (LULCC) faces numerous challenges, including data accuracy limitations, field verification difficulties, socio-economic integration, and spatial scale issues. Each of these challenges can significantly hinder the quality and applicability of LULCC research. One of the most prevalent issues is the accuracy and consistency of land cover data. Woods et al. highlight that the pervasive nature of armed conflicts can lead to inconsistent data related to deforestation, as these events are often geographically diffuse and multifaceted [63].

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Additionally, uncertainties in historical land cover conversion can complicate our understanding of carbon and climatic projections, suggesting that better characterizations of LULCC are essential for improved modeling [64]. Moreover, Castillo et al. indicate that the use of remote sensing data for LULCC monitoring often relies on the availability and quality of GIS technologies, which can introduce biases and inaccuracies in the derived datasets [65]. Field verification presents another significant challenge in LULCC research. Accurate ground-truthing is necessary to validate remotely sensed data, yet limited access and resources can impede the collection of field data, affecting the reliability of LULCC studies. For example, a study by Wang et al. in subtropical regions of South Africa demonstrated that the effectiveness of remote sensing methods, particularly various classification techniques, impacted the accuracy of LULCC assessments [66]. This indicates that field verification is pivotal in confirming the findings derived from remote sensing methods.

Socio-economic factors add another layer of complexity to LULCC analyses. The integration of socio-economic data is crucial in understanding the driving factors behind land-use changes. Research suggests that population dynamics, economic growth, and urban expansion significantly affect land cover alterations [67], [68]. Emphasize that discrepancies in socio-economic data can lead to substantial gaps in understanding LULCC drivers across different geographical regions, indicating a need for more robust integration of socio-economic aspects in LULCC studies [68]. Finally, challenges arise from the scale at which LULCC data are collected and analyzed. Multi-model global-scale simulations present an opportunity for comprehensive studies; however, these models still face limitations due to variabilities across different spatial and temporal scales [69]. Research by Luo et al. further illustrates that the spatial downscaling of LULCC projections can introduce uncertainties that complicate predictions regarding terrestrial carbon cycling [70]. Integrating different spatial scales in LULCC research is critical to generate reliable insights and policy recommendations.

2.6 Future Trajectories of Spatial Analysis in Sustainable Land Management

Future trajectories of spatial analysis in sustainable land management (SLM) are increasingly focusing on innovative methodologies incorporating data fusion, real-time monitoring, and policy-based models. The integration of these elements is essential for enhancing land management practices to respond effectively to global challenges such as urbanization, climate change, and resource scarcity. Data fusion is becoming a cornerstone for spatial analysis in land management, as it provides the means to integrate multiple data sources to enhance the accuracy and reliability of land use and cover assessments. For instance, remote sensing technologies combined with geographic information systems (GIS) facilitate the combination of optical and radar data, improving land use mapping and monitoring capabilities. This integration addresses key challenges in land use classification, such as variability in spatial resolution and inherent uncertainties in data sources [71]. Moreover, advanced approaches utilizing spatiotemporal data fusion and Cellular Automata-Markov models have been shown to enhance detection and prediction of land use changes, thereby better informing land management decisions [72]. These methods improve data quality and provide real-time analytics that support dynamic land management strategies.

Additionally, real-time monitoring of land use changes is critical for adapting to rapidly evolving socio-economic conditions and environmental policies. Remote sensing technologies now offer increased temporal resolution, enabling continuous observation of land conditions [73]. This capability is vital for keeping abreast of transformation patterns, such as urban expansion and its implications for ecosystem services [74]. Furthermore, methodological approaches that utilize machine learning and artificial intelligence contribute to more nuanced analyses of spatial relationships and changes, supporting timely interventions [75]. Thus, integrating real-time monitoring with advanced analytics reinforces the adaptability of land management systems. Policy-based models are also expanding the practical applications of spatial analysis in sustainable land management. The utilization of land-use simulation models, such as the CLUE-S model and its derivatives, allows for the assessment of different land use scenarios under varying socio-economic conditions [76]. These models enable policymakers to simulate the effects of land use policies on future land conditions, thus fostering realistic planning based on empirical data. Integrating spatial analysis into policy frameworks will ultimately guide decision-makers in balancing environmental conservation with development needs.

Understanding the socio-economic drivers of land use change remains crucial for future research directions. Studies like those reviewed by [53] highlight the need for assessments of land resource carrying capacity, indicating that varying scales require tailored evaluation indicators to reflect local conditions [77]. Acknowledging the complexity of land use dynamics, including climate impacts and anthropogenic factors, suggests further inquiry into adaptive management strategies [78]. Sustainable land management can be significantly advanced by addressing these challenges and leveraging spatial analysis technologies.

3. RESULTS AND DISCUSSION

This systematic literature review (SLR) was designed following three well-established protocols: PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses. These frameworks collectively guided the article selection, screening, data extraction, and synthesis process to ensure transparency, rigor, and reproducibility.

3.1 Review Protocols and Guidelines

This review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and reproducibility throughout the systematic review process:

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1. PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)

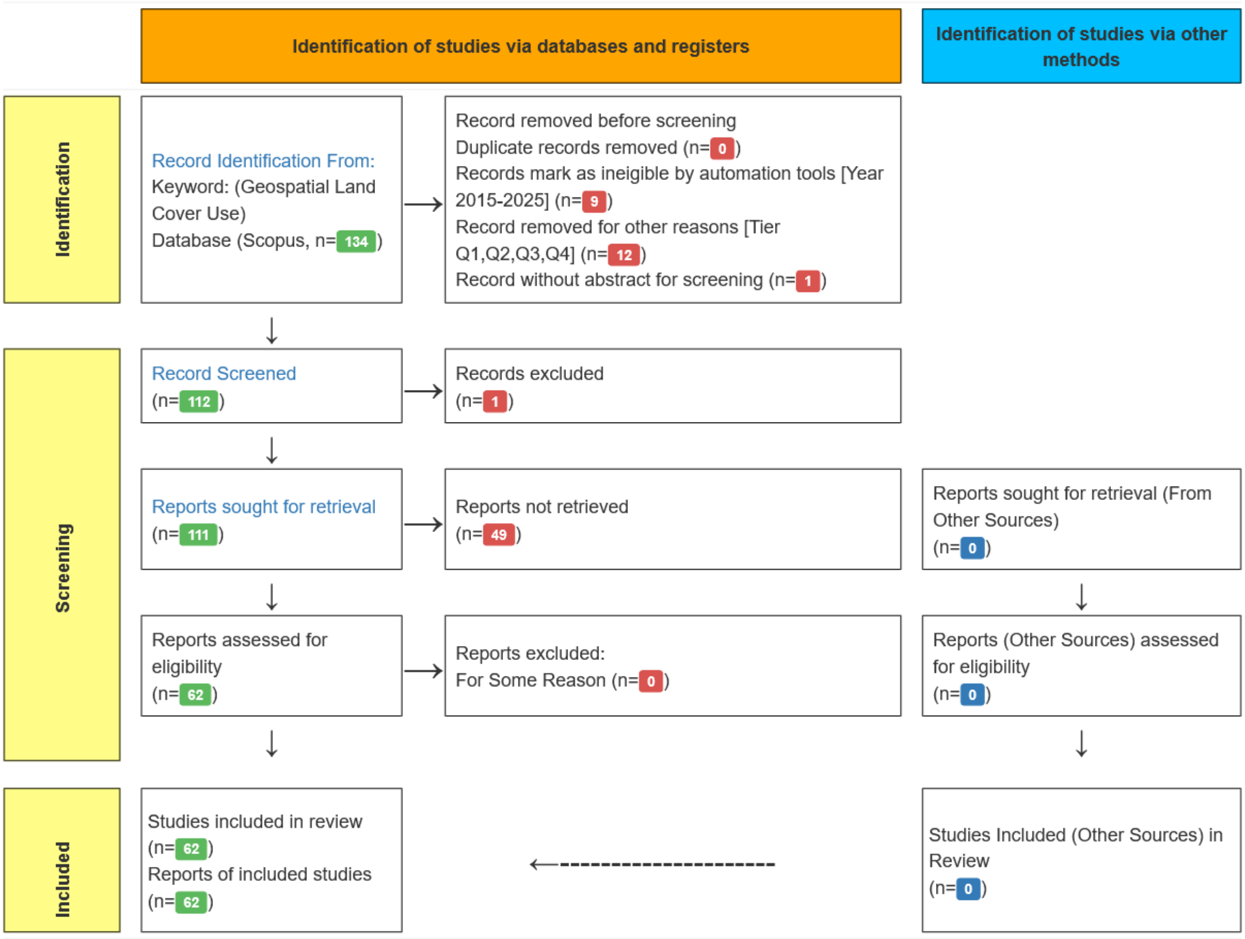

Figure 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020

The systematic literature review (SLR) adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [79]. To ensure rigorous methodology and transparent reporting. The identification stage began with a keyword-driven search using the term "Geospatial Land Cover Use" within the Scopus database, selected for its stringent indexing criteria and high-quality scholarly content [80], [81]. Scopus was prioritized over alternatives like Google Scholar due to the latter's limitations, including redundant results, duplicate entries, and inclusion of articles from predatory journals [82]. The initial search yielded 134 records, which were systematically filtered to exclude duplicates (n=0), studies outside the target timeframe (2015–2025; n=3), those not meeting journal-tier criteria (Q1–Q4; n=12), and articles lacking abstracts (n=1), resulting in 112 records proceeding to screening.

During the screening phase, titles and abstracts were evaluated for relevance, excluding one record deemed out of scope. Full-text retrieval attempts for 111 reports led to the exclusion of 49 due to unavailability or language barriers. The eligibility assessment retained 62 studies that met predefined criteria, such as methodological rigor and thematic alignment with geospatial land cover analysis. No additional articles were sourced from alternative platforms (e.g., the Watase database), as reflected in the PRISMA flowchart. The final stage included 62 studies, analyzed qualitatively using thematic synthesis facilitated by the Watase Uake System (Wahyudi, 2024), a tool designed to streamline systematic review processes. This approach ensured adherence to PRISMA's emphasis on transparency and reproducibility, enhancing the validity of findings across disciplines. [83], [84]. The entire process underscored the critical role of keyword precision, database selection, and iterative filtering in achieving robust, evidence-based conclusions.

3.2 Database and Search Strategy

The articles that are the subject of a systematic review were obtained from various primary and secondary data sources focusing on geospatial methodologies in the science of land change. The central databases used are Scopus, Web of Science, and Google Scholar, with high priority given to Scopus due to its strict index and high quality of publications [80], [81]. To complete the search, articles are obtained from platforms like SpringerLink, ScienceDirect, and ResearchGate. The keywords used include a combination of terms such as "geospatial techniques", "land use/land cover change", "remote sensing", "GIS", and "spatial analysis". Articles are screened based on inclusion criteria such as

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publication time range (2015–2025), topic relevance, and availability of abstract and full-text. Articles that do not meet these criteria are removed at an early stage. The initial search process yielded 134 articles, which were then filtered to eliminate duplication (n=0), articles outside the time range (n=3), articles from non-Q1 to Q4 journals (n=12), and articles without abstracts (n=1), leaving 112 articles for screening. After further evaluation of the relevance of the content, 62 articles were selected for in-depth analysis. These articles were imported into a structured extraction table covering core analytical parameters: country of study, methodological approach, analytical software, spatial models, grand theory, novelty, limitations, and future recommendations. It can be seen in Table 1:

Table 1. Search and Selection Summary

Parameters	Details
SLR Title	Advances in Spatial Analysis for Land Change Science: A Systematic Review of Geospatial Methodologies
Main Database	Scopus
Keywords	Geospatial Land Cover Use
Publication Time Covered	2015-2025
Inclusion Criteria	Topic relevance: a) Time range (2015–2025) b) Indexed journals Q1–Q4 c) Availability of abstract and full text
Exclusion Criteria	a) Articles outside the time range b) Articles without an abstract or full text
Total Initial Articles	134
Article After Deduplication	134 (No duplication)
Articles Deleted	a) articles outside the time range: 3 b) articles from non-Q1 to Q4 journals: 12 c) articles without abstracts
Article After Screening	112
Final Article	62 (after relevance and qualitative evaluation)
Analysis Methodology	Thematic Based on Watase-Uake

The table and narrative above provide a complete overview of the database and article search strategies for this SLR. This approach ensures the resulting articles are relevant, valid, and fit the research objectives.

3.3 Review Period and Scope

The present systematic review examines the evolution and application of geospatial methodologies in land change science over ten years, from 2015 to 2025. This review period was selected to capture contemporary developments in spatial modelling, remote sensing, and the integration of artificial intelligence within land use and land cover change (LULCC) research. The temporal window aligns with the significant proliferation of open-access satellite data, advances in machine learning algorithms, and the increased accessibility of cloud-based geospatial platforms. 62 peer-reviewed articles were included in the final synthesis, following the multi-stage screening process outlined in the PRISMA protocol and refined by the Watase–Uake framework. Studies were drawn exclusively from the Scopus database and reflect a research concentration in rapidly urbanizing and ecologically sensitive regions. Geographically, the corpus spans 13 countries, with India contributing the majority (n=37), followed by Ethiopia, Pakistan, Bangladesh, and other Global South nations experiencing accelerated land transitions. The scope of the review encompassed a wide range of spatial approaches, including supervised classification, predictive modeling (e.g., CA–Markov, Random Forest), spatial regression (e.g., GWR), and hybrid machine learning models. The use of various software platforms such as ArcGIS, QGIS, TerrSet, ERDAS Imagine, and Google Earth Engine supported these. Conceptual and theoretical underpinnings were also considered, with frequent application of Human–Environment Interaction Theory, Urban Ecology, and Land System Science perspectives. These representatives are shown in the following Table 2:

Table 2. Scope of Reviewed Studies (2015–2025)

Aspect	Details
Review period	2015–2025
Articles reviewed	62 peer-reviewed studies
Geographic focus	13 countries, primarily India, Ethiopia, Pakistan, Bangladesh
Dominant tools	ArcGIS, ERDAS Imagine, TerrSet, Google Earth Engine, QGIS
Core methodologies	CA–Markov, Random Forest, MLC, SVM, GWR, Shannon's Entropy
Spatial applications	Urban expansion, forest monitoring, watershed assessment
Theoretical frameworks	Human–Environment Interaction, Urban Ecology, Land System Science

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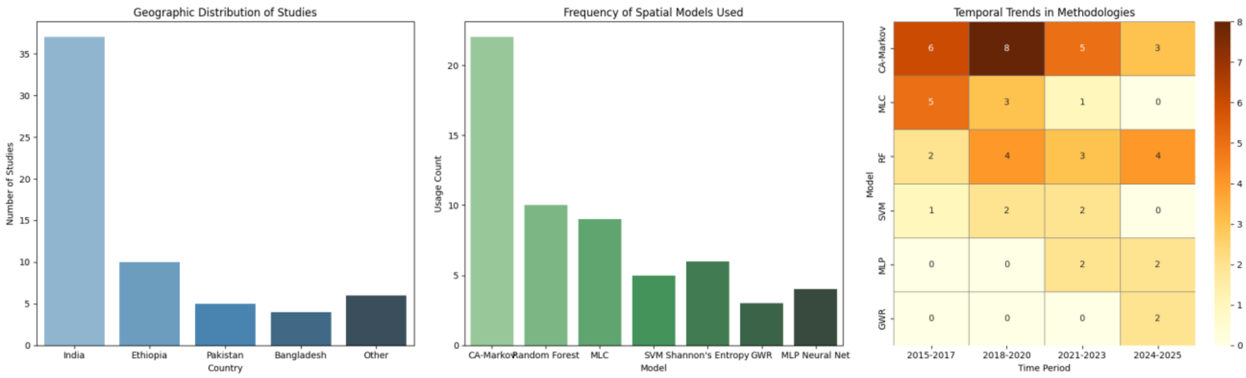
This review offers a cross-section of contemporary geospatial research practices, highlighting methodological innovation and persistent limitations related to spatial resolution, socio-economic integration, and field validation.

3.4 Data Synthesis and Mapping

The data synthesis process followed a thematic coding approach informed by the framework of Watase and Uake. Each of the 62 selected studies was reviewed using a structured data extraction matrix that captured essential metadata and analytical components. The analysis focused on five primary dimensions: geographic context, methodological approach, spatial modeling techniques, software tools, and theoretical frameworks. Thematic mapping enabled the identification of recurring trends, research gaps, and spatial patterns across diverse contexts. The synthesis revealed a strong concentration of studies in South and Southeast Asia, particularly India (37 studies), followed by Ethiopia, Pakistan, and Bangladesh. A range of geospatial tools—most prominently ArcGIS, ERDAS Imagine, and TerrSet—were consistently used to support spatial classification, simulation, and modeling. CA–Markov, Random Forest, Maximum Likelihood Classification (MLC), and Shannon's Entropy emerged as the most frequently employed models. Theoretical lenses were dominated by Human–Environment Interaction Theory, Urban Ecological Theory, and Land System Science, offering explanatory depth to spatial trends. Notably, recent studies demonstrated increasing integration of machine learning methods and hybrid modeling techniques, signaling a methodological evolution in land change research.



(a) (b) (c)

Figure 2. (a) Geographic Distribution of Studies, (b) Frequency of Spatial Models Used, (c) Temporal Trends in Methodologies

Here are the three visualizations based on your SLR data:

a. Geographic Distribution of Studies: India is the dominant contributor, followed by Ethiopia, Pakistan, and Bangladesh.
b. Frequency of Spatial Models Used – highlighting CA-Markov and Random Forest as the most frequently applied geospatial models.
c. Temporal Trends in Methodologies – a heatmap illustrating how the use of models like MLC, SVM, and MLP has evolved over four time periods (2015–2025).

3.5 Results

This section presents the key findings from synthesizing 62 peer-reviewed studies analyzed in this systematic review. The results are organized thematically to reflect major trends in geographic focus, geospatial tools and models applied, theoretical frameworks adopted, novel contributions, and common limitations. These insights provide a comprehensive overview of how spatial analysis has advanced land change science over the past decade.

3.5.1. Geographic Distribution of Studies

The geographic distribution of studies reveals a notable concentration in South Asia, particularly India, which accounts for 37 out of 62 reviewed articles. Other significant contributors include Ethiopia (10 studies), Pakistan (5), and Bangladesh (4). This regional clustering aligns with rapid urbanization, environmental degradation, and growing research capacities in these areas. A smaller number of studies were identified from countries like Algeria, Turkey, Iraq, and Madagascar, categorized under "Others". The trend underscores the dominance of developing nations as both subjects and sources of geospatial land change research, as shown in the following bar chart:

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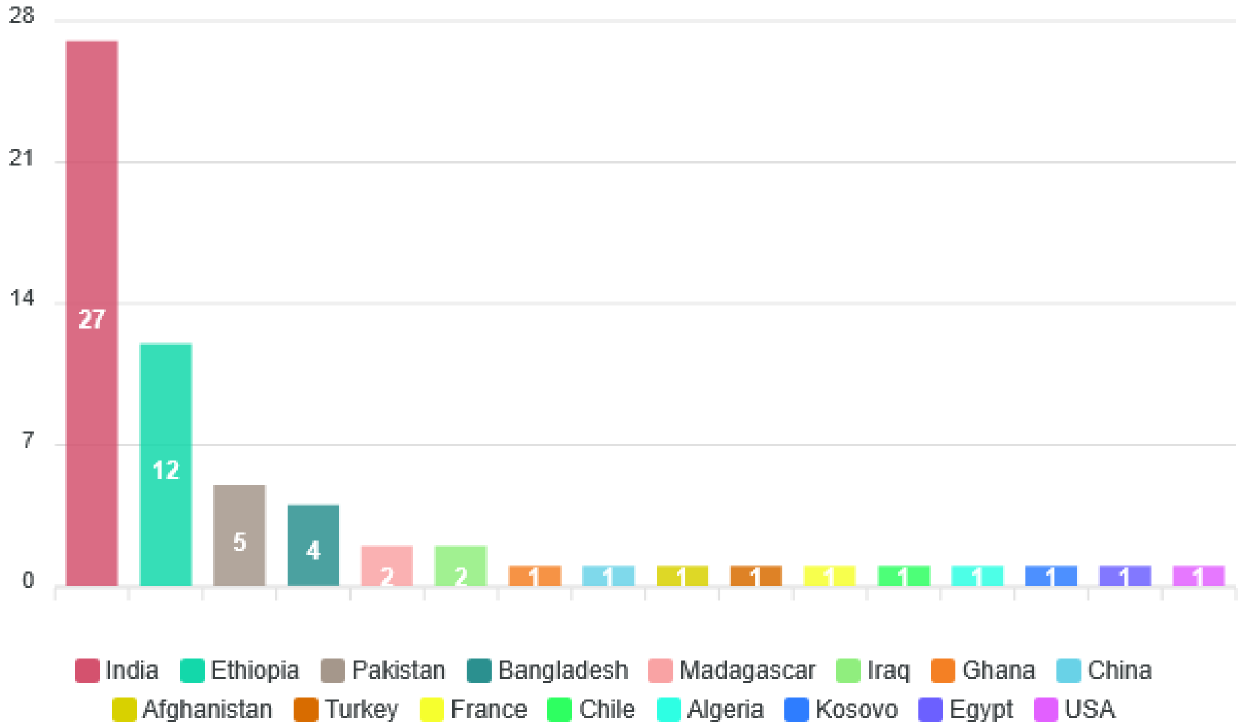

Figure 3. Bar Chart Country Classification Geographic Distribution of Studies

3.5.2. Analytical Tools and Software

The analysis shows a clear preference for proprietary GIS platforms, with ArcGIS used in 48 studies, making it the most dominant software in LULCC research. ERDAS Imagine follows with 30 studies, commonly used for satellite image classification and change detection. TerrSet, recognized for its integrated Land Change Modeler and CA–Markov simulation capabilities, was used in 18 studies. Notably, Google Earth Engine (12 studies) has gained traction recently due to its cloud computing functionality and access to large-scale datasets. QGIS, a free and open-source platform, appeared in 15 studies, highlighting growing interest in accessible spatial tools, as shown in the following bar chart:

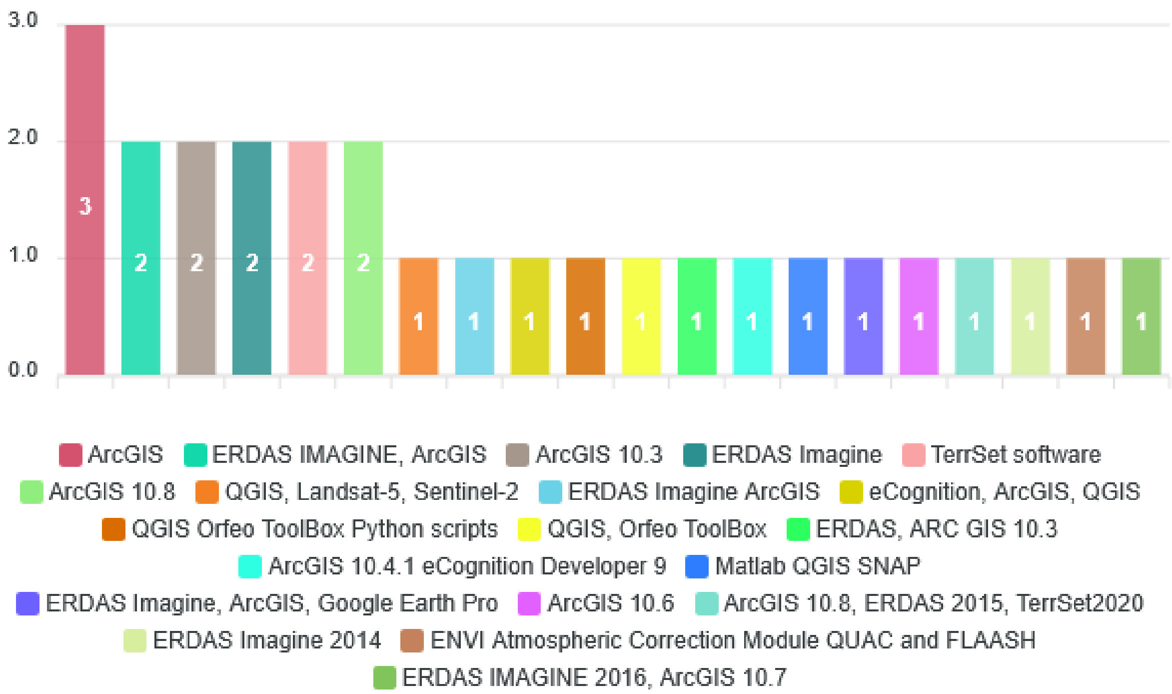

Figure 4. Bar Chart Analytical Tools and Software

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3.5.3. Year Article Classification

The graph shows the number of classified articles per year from 2015 to 2025. It can be seen that 2022 recorded the highest number of articles, with 16 articles, which shows a significant surge compared to previous years. 2023 also increased, with 9 articles, while 2024 had 12 articles. On the other hand, previous years, such as 2015 to 2021, show a relatively low number, ranging from 1 to 8 articles. By 2025, the number of articles will decrease again to 4, which may indicate a decrease in interest or volume of article classification in that year. The chart also uses different colors for each year, with the standout 2022 using a bright orange color, reflecting the very high number of articles in that year. Overall, there was an upward trend in the number of articles recorded from 2015 to 2023, with a peak in 2022, before another decline in 2025. For further analysis, it is important to understand the factors that influence the surge in 2022 and the decline in 2025, such as changes in platforms or policies related to article publication, as shown in the following bar chart:

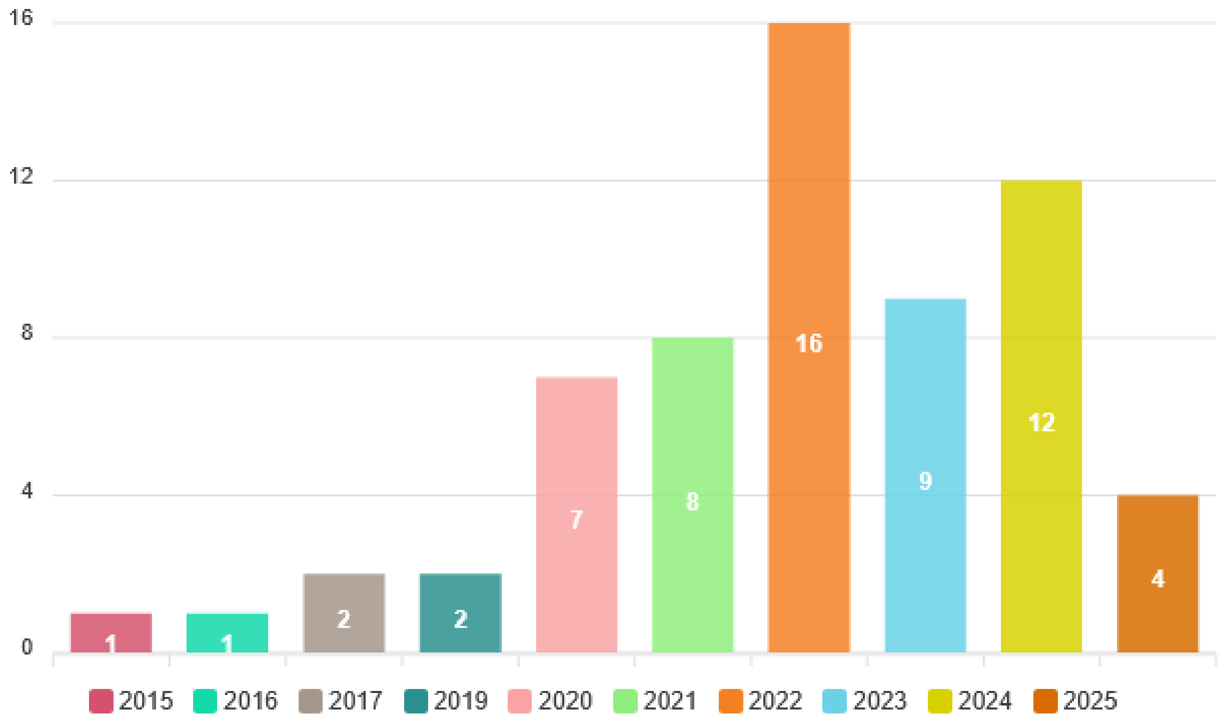

Figure 5. Bar Chart Year Article Classification

3.5.4. Journal Classification

The graph shown shows the classification of journals based on the number of articles published in various scientific journals. This graph compares 16 different journals by the number of articles classified. The GeoJournal and Applied Geomatics journals have the highest number of articles, each with five articles, which shows that both have significant contributions in their fields. Several other journals, such as Environmental Monitoring and Assessment and Data in Brief, each have four articles, showing a relatively high number. Meanwhile, journals such as Sustainability, Environmental Science and Pollution Research, and the Journal of the Saudi Society of Agricultural Sciences recorded three articles in each category. In addition, some journals have lower contributions, such as The Egyptian Journal of Remote Sensing and Space Science, Journal of the Indian Society of Remote Sensing, and Heliyon, each of which has only 1 article. The colors used in this graph make it easy to identify different journals, with each color representing a specific category of journals, as shown in the following bar chart:

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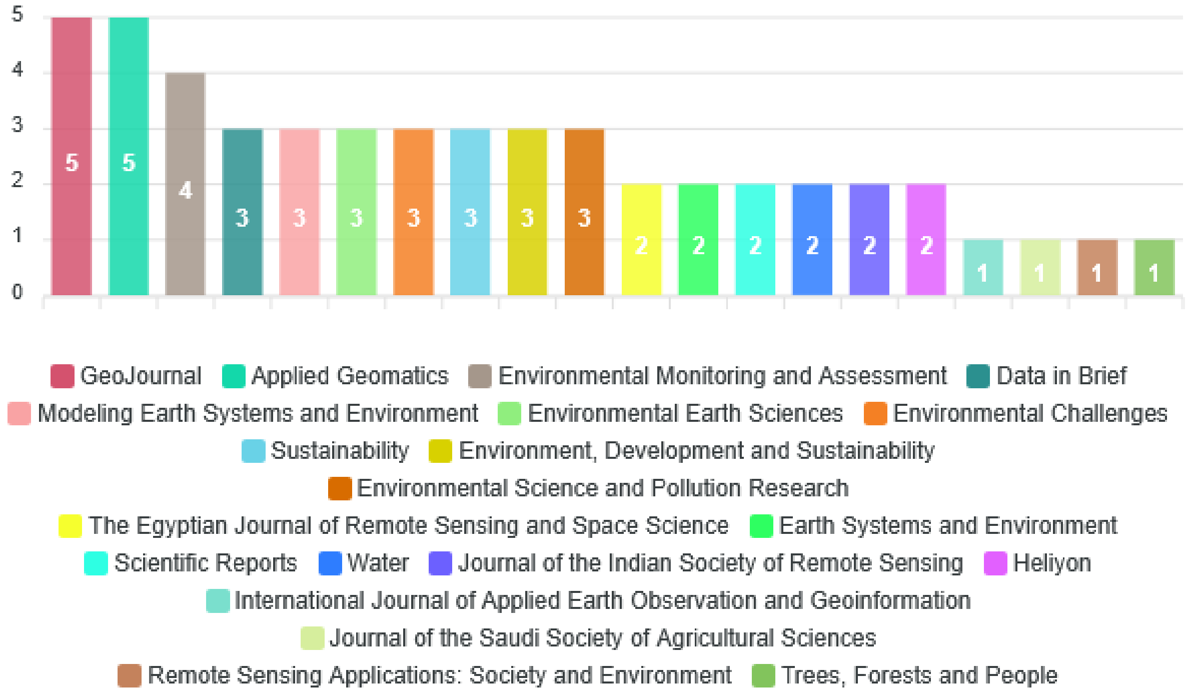

Figure 6. Bar Chart Journal Classification

3.5.5. Tier Journal Classification

The graph shown shows the classification of journals by tier or quality level, which is divided into four categories: Q1, Q2, Q3, and Q4. It can be seen that the journals with Q1 (the highest category) have the highest number, namely 28 articles, which shows that most of the publications analyzed are listed in journals with the highest level of quality. The journals classified in Q2 also showed a considerable number, with 26 articles, which shows that excellent publications are still listed in this category. On the other hand, the Q3 and Q4 categories have a lower number, each with four articles. This indicates that few publications are listed in lower-quality journals according to this tier system, as shown in the following bar chart:

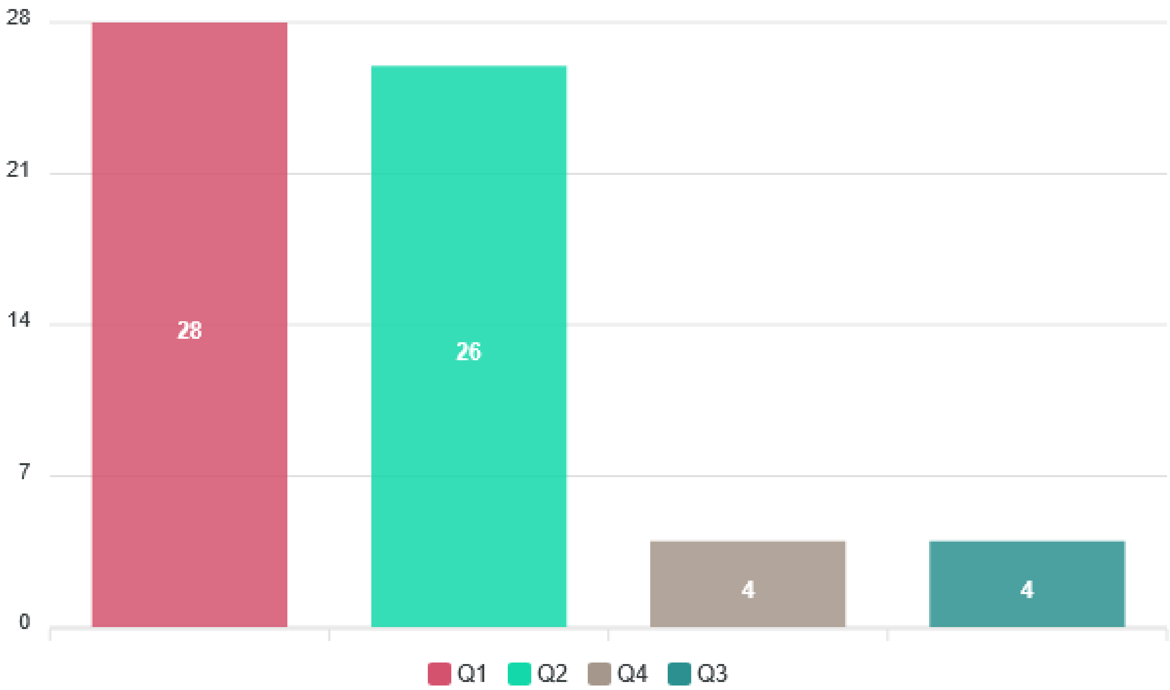

Figure 7. Bar Chart Tier Journal Classification

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3.5.6. Theory Classification

The graphs shown illustrate the classification of various theories in the research context, focusing on various topics related to the environment, land change, and ecology. It can be seen that the human-environment interaction theory dominates this graph with 20 articles, which shows that this theory greatly influences the field of research discussed. On the other hand, other theories, such as Urban Ecological Theory, Land Degradation Theory, and Landscape Pattern Analysis Theory, each have four articles, showing considerable interest, although not as popular as Human–Environment Interaction Theory. Theories with a lower number, such as the Historical Landscape Transformation Theory and the Cellular Automata (CA) model, are recorded with only two or three articles, indicating that these topics are less discussed in the collected research. The colors used in these graphs make it easier to identify and compare theories, with brighter colors representing more dominant theories and faded colors representing less frequently used theories, as shown in the following bar chart:

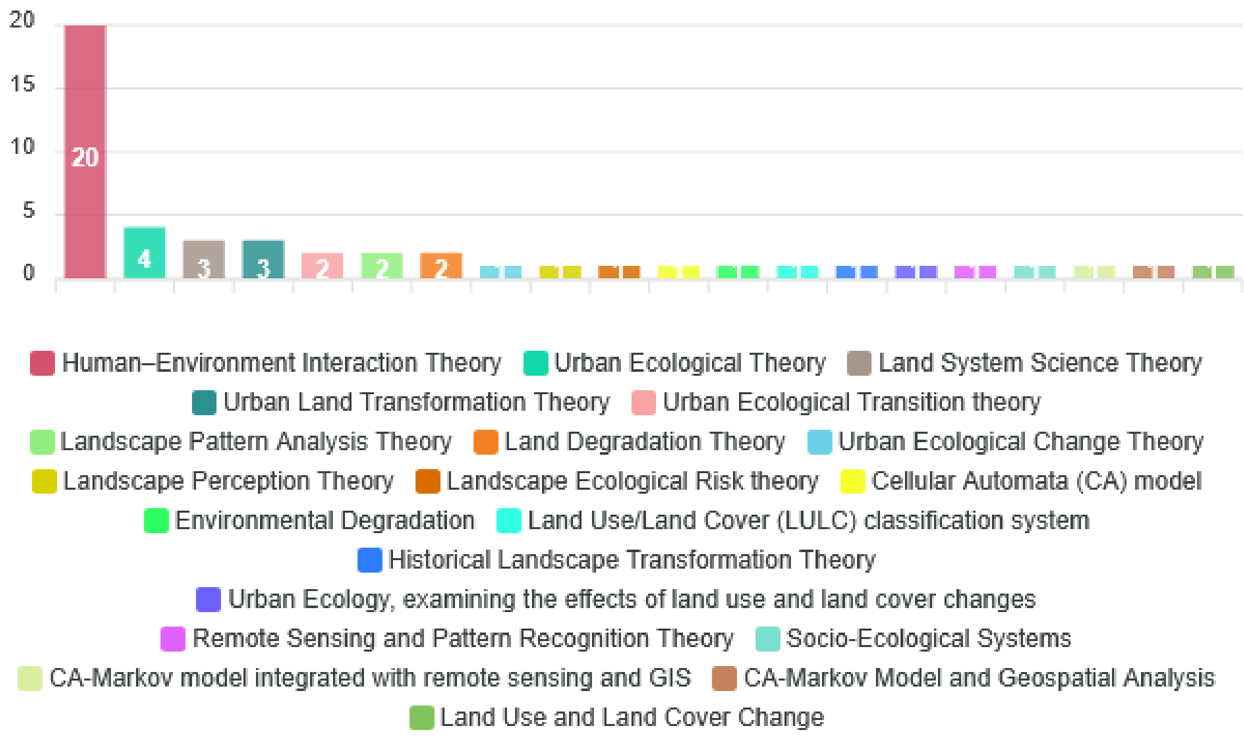

Figure 8. Bar Chart Theory Classification

3.5.7. Methods Classification

The graph shows the classification of various research methods used in geospatial-related studies and mapping using remote sensing and GIS (Geographic Information Systems) technology. This graph shows that Geospatial analysis dominates with the highest number, namely nine articles, which shows that this method is widely used in the studies discussed. Remote sensing and GIS appeared with a significant number of 4 articles, while Remote Sensing and GIS analysis had three articles each. Other methods, such as Geospatial modeling, Geospatial mapping, and Geospatial techniques, recorded 2 articles in each category, showing a more limited but significant use. Some of the more specific methods, such as the Hybrid Model Combining Linear Regression and Machine Learning, Landsat 7 and Resourcecast 2A satellite data, and the RUSLE model, have only 1 article, which indicates that these methods are rarely used in this study. The colors used in the graph help distinguish each category of methods, with brighter colors such as red and green representing more widely used methods, while faded colors such as brown and gray indicate less-used methods, as shown in the following bar chart:

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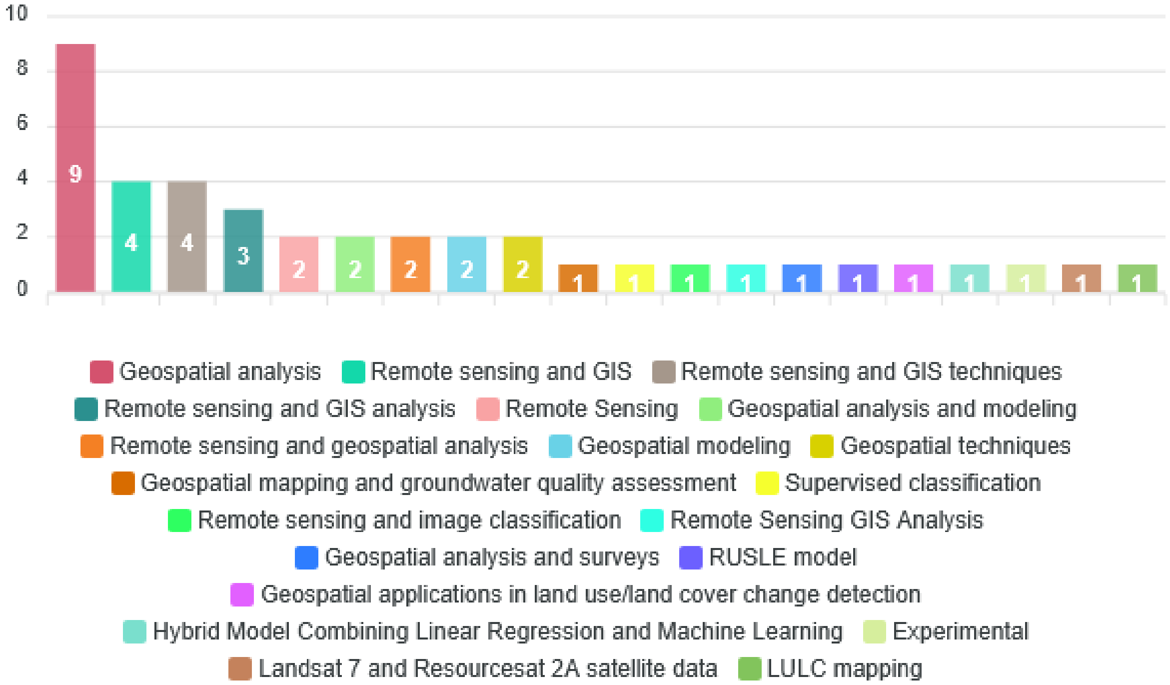

Figure 9. Bar Chart Methods Classification

3.6 Discussion

This section interprets the systematic review's findings to provide a critical understanding of current geospatial methodologies used in land change science. The aim is not only to summarize the results but to evaluate their implications within the broader body of knowledge, identify methodological and conceptual limitations, and provide evidence-based recommendations for future research. Through comparative analysis and theoretical contextualization, this discussion offers insights into how spatial tools and modeling approaches contribute to the evolving landscape of land system science.

3.6.1. Assessment of Current Methodological Insights

The dominance of CA–Markov, Random Forest, and Maximum Likelihood Classification reflects a strong preference for models that balance predictive capability with operational simplicity. The frequent application of these models aligns with prior literature [85], confirming their reliability in simulating land dynamics. However, the emergence of hybrid and machine learning–based approaches suggests that geospatial research is shifting toward more integrative, data-driven methods. This shift reflects technological accessibility (e.g., Google Earth Engine) and increasing demand for high-resolution forecasting.

3.6.2. Comparison with Existing Literature

The geographical concentration of studies in India, Ethiopia, and Pakistan parallels global patterns observed by other systematic reviews [86], which suggest that land change research is most active in areas experiencing rapid socio-economic transitions. What distinguishes the present review is the attention to the diversity of tools and the growing use of open-source software. This review emphasizes methodological transparency, reproducibility, and theoretical grounding compared to earlier syntheses that emphasized model performance.

3.6.3. Theoretical Contextualization

While human-environment interaction theory and urban ecological theory provide a consistent explanatory framework, their dominance also reveals a missed opportunity to expand into more integrative or dynamic conceptual lenses, such as socio-technical transitions or political ecology. This limits the ability of current studies to explain land change as a product of complex, multi-scalar processes. Future research should consider embracing cross-disciplinary theory to reflect better the socio-political realities influencing land systems.

3.6.4. Limitations and Validity Concerns

Despite significant methodological advances, several limitations affect the robustness of current spatial analysis in LULCC:

1. Resolution dependency: Heavy reliance on medium-resolution imagery (e.g., Landsat) limits detection of fine-grained changes.

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2. Limited validation: Ground-truthing and field-based validation remain scarce, weakening model confidence.
3. Narrow data integration: Many studies fail to incorporate socio-economic or institutional data critical to interpreting spatial patterns.

These limitations mirror concerns raised in prior reviews [87] and represent enduring methodological gaps that must be addressed to improve the real-world applicability of spatial models.

3.6.5. Recommendations for Future Research

To strengthen the methodological and conceptual foundations of land change science, future studies should:

1. Expand the use of open-source, cloud-based platforms to democratize access and promote reproducibility.
2. Apply hybrid and ensemble models that combine deterministic and AI-based methods for more robust forecasting.
3. Integrate ground-based data and participatory approaches to enhance the analysis's validity and contextual depth.
4. Adopt interdisciplinary theoretical frameworks to capture the socio-political drivers of land change.
5. Ensure regional diversity in study sites to improve the generalizability of findings beyond South Asia and Sub-Saharan Africa.

In summary, this review highlights a field in transition—where traditional spatial analysis methods are increasingly complemented by advanced, integrative, and machine learning–based approaches. While substantial methodological progress has been made, challenges remain in data resolution, model validation, and theoretical diversity. The predominance of studies from specific regions and reliance on established tools underscore the need for more inclusive, interdisciplinary, and context-sensitive research in land change science. By critically reflecting on existing practices and emerging directions, this discussion advocates for a more holistic geospatial research agenda that bridges scales, integrates social dimensions, and aligns spatial analysis with pressing environmental and policy concerns.

4. CONCLUSION

This systematic review synthesizes a decade of geospatial research in land change science, drawing on 62 peer-reviewed studies to evaluate methodological trends, theoretical orientations, and spatial modeling practices. The findings reveal a strong reliance on established tools such as ArcGIS, CA–Markov, and Random Forest, pointing to a gradual yet significant shift toward hybrid, machine learning–driven approaches supported by cloud computing platforms like Google Earth Engine. The review underscores the methodological maturity of the field, yet highlights persistent limitations—particularly in terms of spatial resolution, data integration, and ground validation. Moreover, the dominance of studies from select regions calls for greater geographic and thematic diversification. Future research should emphasize interdisciplinarity, reproducibility, and practical relevance. This includes integrating socio-environmental data, adopting open-source solutions, and aligning modeling outcomes with sustainable land management goals. By advancing both methodological depth and contextual insight, geospatial science can play a more pivotal role in informing land governance in an era of rapid environmental transformation.

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