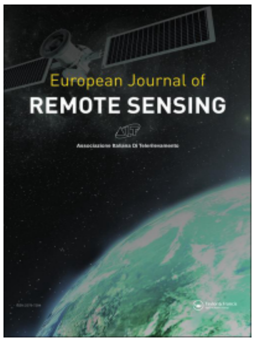

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Advances in vegetation mapping through remote sensing and machine learning techniques: a scientometric review

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ABSTRACT

This study explores the rapid growth in remote-sensing technologies for vegetation mapping, driven by the integration of advanced machine learning techniques. An analysis of publication trends from Scopus indicates significant expansion from 2019 to 2023, reflecting technological advancements and improved accessibility. Incorporating algorithms like random forest, support vector machines, neural networks, and XGBRFClassifier has enhanced the monitoring and analysis of vegetation dynamics at various scales. This progress supports addressing global environmental challenges such as climate change by providing timely data for conservation strategies. China leads in research output, followed by the United States and India, underscoring the field's global significance. Key journals, including "Remote Sensing," and conferences like IGARSS, play pivotal roles in disseminating findings. The majority of publications are research articles, emphasizing the reliance on original research and empirical data. The field's multidisciplinary nature is evident, with contributions spanning Earth Sciences, Agriculture, Environmental Science, and Computer Science. Visualisations using VOSviewer reveal interconnected themes, highlighting topics like land use, climate change, and aboveground biomass. The findings emphasise the importance of continued research and international collaboration to develop innovative solutions for environmental sustainability.

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Vegetation mapping; remote sensing; machine learning; climate change; environmental monitoring

Introduction

The ability of remote-sensing technologies to create detailed vegetation maps has made them vital for environmental management and monitoring. These technologies enable the assessment of vegetation covering, condition, and temporal changes, offering crucial insights into the dynamics of ecosystems. Advanced sensors, satellite platforms, and unmanned aerial vehicles (UAVs) have recently improved the precision and breadth of environmental data gathering. These advancements make it easier to monitor and evaluate a wide range of environmental data, and they also allow for multiscale studies (Cui et al., 2023; Marques et al., 2024; Szpakowski & Jensen, 2019; Timilsina et al., 2020; Vidican et al., 2023). Remote sensing facilitates efficient decision-making in conservation, land use planning, and resource management by offering continuous observation and thorough analysis (Rocchini, 2014; Szpakowski & Jensen, 2019). Advances in satellite imaging technology, such as the increased spectral and geographic resolution of sensors like Landsat, Sentinel, and MODIS, have significantly enhanced the precision and reliability of vegetation maps (Hansen et al., 2013; Morell-Monzó et al., 2020; Pastick et al., 2018, 2020).

Machine learning in the field of vegetation mapping has made significant advancements, greatly enhancing the accuracy, efficiency, and detail of vegetation classification and monitoring. Integrating advanced machine learning algorithms with remote sensing data has further improved the accuracy and depth of vegetation analysis. Algorithms such as Random Forest (RF), Support Vector Machines (SVM), neural networks, and gradient boosting classifiers have facilitated the accurate grouping of different vegetation types and the detection of changes over time (Jozdani et al. 2019). These algorithms can process large volumes of multi-source data, including spectral, spatial, and temporal information, to differentiate between vegetation types, assess health conditions, and monitor changes over time. Deep learning, particularly through Convolutional Neural Networks (CNNs), has enabled sophisticated image analysis, such as the automated extraction of vegetation features and high-resolution mapping of plant communities (Corbane et al., 2021; Maxwell et al., 2021; Timilsina et al., 2020). Integration with advanced sensors and cloud-based platforms like Google Earth Engine allows for large-scale, real-time analysis, making machine learning an indispensable tool in

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biodiversity conservation, land management, and ecological research (Google Earth Engine Team, 2024).

However, machine learning in the domain of vegetation mapping faces several challenges. One of the primary issues is the need for high-quality labelled training data. Accurate vegetation mapping often requires large, well-labelled datasets, which are time-consuming and costly to collect, particularly for diverse or remote regions (Kaiser et al., 2017; Liang et al., 2020; Stanimirova et al., 2023). Additionally, model performance can be hindered by the quality and resolution of remote sensing data. Factors such as cloud cover, atmospheric conditions, and sensor limitations can affect data quality, leading to potential inaccuracies in vegetation classification. Spectral and spatial resolutions are also critical; lower spectral resolution can limit the differentiation of vegetation types, while lower spatial resolution can obscure fine-scale patterns in heterogeneous landscapes (Di & Yu, 2023; Dou et al., 2024; Lin et al., 2022; Wilson et al., 2016). Sensors like Landsat, Sentinel, and MODIS offer varying levels of spectral and spatial resolution, which may not always meet the requirements for detailed vegetation analysis. Recent advances, such as hyperspectral imaging and the use of finer spatial resolution sensors like WorldView-3 and PlanetScope, have begun to address these limitations by providing richer spectral information and finer spatial details (Liu et al., 2020; Satellite Imaging Corporation, 2024; Whig et al., 2024; Xie et al., 2008). These advances allow machine learning models to capture more subtle differences in vegetation characteristics, improving classification accuracy and the detection of small-scale changes. However, integrating such high-resolution data still poses challenges in terms of data processing and storage, requiring further advancements in computational methods (Ayhan et al., 2020; Lu et al., 2022).

Furthermore, despite the effectiveness of machine learning models, they often function as "black boxes", making it difficult to interpret their decisions and understand the ecological processes they detect. This lack of interpretability can be a barrier to their acceptance in ecological research and management practices (Shams et al., 2024; Welchowski et al., 2022). Additionally, the generalization of models across different regions and conditions is another challenge, as models trained in one area may not perform well in other regions with different vegetation types, climate conditions, or spectral characteristics. This necessitates ongoing model tuning and adaptation to ensure accuracy across diverse landscapes (Ayhan et al., 2020; Turner et al., 2019; Yang et al., 2022). Despite these challenges, advancements in machine learning, combined with evolving remote sensing technologies, continue to push the boundaries of vegetation mapping, offering increasingly precise and scalable tools for ecological analysis.

The aim of this research is twofold: first, to conduct a comprehensive literature review exploring the applications of remote sensing in monitoring vegetation growth patterns, detecting land cover changes, assessing land degradation and fragmentation, evaluating the impact of topography on vegetation health, and estimating biomass and evapotranspiration. This research seeks to contribute to the field by highlighting the advancements in combining remote sensing technologies with machine learning algorithms, which offer significant improvements in the accuracy, depth, and scale of vegetation analysis. These methods can better track environmental changes, support biodiversity conservation, and enhance land management practices (Bauer et al., 2024; Matyukira & Mhangara, 2023b; Mullissa et al., 2024; Pettorelli et al., 2005). Additionally, this paper aims to offer insights into the evolving techniques that allow more precise assessment of ecosystem health and changes in vegetation over time, thereby contributing to the body of knowledge essential for sustainable environmental monitoring and management. By systematically reviewing the literature, this research identifies critical themes and advancements that highlight the growing potential of remote sensing and machine learning in tackling environmental challenges.

Approaches to vegetation mapping and analysis using remote-sensing technologies

Advancements in machine learning algorithms for vegetation classification

Remote sensing and machine learning have evolved significantly over the past few decades, each contributing to vegetation mapping and classification advancements. The use of remote sensing to map vegetation began in the 1960s with the advent of aerial photography and early satellite imaging, marking the start of widespread remote sensing applications. During this initial phase, these technologies facilitated the visual evaluation of vegetation patterns across vast territories, initiating the first phase of remote sensing applications in environmental monitoring (NASA Earth Observatory, 2023, Geological Survey, 2023). The launch of the Landsat program in 1972 was a pivotal event, producing the first multi-spectral satellite images capable of efficiently studying vegetation. Early studies utilised these images to classify various types of vegetation and monitor changes in land cover (Cohen & Goward, 2004; Tucker, 1979) demonstrating the potential of satellite imagery for comprehensive environmental monitoring.

In parallel, the field of machine learning began to take shape. In the mid-20th century, early machine learning efforts focused on pattern recognition and statistical learning, laying the groundwork for more sophisticated algorithms. The development of decision trees, neural networks, and support vector machines (SVM) in the 1980s and 1990s marked significant milestones (Breiman, 2001; Cortes & Vapnik, 1995). These advancements allowed for better handling of complex datasets and improved predictive accuracy. As machine learning techniques became more advanced, they began to be applied to remote sensing data, enhancing vegetation classification accuracy (Chaves et al., 2020; Maxwell et al., 2018). Technical advancements in digital image processing throughout the 1990s significantly improved the analysis of data obtained from remote sensing. The precision of vegetation maps has increased due to the development of algorithms for image classification, such as the Maximum Likelihood Classifier (MLC), providing environmental scientists with more accurate tools. Additionally, the development of vegetation indices, such as the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI), enabled quantitative analysis of vegetation health and productivity (Arifeen et al., 2021; Lillesand et al., 2004; Rahman et al., 2017; Rani et al., 2023). These indices became widespread for analysing environmental impacts and monitoring vegetation growth and are directly related to machine learning as they serve as key input features for various models. By incorporating vegetation indices into machine learning algorithms like decision trees, neural networks, and SVM, researchers can enhance the accuracy and efficiency of vegetation classification and monitoring tasks. Machine learning models leverage these indices to identify patterns, distinguish between different vegetation types, assess vegetation health, and predict changes over time (Pan et al., 2023; Turhal, 2022; Xie et al., 2019). Furthermore, the availability of higher-resolution satellite images from sensors like SPOT and the continuous enhancements of Landsat sensors significantly improved spatial resolution and spectral capabilities, facilitating more detailed and accurate vegetation analysis (Hansen et al., 2013; Morell-Monzó et al., 2020; Qarallah et al., 2023; Radoux et al., 2016; Townshend et al., 2000; Geological Survey, 2023).

Since its first use, vegetation mapping has advanced significantly with the integration of remote sensing data into Geographic Information Systems (GIS) in the 2000s. This combination allowed for comprehensive geographical analysis, enabling the mapping of vegetation patterns in relation to other environmental factors such as topography, soil types, and climate (Brown et al., 2016; Foody, 2002; Lv et al., 2019). GIS technology facilitated the management and analysis of large datasets, enhancing the ability to monitor changes in land cover and assess their impact on ecosystems (Arifeen et al., 2021; Brown et al., 2016; Foody, 2002; Rouse et al., 1974). Platforms like Google Earth Engine further revolutionised the field with cloud-based processing capabilities and access to a vast library of satellite images, making large-scale environmental assessments more accessible and efficient (Gorelick et al., 2017).

In recent years, the integration of machine learning techniques with remote-sensing data has become increasingly important to tackle the complexities and scale of environmental data. Advanced algorithms, particularly deep learning and neural networks, have greatly enhanced image classification tasks. Convolutional Neural Networks (CNNs) have demonstrated superior performance by automatically learning hierarchical features from raw satellite imagery, significantly improving the accuracy and comprehensiveness of vegetation mapping (Ma et al., 2019; Zhu et al., 2017). Additionally, machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM) have been widely used for classification tasks. RF employs an ensemble of decision trees to manage high-dimensional data and identify key features, aiding in differentiating vegetation types based on their spectral signatures while minimizing overfitting (Berhane et al., 2018; Dobrinić et al., 2021; Wang et al., 2018). SVM, on the other hand, finds an optimal hyperplane in a high-dimensional space to classify vegetation using spectral and spatial features, making it particularly useful in scenarios with limited training data (Fu et al., 2017; Hasan et al., 2019; Xie et al., 2019). Unsupervised learning methods like K-means clustering also play a valuable role in grouping similar spectral signatures, helping to identify various vegetation zones without labelled training samples (Cohn & Holm, 2021; Tavallali et al., 2021).

The integration of remote sensing with machine learning is thus crucial for facilitating more precise, detailed, and scalable ecological research. For example, a study by Kluczek et al. (2024) demonstrates this integration by combining multitemporal optical and radar satellite data to enhance vegetation mapping accuracy, account for seasonal variability, and provide a robust methodology for biodiversity conservation, land management, and ecological monitoring in mountainous regions. Similarly, Bartold and Kluczek (2024) show that augmenting deep neural networks with metadata significantly improves wild animal classification accuracy, offering valuable tools for biodiversity conservation, wildlife management, and ecological research. Furthermore, Sharma (2022) highlights the practical applications and successes of integrating machine learning with multispectral data, achieving detailed, high-resolution (10-meter) countrywide mapping of plant ecological communities using CNNs, thereby enhancing land management, biodiversity conservation, and ecological research. By integrating these advanced machine learning algorithms with remote sensing platforms such as Google Earth Engine, researchers can process and analyse satellite imagery in real-time, leading to further advancements in the field of environmental monitoring and ecosystem assessment (Gorelick et al., 2017).

Another significant advancement in the application of machine learning to remote sensing is the introduction of extreme gradient-boosting algorithms, such as XGBoost and its variants (Chen & Guestrin, 2016). These algorithms have complemented traditional machine learning techniques by offering superior performance in handling large datasets and high-dimensional features, which are common in remote sensing data (Chen & Guestrin, 2016; Matyukira & Mhangara, 2023b). Extreme gradient boosting combines the strengths of decision trees and gradient boosting, providing robust and efficient classification results. Its ability to handle missing values and its scalability have made it a popular choice for vegetation classification tasks, further enhancing the accuracy and efficiency of remote sensing analyses (Pham et al., 2020; Zhang et al., 2020).

Vegetation growth dynamics using remote-sensing technologies

Remote sensing technologies have become indispensable for environmental monitoring and management due to their ability to map vegetation comprehensively. These technologies enable the evaluation of vegetation coverage, condition, and temporal fluctuations, providing crucial insights into ecosystem dynamics (Knauer et al., 2014). The continuous advancements in satellite remote sensing, such as the development of high-resolution sensors and sophisticated data processing algorithms, have significantly enhanced researchers' ability to monitor vegetation health, productivity, and changes over time (Li et al. 2023c; Pradhan et al., 2024).

Time-series analysis of remote sensing data is a crucial technique for monitoring temporal changes in vegetation phenology and growth patterns (Kooistra et al., 2024). Common methods for assessing vegetation health and productivity include using NDVI, EVI, and other vegetation indices that provide accurate measurements of plant greenness, which are closely correlated with photosynthetic activity and biomass (Li et al. 2023b; Pradhan et al., 2024). These indices are instrumental in detecting seasonal variations, identifying periods of maximum growth and evaluating long-term trends in vegetation dynamics. By analysing temporal changes through remote sensing data, researchers can better understand vegetation's response to climate fluctuations, human activities, and natural disturbances (Nyamjav et al., 2024; Obuchowicz et al., 2024; Pettorelli et al., 2005). Furthermore, phenological metrics derived from remote sensing data, such as the start of the season (SOS), end of the season (EOS), and length of the growing season (LOS), provide essential information about plant growth over time (White et al., 2009). These measures help detect changes in phenological events due to climate change and other environmental variables. For instance, higher temperatures often result in an earlier onset of SOS and a longer duration of LOS. By observing these changes, scientists can more accurately predict the effects of climate change on ecosystems, adjust agricultural practices, and conserve biodiversity (Chen & Zhang, 2023; Fang et al., 2023).

In addition to vegetation indices, several advanced methods are employed for assessing vegetation health and analysing time-series data. One of the most common approaches is the use of radiative transfer models such as PROSPECT + SAIL models, which simulate light interaction with vegetation to estimate biophysical parameters like leaf area index (LAI) and chlorophyll content (Berger et al., 2018; Gupta & Pandey, 2022; Jacquemoud et al., 2009). A recent study utilised PROSAIL model inversion on Google Earth Engine to estimate aboveground biomass continuously over time on the Tibetan Plateau (Xie et al., 2022). This method provided detailed insights into vegetation structure and function, highlighting the benefits of combining biophysical models with remote sensing data for comprehensive vegetation analysis. Additionally, LiDAR and radar technologies are increasingly being used to measure vegetation height and biomass, offering information that cannot be captured by optical sensors alone (Edson & Wing, 2011; Maesano et al., 2020).

However, despite these advancements, several challenges remain in analysing vegetation growth dynamics using remote-sensing data. One of the major challenges is the data quality and resolution. While temporal resolution has improved, there are still limitations in capturing rapid vegetation changes, especially in areas with high variability due to seasonal or anthropogenic factors (Fan et al., 2022; Li et al., 2023a). In regions with frequent cloud cover, optical data collection can be interrupted, necessitating the use of radar or LiDAR technologies. Additionally, lower spectral resolution may hinder the differentiation between various vegetation types in heterogeneous landscapes, making it difficult to capture subtle vegetation characteristics (Ougahi et al., 2022; Wegehenkel, 2009).

Moreover, vegetation indices such as NDVI, while widely used, have limitations in areas of dense vegetation where they tend to saturate, reducing sensitivity to biomass changes (Fu et al., 2022; Hassan et al., 2023). To overcome these challenges, alternative approaches such as data fusion techniques – which combine optical, radar, and LiDAR data – are being developed to offer a more comprehensive assessment of vegetation health (Illarionova et al., 2024; Tian et al., 2024). Furthermore, the analysis of vegetation dynamics is complicated by the variability in environmental factors, such as climate variability and human-induced changes. Phenological shifts, for instance, may vary significantly across ecosystems, making it difficult to create generalisable models for predicting vegetation responses (Hassan et al., 2023; Roberts et al., 2015)

Finally, integrating environmental variables like temperature, precipitation, and soil moisture into remote sensing data remains a complex task. Although studies have demonstrated correlations between these factors and vegetation indices (Tsai & Der Yang, 2016; Zhong et al., 2010), predicting vegetation dynamics accurately requires sophisticated models capable of capturing these intricate interactions. Additionally, the increasing occurrence of extreme weather events adds further complexity, making it essential to develop robust models that integrate remote sensing data with in-situ measurements. These advancements are crucial for improving predictions of vegetation responses and guiding ecosystem management practices (Fang et al., 2023).

Analysis of land cover and land use change utilising remote-sensing technologies

Remote sensing technologies are crucial in identifying and examining changes in land cover and land use. These changes are essential for comprehending environmental shifts and guiding sustainable land management strategies. Monitoring these changes over time allows for valuable observations of the effects of human activities and natural processes on landscapes. Researchers use various remote sensing methods to obtain precise information on the evolution of land cover and land use. This knowledge is invaluable for developing effective conservation strategies and informing policy decisions (Fang et al., 2023; Knauer et al., 2014; Pradhan et al., 2024). Change detection methods, such as post-classification comparison, image differencing, and principal component analysis (PCA), are often used to detect changes in land cover using multi-temporal remote sensing data. Post-classification comparison is the separate categorisation of images from various periods, followed by comparing the outcomes to identify any alterations (Liu & Zhou, 2004). Image differencing is a process where the pixel values of one date are subtracted from the pixel values of another date, which helps to identify places where there have been substantial changes (Panuju et al. 2020). Principal Component Analysis (PCA) decreases the number of dimensions in the data, improving the ratio of useful signal to unwanted noise and increasing the efficiency of detecting changes (Li et al., 2024b; Wu et al., 2015). These tools have shown efficacy in monitoring several land cover changes, such as urbanisation, deforestation, and agricultural development (Asokan & Anitha, 2019; Cheng et al., 2023; Marukatat, 2023; Yu et al., 2023).

Remote sensing technology has been instrumental in tracking urbanisation and deforestation, key drivers of environmental transformation. High-resolution satellite imagery facilitates detailed mapping of land cover changes, revealing the extent and patterns of urban growth and forest clearance (Panuju et al. 2020). By analysing remote sensing data, researchers can observe the impact of urban development on natural environments, such as the proliferation of impervious surfaces and built-up areas. Similarly, deforestation activities can be scrutinised to ascertain the pace and spatial pattern of forest depletion. These insights are vital for understanding the consequences of land-use changes and formulating interventions to mitigate their adverse effects (Joseph & Jaya Surya, 2019; Kumar, 2011).

Building on this understanding, evaluating the effects of changes in land cover and land use on ecosystems and biodiversity becomes a critical next step for implementing sustainable management practices (D. Kumar, 2011). Remote sensing data provide significant information for estimating the impacts of these changes on habitat fragmentation, species distribution and ecosystem services (Matyukira & Mhangara, 2023b). One such impact is habitat fragmentation, often a result of urbanisation or deforestation. To understand its effects on biodiversity, researchers can analyse landscape metrics derived from remote sensing data (Musetsho et al., 2021; Rong & Fu, 2023). In addition, remote sensing may be used to observe changes in land use patterns, such as the transformation of forests into agricultural areas, which has substantial consequences for carbon sequestration, water cycles, and soil quality (Assede et al., 2023; Cheng et al., 2023). Researchers may create complete models to forecast future land use scenarios and their possible effects by combining remote sensing with ecological and socio-economic data. This integration helps formulate policies for sustainable development and conservation (Jiang et al., 2021; Vitale & Salvo, 2024).

While remote sensing technologies have greatly enhanced the examination of land cover and land use changes, specific limitations intrinsic to these tools must be acknowledged. A significant difficulty is the accessibility and quality of remote sensing data. High-resolution satellite imagery, essential for comprehensive monitoring, may be inaccessible due to expense, cloud cover interference, or limited satellite revisit time, especially in tropical areas susceptible to persistent cloud cover (Breunig et al., 2023).

Furthermore, the validation of remote sensing data necessitates access to accurate ground truth data, which can be costly and logistically difficult to acquire, particularly in distant or politically dangerous areas. The absence of dependable validation data may undermine the accuracy of land cover classifications, resulting in inaccuracies in identifying land use changes (Olofsson et al., 2014; Stehman & Foody, 2019).

The classification algorithms employed in remote sensing are frequently constrained by their sensitivity to spectral similarities among various land cover types. For instance, differentiating between specific vegetation types and urban areas might be challenging when their spectral signatures overlap, potentially resulting in misclassification (Gündüz & Orman, 2024; Mehmood et al., 2022). The intricacy of data processing and the substantial computational expenses linked to managing extensive multi-temporal remote sensing data may be prohibitive for certain researchers or organizations. These challenges, including the time and resources required for data preprocessing and analysis, must be balanced against the powerful insights that remote sensing offers in understanding land cover and land use dynamics (Southworth & Muir, 2021, Di and Yu 2023; Yao et al., 2020). Consequently, although remote sensing is an invaluable instrument, these constraints must be recognized to guarantee precise monitoring and informed decision-making in land management.

Utilising remote sensing technologies to monitor land degradation and fragmentation

Remote sensing technologies are efficient tools for monitoring land degradation and fragmentation, which are significant environmental concerns impacting ecosystem health and species diversity. These technologies provide detailed, multi-temporal data that are essential for the ongoing evaluation of land degradation indicators such as soil erosion, loss of plant cover, and desertification (Giri Tejaswi Rome, 2007; Reddy et al., 2018; Shange, 2020; Symeonakis, 2022). Spectral indices like the NDVI and the Soil Adjusted Vegetation Index (SAVI) are instrumental in measuring the extent and condition of vegetation, offering valuable insights into the health of the land (Reddy et al., 2018). By aiding in detecting regions undergoing deterioration and assessing the magnitude of these changes over time, NDVI and SAVI enhance our ability to monitor and address the critical issue of land degradation. The integration of remote sensing data with spectral indices allows for a more comprehensive understanding and management of environmental changes, ensuring the preservation of ecosystems and biodiversity (Giri Tejaswi Rome, 2007; Lu et al., 2015; Mambo & Archer, 2007; Yengoh et al., 2016).

Various remote sensing methods are key for effectively monitoring land cover changes, which in turn can indicate land degradation. Supervised and unsupervised classification techniques are commonly used for categorizing land cover types. Supervised classification utilises predefined training datasets, enabling the algorithm to classify images according to known land cover categories. In contrast, unsupervised classification relies on the spectral properties of pixels to group them into clusters without prior knowledge of land types (Parashar, 2023). Object-Based Image Analysis (OBIA) is another important method that segments high-resolution satellite images into objects and classifies them based on both spectral and spatial properties such as texture and shape, improving classification accuracy in complex landscapes (Dronova, 2015; Kumar et al., 2020).

Additionally, change detection techniques such as post-classification comparison, image differencing, and NDVI differencing play a vital role in identifying land cover transitions over time. These techniques allow for detecting changes like deforestation, urbanization, and agricultural expansion, which often contribute to land degradation (Asokan & Anitha, 2019; Cheng et al., 2024; Parelius, 2023). Incorporating these methods into land monitoring systems enhances the detection of subtle changes in land cover and provides better insights into ongoing degradation processes.

Similarly, fragmentation analysis is an essential application of remote sensing in environmental monitoring. It addresses habitat fragmentation – dividing continuous habitats into smaller, isolated patches. Metrics such as patch size, edge density, and connectedness, derived from remote sensing data, provide insights into habitats' spatial arrangement and integrity (Singh et al., 2014). Analysing these metrics helps researchers understand fragmentation's extent and impact on ecosystems. This knowledge is vital for conservation efforts and land-use planning to mitigate negative effects on biodiversity and ecosystem services (Dupin et al., 2013; Mambo & Archer, 2007; Singh et al., 2014; Zlinszky et al., 2015).

In parallel, monitoring desertification is crucial for evaluating land deterioration, especially in dry and semi-dry regions. Remote sensing approaches, including the Land Degradation Neutrality (LDN) frameworks, leverage satellite data to track changes in land cover and soil characteristics over time (Kust et al., 2023). Such monitoring is key to identifying areas vulnerable to desertification. The data obtained from these tools are essential for mapping and observing desertification trends, which in turn supports the development of policies aimed at combating land degradation. By integrating remote sensing data with ground-based observations and climate factors, researchers can create comprehensive models to predict and manage desertification, thereby helping to maintain land productivity and ecological balance in susceptible areas (Dharumarajan et al., 2022; El Hassan, 2004; Hill & Helldén, 2005; Xu, 2023).

Assessing the impact of terrain on plant health using remote sensing technologies

Topography is crucial in influencing vegetation distribution and vitality because variations in elevation, slope, and aspect create a diversity of microhabitats (Xun et al., 2023). Remote sensing technologies, including Digital Elevation Models (DEMs), facilitate a comprehensive analysis of topographic factors on vegetation. DEMs derived from remote sensing data offer detailed topographical information, allowing researchers to explore the effects of elevation gradients on vegetation patterns (Guth et al., 2021). Remote sensing data such as those derived from radar (e.g. SRTM – Shuttle Radar Topography Mission, or TanDEM-X) and LiDAR (Light Detection and Ranging) can be used to directly obtain ground elevation information through the generation of Digital Elevation Models (DEMs). These datasets provide detailed topographical information at various resolutions. SRTM, for example, provides global elevation data at a 30-meter resolution, while LiDAR offers even more precise elevation data, typically down to meter or sub-meter accuracy (Guth et al., 2021, 2024; Wei & Bartels, 2012). These remote sensing methods invert elevation data directly from satellite or aerial observations, allowing researchers to analyse terrain features like slope, aspect, and elevation, which are critical for understanding vegetation patterns. For instance, elevation can significantly influence plant growth and health by affecting temperature and moisture availability, which are vital factors. By examining these elevation-related factors, scientists can gain a deeper understanding of the spatial distribution of various plant species and their responses to topographic changes (Brocard et al., 2023; Khalaf et al., 2021; Matsuura & Suzuki, 2013; Odgaard et al., 2014).

In tandem with the analysis provided by DEMs, remote sensing is also instrumental in evaluating vegetation vigour through topographic correction. Since remote sensing data frequently require modifications to account for topographic impacts such as slope and aspect on reflectance measurements, topographic correction techniques are employed to alter the reflectance data (Zhang, 2011). This process ensures that vegetation indices like the NDVI are more accurate. Precise vegetation indices are critical for assessing vegetation health and productivity because they provide reliable assessments of plant biomass and photosynthetic activity. Therefore, topographic correction not only complements the insights gained from DEMs but also enhances the accuracy and relevance of vegetation vigour evaluations by removing the impact of the underlying topography (Gao & Zhang, 2009; Ma et al., 2021; Riaño et al., 2003; Yao et al., 2022).

Furthermore, topography-induced microclimates significantly impact vegetation vigour in the Southern Hemisphere, as differences in terrain may generate localised climatic conditions that affect plant development. North-facing slopes in the Southern Hemisphere receive more sunshine, resulting in higher temperatures and less moisture, while south-facing slopes are colder and have more moisture (Barry & Blanken, 2016). These microclimatic differences impact the species makeup, growth rates, and general health of plants. By combining remote sensing data with topography information, researchers can examine microclimates' influence on plants' distribution and health (Jucker et al., 2018). Such assessments are crucial for forecasting the impact of climate change on vegetation patterns since variations in temperature and precipitation patterns may modify the microclimatic conditions that plants rely on for their survival and development. Understanding these relationships enables scientists to formulate more efficient conservation and land management techniques (Bramer et al., 2018; Chen et al., 2013; De Frenne et al., 2013; Jung et al., 2016).

In addition to topography, vegetation growth and health are also influenced by both environmental factors and human activities, which can be monitored using remote-sensing technologies. Environmental factors such as temperature, precipitation, and soil moisture can be captured using satellite data from missions like MODIS (Moderate Resolution Imaging Spectroradiometer) and Sentinel-2, which track climate variables over time (Dhillon et al., 2023; Lange et al., 2017). Similarly, human activities such as land use changes, deforestation, and urbanization can be monitored through remote sensing, using methods such as land cover classification and change detection. These factors significantly impact vegetation by altering local climates and soil conditions, affecting plant growth and health (Abebe et al., 2022; Nedd et al., 2021). For example, a study using the CCDC algorithm with optical and SAR images investigated marsh vegetation phenology in the Honghe National Nature Reserve, China, and found that hydro-meteorological factors significantly drive phenological changes (Fu et al., 2022). Additionally, another study in the same reserve employed the LandTrendr algorithm and Google Earth Engine to analyse the dynamic relationship between marsh vegetation and hydrological changes over a 35-year period, further demonstrating how remote sensing can be used to monitor complex environmental interactions over time (Fu et al. 2022). Integrating data on climate and human-induced changes, alongside topographic information, provides a more holistic understanding of the drivers affecting vegetation patterns

Remote sensing technologies for estimating biomass and evapotranspiration

Estimating biomass and quantifying evapotranspiration are crucial for comprehending ecosystem production and water use, which are fundamental environmental and resource management aspects (Khan et al., 2019; Zhou et al., 2008). Remote sensing technologies are used to estimate biomass using many sophisticated approaches such as vegetation indices, radar, LiDAR, and UAVs. Vegetation indices, such as NDVI, are commonly used for biomass estimation by correlating the reflectance of vegetation to biomass levels. Radar data, particularly from Synthetic Aperture Radar (SAR), provide structural information by penetrating vegetation canopies, enabling biomass estimation. LiDAR offers a precise 3D measurement of plant structures, including height, which is essential for biomass calculations (Borsah et al., 2023; Kumar et al., 2015; Sinha et al., 2015).

The use of UAVs equipped with advanced RGB and multispectral sensors has significantly enhanced the precision and spatial resolution of biomass estimation. These drones, as highlighted by Tait et al. (2019) and Bazrafkan et al. (2023), are capable of capturing high-resolution images across various spectral bands, enabling precise spatial and spectral vegetation analysis. RGB sensors offer insights into the visible spectrum for visual assessments, while multispectral sensors provide critical data at specific wavelengths like the near-infrared for in-depth vegetation studies. The detailed imagery from UAVs is particularly beneficial for monitoring minute changes in plant structure, proving invaluable in hard-to-reach areas or when high-detail information is required (Lussem et al., 2019; Nex & Remondino, 2014). However, despite their high resolution and flexibility, UAVs face challenges in covering large spatial scales due to their limited flight range, data volume constraints, and regulatory restrictions. For larger areas, satellite-based methods such as synthetic aperture radar (SAR) and LiDAR remain more effective (Nedd et al., 2021; Saadatseresht et al., 2015)

Advancements in remote sensing techniques for measuring evapotranspiration have been marked by the sophisticated use of thermal infrared data and energy balance models. Thermal infrared sensors, which Holmes (2019) elaborates on, are instrumental in gauging vegetation surface temperatures to estimate rates of water transpiration and soil evaporation. Energy balance models like SEBAL and METRIC, discussed by (Allen et al., 2007) and Elhag et al. (2011), leverage these thermal data alongside meteorological and environmental factors to precisely calculate evapotranspiration rates. These models are particularly suited for large-scale applications where satellite-based remote sensing can efficiently capture vast areas, a task where UAVs often struggle due to their operational limitations. Such large-scale, accurate evapotranspiration data are crucial for managing water resources effectively, particularly in arid and semi-arid regions, where efficient water use is critical for the sustainability of agriculture and ecosystem health (Gxokwe et al., 2020; Nedd et al., 2021; Saadatseresht et al., 2015).

Furthermore, the combination of biomass estimation and evapotranspiration data with carbon and water flow measurements enriches our understanding of ecosystem dynamics. Remote sensing is pivotal in providing spatially accurate data for modelling carbon and water movements on various scales, assisting in assessing the impact of different plant types on the carbon cycle, as noted by Allen et al. (2007), Srinet et al. (2022) and Huang et al. (2024). UAVs, as in Bendig et al. (2014), suggest augmenting these capabilities with their flexible and immediate data collection, adapting them to specific research needs and schedules. These models are essential for appraising climate change effects on ecosystem services and formulating mitigation strategies. Integrating remote sensing data with terrestrial observations and other environmental variables offers researchers a deeper understanding of carbon-water cycle interactions, leading to the development of comprehensive models that enhance environmental management practices, as highlighted by Initiative (2016) and Niu et al. (2021) and Niu et al. (2021).

Materials and method

Employing Scopus and Excel for targeted literature review in vegetation mapping

Scopus is a comprehensive, multidisciplinary bibliographic database that indexes various peer-reviewed literature, including journals, conference proceedings, and patents, across diverse science, technology, medicine, social sciences, and arts and humanities fields (Burnham, 2006). Its extensive coverage and robust search capabilities make it an invaluable resource for conducting thorough literature reviews (Kadam et al., 2020). Scopus provides advanced search functionalities that allow for the precise construction of queries using logical operators and field-specific filters, which are essential for refining searches and retrieving highly relevant studies (Burnham, 2006; Kadam et al., 2020). Additionally, its analytical tools enable detailed examination of citation patterns, authorship networks, and research trends, offering insights into the impact and progression of specific fields. These features make Scopus particularly well-suited for our research on vegetation mapping through remote sensing, as it ensures access to high-quality, peer-reviewed articles and facilitates the identification of key contributions and emerging trends in the intersection of remote sensing technologies and advanced machine learning techniques (Burnham, 2006; Kadam et al., 2020; Matyukira & Mhangara, 2023a).

Leveraging the extensive coverage and advanced search capabilities of Scopus, our research on vegetation mapping through remote sensing was able to tap into a rich repository of high-quality, peer-reviewed articles. By utilising Scopus's precise query construction using logical operators and field-specific filters, we were able to define the research scope clearly and identify key terminologies as detailed in Table 1. These included terms related to both vegetation mapping and remote sensing, as well as advanced machine learning techniques such as “random forest”, “support vector machine”, “neural networks”, “deep learning”, and “XGBRFClassifier”. The additional search terms related to specific applications further honed our exploration, ensuring a targeted yet comprehensive review of the subject matter.

The construction of the Scopus query was meticulously executed, incorporating both primary and secondary keywords. Logical operators such as AND, OR, and NOT were employed to interconnect relevant concepts, as demonstrated in Table 1. This systematic strategy expedited the retrieval of studies pertinent to vegetation mapping and remote sensing. The search was further refined by focusing on specific research disciplines listed in Table 1, including earth and planetary sciences, environmental science, agricultural and biological sciences, computer science, engineering, geography, planning, and development. This refinement was instrumental in aligning the search results with the study's objectives by concentrating on the intersection of vegetation mapping, remote sensing, sophisticated computational methods, and interdisciplinary environmental applications.

To enhance the precision of our search outcomes, we strategically excluded generic or unrelated terms that could yield irrelevant or overly broad information for our inquiry. As indicated in Table 1, terms such as “antennas”, “artificial intelligence” (in a broader context), “China”, “crops”, “engines”, “forestry”, “image analysis”, “image enhancement”, “image processing”, “India”, “procedures”, “satellite data”, “soils”, and “United States” were omitted. This exclusionary tactic ensured a focused aggregation of literature pertinent to vegetation mapping via remote sensing and machine learning techniques. By judiciously selecting and excluding keywords while honing in on essential subject areas, our methodology not only streamlined the literature collection process but also guaranteed the incorporation of high-calibre research directly relevant to our study goals.

Incorporating visual tools such as Scopus's export function alongside Excel's conditional formatting and filtering features enabled us to effectively identify and eliminate duplicate document titles. After deactivating these duplicates, we harnessed Scopus's analytical tools to scrutinise the data based on various parameters like country of origin and authorship. This analysis facilitated the distillation of key findings into succinct summary tables and graphical representations, including bar charts, line charts, pie charts, and global maps. The creation of an array of tables and figures was pivotal in providing a structured synthesis of the literature review findings. Visualising the geographical distribution of research efforts highlighted the global scope of scholarly activities in this domain. Author contribution analysis was employed to pinpoint leading researchers and their collaborative networks within this specialised field. The trend analysis of publications over time underscored the growing scholarly interest in common machine-learning approaches applied to vegetation mapping through remote sensing.

Bibliometric visualisation and analysing of data in VOSviewer

VOSviewer is a powerful software tool designed for constructing and visualising bibliometric networks, offering an intuitive interface for analysing

Table 1. Scopus search engine and queries used for the scope of this study.

Search Engine	Website	Query
Scopus	scopus.com	TITLE-ABS-KEY (“vegetation mapping” AND “remote sensing” AND (“machine learning” OR “Random Forest” OR “Support Vector Machine” OR “neural networks” OR “deep learning” OR “XGBRFClassifier”) AND (“vegetation classification” OR “vegetation growth dynamics” OR “land cover change” OR “land degradation” OR “fragmentation” OR “topographic influences” OR “vegetation vigor” OR “biomass estimation” OR “evapotranspiration”)) AND (LIMIT-TO (SUBJAREA, “EART”) OR LIMIT-TO (SUBJAREA, “ENVI”) OR LIMIT-TO (SUBJAREA, “AGRI”) OR LIMIT-TO (SUBJAREA, “COMP”) OR LIMIT-TO (SUBJAREA, “ENGI”) OR LIMIT-TO (SUBJAREA, “GEOG”)) AND (EXCLUDE (DOCTYPE, “le”) OR EXCLUDE (DOCTYPE, “re”)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (EXCLUDE (EXACTKEYWORD, “China”) OR EXCLUDE (EXACTKEYWORD, “Antennas”) OR EXCLUDE (EXACTKEYWORD, “Crops”) OR EXCLUDE (EXACTKEYWORD, “Times Series”) OR EXCLUDE (EXACTKEYWORD, “Soils”) OR EXCLUDE (EXACTKEYWORD, “Time Series”) OR EXCLUDE (EXACTKEYWORD, “Article”) OR EXCLUDE (EXACTKEYWORD, “India”) OR EXCLUDE (EXACTKEYWORD, “United States”) OR EXCLUDE (EXACTKEYWORD, “Engines”) OR EXCLUDE (EXACTKEYWORD, “Image Enhancement”) OR EXCLUDE (EXACTKEYWORD, “Image Processing”) OR EXCLUDE (EXACTKEYWORD, “United Kingdom”) OR EXCLUDE (EXACTKEYWORD, “Study Areas”))

relationships within large datasets derived from academic publications (Jan van Eck & Waltman, 2023). Its primary advantages include handling extensive bibliographic data and generating detailed visual maps that illustrate complex networks of authorship, co-citation, and keyword co-occurrence (Centre for Science and Technology Centre for Science and Technology & Studies, 2023). VOSviewer supports the use of thesaurus files to manage synonyms and term variations, ensuring consistency in data analysis (Centre for Science and Technology Centre for Science and Technology & Studies, 2023). Its visualisation capabilities are particularly robust, allowing researchers to create both network and density visualisations that reveal underlying patterns and trends in the data (Jan van Eck & Waltman, 2023). These features make VOSviewer an indispensable tool for our research, as it enables the effective synthesis and interpretation of vast amounts of bibliometric data, facilitating a deeper understanding of the research landscape in vegetation mapping through remote sensing and advanced machine learning techniques (Matyukira & Mhangara, 2023a).

Building on VOSviewer's robust capabilities for constructing and visualising bibliometric networks, our research methodology involved seamless integration of this tool with our Scopus-derived bibliometric data. By importing data in CSV format, we captured essential details such as authors, titles, sources, and citation counts, which laid the foundation for our subsequent analysis. The creation of a thesaurus file was a critical step in managing synonyms and term variations, ensuring consistency across our dataset.

With VOSviewer's intuitive interface, we generated a map using these bibliographic data, applying the thesaurus file during import to standardise terms. Both computational efficiency and expert judgment guided our systematic approach to determining criteria for item inclusion. This allowed us to focus on cluster formation that was relevant to our research topic, creating a clear and informative visualisation that highlighted key patterns and relationships within the field of vegetation mapping through remote sensing and advanced machine learning techniques.

This meticulous process resulted in a network visualisation that effectively displayed nodes and edges representing elements such as authors or keywords and their connections. Transitioning to density visualisation mode enabled us to analyse item distribution and identify areas of high concentration, discern clusters, and detect trends that emphasised significant themes or authors. After conducting a systematic study, we exported our visualisations as image files for presentation purposes and optionally extracted the raw data for further detailed analysis. This methodical approach enhanced our understanding of the research landscape and provided us with valuable insights into the progression of vegetation mapping through remote sensing.

Results and analysis

Publication trends in remote sensing and vegetation mapping

The analysis of the publication trend from Scopus, as illustrated in Figure 1(a) and Table 2, highlights the dynamic growth and increasing interest in applying remote sensing for vegetation mapping, particularly with integrating advanced machine learning techniques. The number of articles published yearly has notably increased, particularly recently. For instance, starting with a modest count of 1 article per year from 2002 to 2004 and sporadic increases thereafter, the trend significantly accelerated from 2018 onwards. The number of publications rose from 6 articles in 2018 and 2019 to a remarkable 48 articles in 2023. This upward trend underscores the critical importance and necessity of continuing research in this field, reflecting the growing recognition of the value of combining remote sensing technologies with advanced analytical methods to enhance vegetation mapping efforts. The total number of articles reaching 162 by 2024 further emphasises this research area's expanding scope and relevance.

Remote sensing technologies, coupled with machine learning algorithms such as random forest, support vector machines, neural networks, and XGBRFClassifier, have significantly enhanced our ability to monitor, analyse, and understand vegetation dynamics across various spatial and temporal scales (Belgiu & Drăgu, 2016; Hansen et al., 2013; Maxwell et al., 2018; Song et al., 2016). The sharp rise in publications from 2019 to 2023 reflects the technological advancements and increased accessibility of these tools, making conducting more precise and comprehensive vegetation studies possible (Maxwell et al., 2018).

Continuing research in this area is essential for several reasons. Firstly, ongoing climate change and environmental degradation pose significant challenges to global ecosystems. Advanced remote sensing and machine learning techniques are crucial for monitoring these changes, providing timely data that can inform conservation and management strategies (Joshi et al., 2016; Pham et al., 2019; Wulder et al., 2004). Secondly, integrating these technologies facilitates the detection of subtle changes in vegetation health and distribution, which are vital for early warning systems and disaster management, such as in the case of forest fires, pest infestations, and drought conditions (Hansen et al., 2013). Lastly, continuous improvement and adaptation of these methods will drive innovation in environmental research, allowing

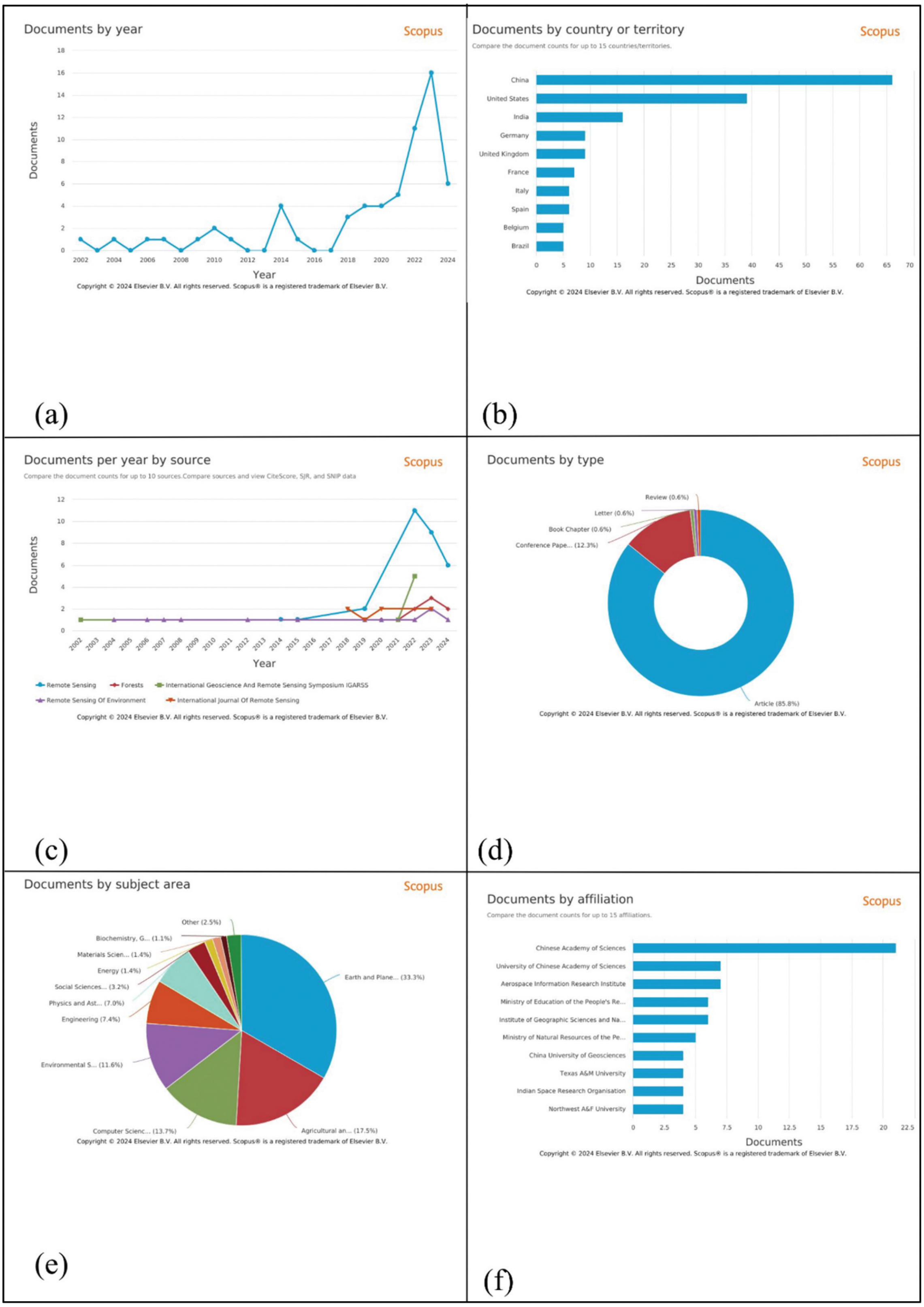

Figure 1. Examination of research publications in remote sensing and vegetation mapping.

Table 2. Worldwide articles per year from the Scopus database from 2000 to 2024.

Year	2002	2004	2006	2007	2008	2009	2010	2011	2012	2013	2014
No. Articles	1	1	1	3	1	1	3	2	2	1	4
Year	2015	2016	2018	2019	2020	2021	2022	2023	2024	Total	
No. Articles	2	2	6	6	6	11	35	48	26	162	

for more accurate predictions and effective interventions. As global environmental challenges become more complex, the need for advanced tools to monitor and mitigate their impacts becomes increasingly urgent, making sustained research in remote sensing and vegetation mapping not just necessary but imperative for future sustainability (Bhandari et al., 2012; Jiang et al., 2007).

Geographical breakdown of research on remote sensing and vegetation mapping

China has the highest number of research publications as shown in Figure 1(b), in the field of remote sensing and vegetation mapping, indicating its leadership in this area. The United States closely follows China, also making significant contributions and showing leadership in this research field. India's ranking as the third-largest contributor underscores its increasing emphasis on using remote sensing technology for the purpose of environmental monitoring and vegetation analysis. Germany, the United Kingdom, France, Italy, Spain, Belgium, and Brazil, among other European nations, demonstrate significant contributions, indicating a broad international interest in this topic. Many geographical locations emphasise the worldwide significance and cooperative character of research in remote sensing and vegetation mapping.

The reason for China's significant role in remote sensing research is its huge investment in satellite technology and environmental monitoring programs. The United States' robust position results from its enduring leadership in technology innovation and environmental research. Both nations have developed comprehensive remote-sensing infrastructure and research institutes, which have facilitated progress in this domain (Chen & Chen, 2018; Wulder et al., 2018). India's rising production is probably fueled by its focus on sustainable agriculture and forest management, bolstered by national efforts such as the Indian Space Research Organisation's remote-sensing projects (Roy et al., 2015). The European nations have made noteworthy advances in comprehending and tackling environmental difficulties by using improved remote sensing methods, as shown by the studies conducted by Anjos et al. (2015), Dalouman et al. (2023), and de Souza Soler & Verburg (2010). The worldwide dissemination of research emphasises the significance of international cooperation and information sharing in promoting remote sensing for vegetation mapping and environmental sustainability.

Distribution of publications in remote sensing and vegetation mapping by source

The analysis of remote sensing and vegetation mapping research conducted between 2002 and 2024 reveals a substantial rise in publications, particularly from 2018 onwards, as depicted in Figure 1(c) and Table 3, reaching a prominent peak in 2023. The journal "Remote Sensing" has the largest number of articles, especially from 2019 onwards, highlighting its significant role in sharing research on this subject. This increase in publications may be credited to the rapid progress in remote sensing technology and the expanding use of machine learning methods in vegetation research. Publications such as "Remote Sensing of Environment" and "International Journal of Remote Sensing", as well as conferences like the "International Geoscience and Remote Sensing Symposium (IGARSS)", also make significant contributions to the field of remote sensing in environmental monitoring and management. The journal "Remote Sensing" showed a notable increase in articles, especially from 2019 onwards, with 11 articles in 2021 and 9 in 2022, Table 3. Similarly, "Remote Sensing of Environment" maintained a consistent presence, contributing significantly to the field. The "International Journal of Remote Sensing" and "IGARSS" conferences also played pivotal roles, with a notable increase in their contributions in the latter years of the study period sources reflect the diverse interests and wide range of applications of remote sensing (Hansen et al., 2013; Maxwell et al., 2018).

The significant rise in publications in the journal "Remote Sensing" corresponds to the wider pattern of incorporating sophisticated analytical techniques, such as deep learning and neural networks, in

Table 3. Top 5 articles per journal from the Scopus database from 2000 to 2024.

Year	2002	2004	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Remote Sensing											1	1
Remote Sensing of Environment		1	1	1	1				1			1
Forests												
International Geoscience and Remote Sensing Symposium IGARSS	1											
International Journal of Remote Sensing												

Year	2016	2018	2019	2020	2021	2022	2023	2024
Remote Sensing			2			11	9	6
Remote Sensing of Environment			1	1		1	2	1
Forests				1	1	2	3	2
International Geoscience and Remote Sensing Symposium IGARSS					1	5		
International Journal of Remote Sensing		2		1		2	2	

vegetation mapping research. This tendency emphasises the crucial significance of the journal in advancing groundbreaking approaches and applications in the discipline. The ongoing contributions from "Remote Sensing of Environment" and the "International Journal of Remote Sensing" underscore the well-established venues these publications provide for impactful research (Belgiu & Drăgu, 2016; Wulder et al., 2018). Moreover, the inclusion of IGARSS in the publishing landscape indicates the significance of conference proceedings in spreading advanced research and promoting cooperation among scientists and practitioners. The increase in publications from these sources highlights the growing research community and the urgent need for more investigation and advancement in remote sensing technologies to tackle intricate environmental issues (Joshi et al., 2016; Matyukira & Mhangara, 2023a; Pham et al., 2019; Roy et al., 2015).

Types of documents in remote sensing and vegetation mapping research

The distribution of various remote sensing and vegetation mapping publications, Figure 1(d), demonstrates that a substantial majority, 85.8%, of the papers are research articles, highlighting a strong emphasis on original research and experimental discoveries in this discipline. Conference papers account for 12.3% of the publications, underscoring the significance of academic conferences in sharing recent progress and promoting dialogue among scholars. The other categories, such as book chapters, letters, and reviews, account for just 0.6% of the total publications. This indicates that these publication platforms are less often used in this field of study.

The prevalence of research publications highlights the field's dependence on comprehensive experimental investigations and empirical data to progress knowledge and innovate new technologies. Research publications include in-depth analysis of methodology, findings, and debates, which are crucial for the scientific community to expand on previous research and foster innovation (Hansen et al., 2013; Maxwell et al., 2018). The significant percentage of conference papers demonstrates the ever-changing nature of this field of research, where quick technological progress and the implementation of novel methods require frequent sharing of knowledge and collaboration, which is facilitated by conferences like the International Geoscience and Remote Sensing Symposium (IGARSS) (Joshi et al., 2016; Roy et al., 2015). The limited number of reviews and book chapters suggests that although these formats are useful for consolidating existing knowledge and offering a broader perspective, they are not the main means of presenting innovative research findings in remote sensing and vegetation mapping (Pham et al., 2019).

Subject Area Distribution of Research in Remote Sensing and Vegetation Mapping

The extensive array of fields involved in remote sensing and vegetation mapping indicates that the majority of papers, Figure 1(e), namely 33.3%, pertain to Earth and Planetary Sciences, highlighting the essential relevance of geospatial science in this particular study domain. The prevalence of this dominance underscores the need to comprehend the Earth's surface and atmosphere since they are pivotal for precise vegetation mapping and environmental monitoring (Chen & Chen, 2018; Wulder et al., 2018). Agricultural and Biological Sciences represent 17.5% of the published works, emphasising the practical use of remote sensing in agriculture. This includes activities such as monitoring crops, estimating yields, and implementing sustainable land management practices (Roy et al., 2015; Shoko et al., 2015, 2016; Wulder et al., 2018). The substantial contributions from Environmental Science (11.6%) and Computer Science (13.7%) emphasise the multidisciplinary character of this subject, combining environmental monitoring with sophisticated computational tools and data analysis methodologies (Maxwell et al., 2018, 2021; Pham et al., 2019).

The inclusion of other disciplines, Figure 1(e), such as Engineering (7.4%), Physics and Astronomy (7.0%), and Social Sciences (3.2%), underscores the diverse range of applications and research interests in remote sensing. Engineering plays a crucial role in advancing the development of novel remote sensing devices and platforms, including unmanned aerial vehicles (UAVs) and satellites. These technologies are vital for collecting data (Hansen et al., 2013; Matyukira & Mhangara, 2023a). Physics and Astronomy are essential in remote sensing technologies since they include physical concepts to comprehend how the electromagnetic spectrum interacts with plants. Incorporating Social Sciences indicates a desire to explore the social consequences and policy dimensions of environmental monitoring and land use management. The wide range of subject areas covered in remote sensing and vegetation mapping research demonstrates this field's extensive practicality and interdisciplinary character. This emphasises the importance of ongoing collaboration among different scientific disciplines to tackle complex environmental issues effectively (Dalouman et al., 2023; Joshi et al., 2016; Roy et al., 2015; Chen & Chen, 2018).

Analysis of research affiliations in remote sensing and vegetation mapping

According to the prominent research institutes in remote sensing and vegetation mapping, the Chinese Academy of Sciences (CAS) stands out as the institution with the most publications, Figure 1(f), surpassing other affiliations by a substantial margin. China's dominant position in scientific research and environmental monitoring may be linked to its significant investment and strategic focus on remote sensing technology (Chen & Chen, 2018). Chinese universities, such as the University of Chinese Academy of Sciences and the Aerospace Information Research Institute, part of the CAS network, play a significant role in promoting remote sensing research. These institutions are well known for their thorough research programs and large cooperation networks, which enable them to produce influential research results (Liu & Zhang, 2024; Rakhmankulova et al., 2024; Xu & Bai, 2024).

Additional significant associations include the Ministry of Education and the Institute of Geographic Sciences and Natural Resources Research, both of the People's Republic of China and the Ministry of Natural Resources. These organisations represent the Chinese government's comprehensive scientific research strategy to enhance environmental management and policy development (Wulder et al., 2018). Notable international collaborators include Texas A&M University and the Indian Space Research Organisation (ISRO). Texas A&M University is renowned for its strong research programs in geospatial science and engineering, while ISRO's proficiency in satellite technology and remote sensing applications showcases India's increasing focus on sustainable agriculture and natural resource management (Roy et al., 2015). The wide range of these associations demonstrates the worldwide cooperation and multidisciplinary character of remote sensing and vegetation mapping research, highlighting the significance of multinational alliances in tackling intricate environmental issues (Anjos et al., 2015; Bhandari et al., 2012; Chen & Chen, 2018; Dalouman et al., 2023; Jiang et al., 2007; Roy et al., 2015; Wulder et al., 2018).

Summary of the significance and need of remote sensing and vegetation mapping research using the Scopus database

The analysis of the Scopus database reveals a substantial increase in publications related to remote sensing and vegetation mapping. This development may be attributed to technological improvements and machine learning methods like Random Forest and neural networks. The data shows a steady increase in the number of articles from 2002 to 2016, foll owed by a significant surge from 2018 to 2023, with the number of articles peaking at 48 in 2023. This substantial growth highlights the urgent need for continuous research to tackle climate change and environmental difficulties.

China and the United States are at the forefront regarding publication volume, indicating significant expenditures in satellite technology and environmental monitoring. Well-known publications such as "Remote Sensing" and "Remote Sensing of Environment" are crucial in spreading new approaches, as evidenced by their consistent and increasing contributions to the field. For instance, "Remote Sensing" saw a notable rise in articles, particularly from 2019 onwards, while "Remote Sensing of Environment" has maintained a consistent presence. The significant increase in publications, particularly between 2019 and 2023, underscores the field's dependence on factual information and cooperation across many disciplines to enhance understanding and encourage creativity. This trend underscores the critical importance of continuing research and innovation in remote sensing and vegetation mapping to address pressing environmental challenges.

Interconnected themes in remote sensing and vegetation mapping research

Examination of VOSviewer network visualization

The VOSviewer network visualisation Figure 2(a) and Table 4 showcase the interconnections between important issues in vegetation mapping research using remote sensing. The primary focal points consist of "vegetation mapping", "remote sensing", and "machine learning", signifying their pivotal positions within this domain, as indicated by their high total link strengths and occurrences. Specifically, "vegetation mapping" has a total link strength of 159 and 59 occurrences, "remote sensing" has a total link strength of 157 and 58 occurrences, and "machine learning" has a total link strength of 141 and 50 occurrences.

The links between these nodes and other terms like "land use", "land cover", "climate change", "evapotranspiration", "aboveground biomass", and "accuracy assessment" suggest that researchers often investigate these subjects together. For instance, "land use" and "land cover" both have a total link strength of 38 and 10 occurrences each, highlighting their connection to the primary focal points. The term "accuracy assessment" is also prominent, with a total link strength of 49 and 14 occurrences, reflecting its importance in validating the research methods used. The interlinking of several disciplines highlights the diverse character of the study, as it combines sophisticated machine-learning methods to tackle different areas of environmental monitoring and vegetation analysis. The significant correlations among these topics indicate a resilient and expanding collection of research that

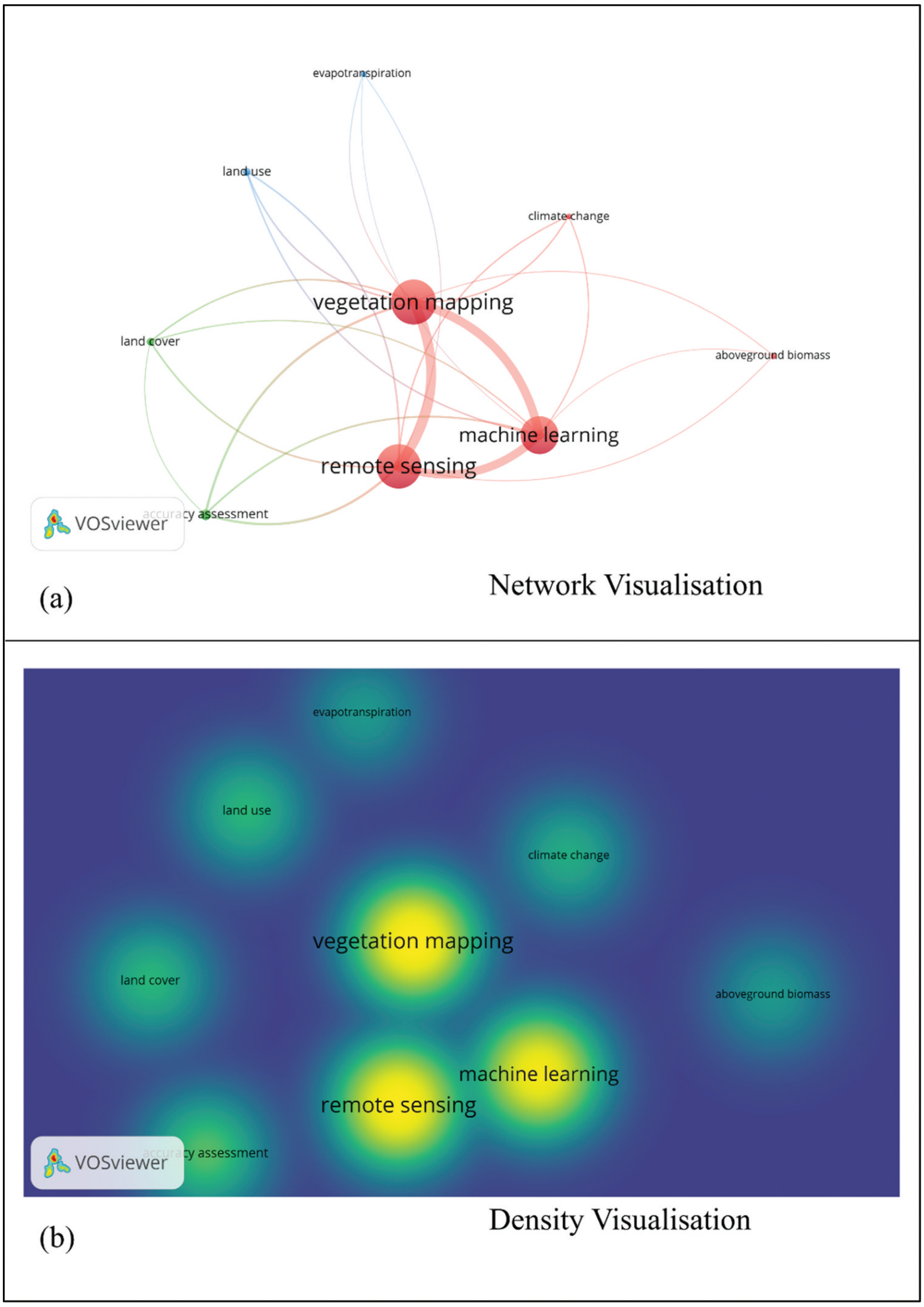

Figure 2. Visualisation of key research themes in vegetation mapping using remote sensing, (a) network visualisation, (b) density visualisation.

Table 4. Network visualisation map structural information.

Label	cluster	weight <Links>	Weight <Total link strength>	Weight <Occurrences>	score <Avg. citations>
Vegetation mapping	1	8	159	59	22
Remote sensing	1	8	157	58	22
Machine learning	1	8	141	50	23
Land use	3	7	38	10	16
Land cover	2	7	38	10	18
Evapotranspiration	3	7	19	5	3
climate change	1	8	33	8	11
Accuracy assessment	2	7	49	14	26
Aboveground biomass	1	4	16	5	4

uses remote sensing and machine learning to enhance our understanding of vegetation dynamics and associated environmental processes.

Examination of VOSviewer density visualisation

The VOSviewer density visualisation Figure 2(b) showcases the significance and dominance of major research topics in vegetation mapping via remote sensing. The nodes that stand out the most are "vegetation mapping", "remote sensing", and "machine learning", indicating their significant contributions to the literature. The research area encompasses several interconnected subjects such as "land use", "land cover", "climate change", "evapotranspiration", "aboveground biomass", and "accuracy assessment", highlighting the complex nature of this field of study. The high density at these nodes indicates significant research activity and strong linkages, highlighting the need to use advanced machine learning algorithms to improve the precision and effectiveness of remote sensing methods for vegetation monitoring. Research topics such as vegetation mapping, remote sensing, and machine learning are fundamental while studying land use and land cover change is crucial for comprehending environmental effects. It is important to consider climate change when researching how vegetation changes over time. We use metrics like evapotranspiration, which is the combined process of water evaporation from the land and plant transpiration, and aboveground biomass, which is the total weight of plant material above the ground, as important indicators of the overall health of vegetation. The validation of remote sensing data remains dependent on the accuracy evaluation. The Cradle Nature Reserve in the COHWHS offers a varied karst topography that is ideal for sophisticated approaches to monitoring and assessing vegetation efficiently. This setting emphasises the potential for effective study in vegetation dynamics and environmental monitoring by utilising the interrelated themes found in the visualisation processes.

Findings from the scientometric review

(1) The analysis highlights a substantial increase in publications related to remote sensing and vegetation mapping from 2002 to 2024, with a marked acceleration from 2018 onwards. The number of articles rose significantly from 6 in 2018 and 2019 to 48 in 2023, reaching a total of 162 articles by 2024. This upward trend underscores the growing recognition of the importance of combining remote sensing technologies with advanced analytical methods for vegetation mapping.

(2) There has been a significant rise in publications reflecting advancements in remote sensing technology and the expanding use of machine learning algorithms such as random forests, support vector machines, neural networks, and XGBRFClassifier. These technologies have enhanced the ability to monitor, analyse, and understand vegetation dynamics across various spatial and temporal scales.

(3) The study reveals that China leads in the number of research publications, followed closely by the United States. India ranks as the third-largest contributor, highlighting its increasing emphasis on remote sensing technology for environmental monitoring and vegetation analysis. Significant contributions also come from European nations, emphasising the global and cooperative nature of research in this field.

(4) Journals like "Remote Sensing", "Remote Sensing of Environment", and the "International Journal of Remote Sensing", along with conferences such as the "International Geoscience and Remote Sensing Symposium (IGARSS)", play crucial roles in disseminating research. "Remote Sensing" showed a notable increase in articles, particularly from 2019 onwards, reflecting its significant role in advancing the field.

(5) The VOSviewer network visualisation and Table 4 identify "vegetation mapping", "remote sensing", and "machine learning" as the primary focal points, with high total link strengths and occurrences. "Vegetation mapping" has a total link strength of 159 with 59 occurrences, "remote sensing" has 157 with 58 occurrences, and "machine learning" has 141 with 50 occurrences.

(6) The analysis reveals significant interconnections between primary themes and other important topics such as "land use", "land cover", "climate change", "evapotranspiration", "aboveground biomass", and "accuracy assessment". For instance, "land use" and "land cover" both have a total link strength of 38 and 10 occurrences each, highlighting their relevance in vegetation mapping research.

(7) Research Gaps and Emerging Areas:
- Despite its importance, "evapotranspiration" has a relatively low occurrence (5) and total link strength (19), as shown in Table 4, indicating a gap in comprehensive studies.
- Aboveground Biomass estimation also has low occurrences (5) and total link strength (16), suggesting the need for more research in biomass estimation using remote sensing technologies.

- As shown in Table 4, climate change is identified as a crucial but less integrated area, presenting opportunities for further investigation. Climate Change has (8) occurrences and a total link strength of 33.

(8) Most publications (85.8%) are research articles emphasising original research and experimental discoveries. Conference papers account for 12.3%, highlighting the importance of academic conferences in sharing recent progress. Other categories, such as book chapters, letters, and reviews, account for just 0.6%, indicating that these formats are less commonly used in this field.

(9) The subject area distribution reveals an extensive range of fields involved, including Earth and Planetary Sciences (33.3%), Agricultural and Biological Sciences (17.5%), Environmental Science (11.6%), and Computer Science (13.7%). Other fields such as Engineering, Physics and Astronomy, and Social Sciences also contribute, underscoring the multidisciplinary nature of remote sensing and vegetation mapping research.

(10) The Chinese Academy of Sciences (CAS) is the leading institution in terms of publications, supported by significant national investments in remote sensing technology. Notable international collaborators include Texas A&M University and the Indian Space Research Organisation (ISRO), demonstrating the global and collaborative nature of the research.

These findings highlight the evolving landscape of remote sensing and vegetation mapping research, emphasising both established areas and potential gaps for future investigation.

Future research directions, emerging technologies, and potential challenges

The future of remote sensing and vegetation mapping research depends on the integration of rising technology and the resolution of existing issues. There is a distinct necessity to enhance research in domains such as evapotranspiration and aboveground biomass estimation, where substantial gaps persist. Future studies should focus on leveraging multi-source data fusion, combining optical, radar, and LiDAR data to enhance accuracy. Additionally, climate change remains underexplored in this context, and future research should aim to better understand its impact on vegetation dynamics by utilizing long-term satellite data and machine learning models for predictive analysis (Balestra et al., 2024; Jin & Mountrakis, 2022; Li et al., 2024a; Zhang, 2010). Deep learning techniques, including convolutional neural networks (CNNs), provide a means to augment the extraction of vegetative characteristics and refine temporal analysis. Integrating UAVs with satellite data to extend their application beyond small-scale investigations could address existing limits concerning flight range and regulatory restrictions (Nex & Remondino, 2014).

Emerging technologies such as hyperspectral imaging, advanced LiDAR, and synthetic aperture radar (SAR) hold great promise for enhancing the accuracy of vegetation mapping. These technologies, in conjunction with edge computing and AI, can enable real-time monitoring and analysis; nevertheless, their integration necessitates addressing data processing and storage difficulties (Khonina et al., 2024; Kuras et al., 2021; Li et al., 2024b). Furthermore, the advancement of quantum computing may provide a remedy for managing extensive datasets, facilitating swifter and more efficient analysis. Ensuring global access to these technologies is essential for equitable advancement, as numerous locations, especially in poor nations, lack the resources for efficient implementation of these innovations (Khonina et al., 2024; McKinsey & Company, 2024; World Economic Forum, 2022). Fostering international collaborations will be key to addressing global environmental challenges, ensuring that research benefits both local ecosystems and the global scientific community (Avilés Irahola et al., 2022; Mariani et al., 2022).

Conclusion

This study highlights significant advancements in combining remote sensing technologies with machine learning algorithms for vegetation mapping. A comprehensive literature review using the Scopus database provided an in-depth understanding of the current research landscape. Employing a systematic search strategy focused on key terminologies related to vegetation mapping and advanced machine learning techniques, we gathered and analysed high-quality studies, ensuring a thorough exploration of the field. Integrating VOSviewer into our methodology enabled effective visualisation and analysis of bibliometric data, revealing key patterns and relationships within the research field. Network and density visualisations highlighted significant clusters and trends, enhancing our understanding of the research progression and focus areas on vegetation mapping through remote sensing.

The systematic review via Scopus revealed a robust and growing body of research emphasising the effectiveness of remote sensing technologies combined with machine learning algorithms. Techniques such as random forest, support vector machines, and neural networks have significantly enhanced remote sensing data analysis. VOSviewer proved valuable in visualising complex relationships and trends and identifying influential research areas, key authors, and collaborative networks. Our research underscores the critical importance of advanced remote sensing and machine learning techniques in addressing global environmental challenges. These technologies show significant potential in tackling issues like land cover change, vegetation health assessment, and biomass estimation. However, several research gaps remain. There is a need for more comprehensive studies on evapotranspiration and aboveground biomass, which have relatively low occurrences and link strengths. Additionally, integrating climate change data with remote sensing technologies is underexplored, presenting opportunities for further investigation.

Advances in satellite and UAV technologies, combined with sophisticated data processing algorithms, enable detailed and large-scale environmental monitoring, supporting more accurate and timely decision-making in environmental management. Continuous research and innovation are essential for developing effective strategies for environmental management, conservation, and sustainable development.

Highlights

- Remote sensing and vegetation mapping research has grown, notably using random forest, support vector machines, neural networks, and XGBRFClassifier.
- Chinese researchers publish the most, followed by the USA and India, suggesting worldwide interest and investment in remote sensing and vegetation mapping.
- More research papers are published in key journals like "Remote Sensing" and "Remote Sensing of Environment" and at significant conferences like IGARSS.
- Vegetation mapping, remote sensing, and machine learning are strongly linked in the VOSviewer network and density visualisations

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Author contributions

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Data availability statement

The corresponding author can provide the datasets used in the current study upon reasonable request.

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