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Vegetation Indices for Multidomain Prediction via Deep Learning: A Scientometric Analysis

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Deep learning has considerably enhanced vegetation index prediction accuracy and efficiency, leading to a significant increase in academic publications across multiple domains. However, most existing studies concentrate on specific applications, lacking systematic reviews that explore its interdisciplinary knowledge structure and broader multidomain potential. Therefore, in this study, we investigated vegetation indices and deep learning advancements from both technical and scientometric perspectives. We begin by reviewing the application of deep learning in vegetation index prediction, emphasizing the structural features of several mainstream models and their practical performance within integrated frameworks. Then, on the basis of 173 relevant articles collected from the Web of Science database from 2015 to 2025, we employed CiteSpace to construct detailed networks of author co-citations, journal co-citations, keyword co-occurrences, and international collaboration. Through citation burst detection and betweenness centrality analyses, we uncover evolving research trends, key hotspots, and global cooperation patterns in this dynamic interdisciplinary field. The findings highlight growing research interest, with central themes focusing on method optimization, cross-domain application expansion, and strengthened international collaboration. In this study, we provide a new theoretical perspective for the application of deep learning in vegetation index prediction across multiple domains, while also offering fresh insights for future interdisciplinary collaboration and technological innovation directions.

1. Introduction

Vegetation is a core component of terrestrial ecosystems, and its health and dynamics are crucial for the carbon cycle, water resource management, and ecological conservation.[1] To quantify vegetation growth status, biomass, and chlorophyll content, researchers have developed various vegetation indices, such as the normalized difference vegetation index (*NDVI*) and enhanced vegetation index (*EVI*). By integrating reflectance from different spectral bands, these indices have become key tools for assessing vegetation health.[2,3] Multisource remote sensing

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data, represented by Moderate Resolution Imaging Spectroradiometer (MODIS), the Landsat series, and Sentinel-2, provide efficient and multiscale methods for deriving vegetation indices, enabling dynamic vegetation monitoring at regional and even global scales. However, traditional vegetation index prediction methods face significant limitations as empirical regression models exhibit poor generalization ability across different surface landscapes, while physics-based radiative transfer models require extensive parameterization and incur high computational cost.(4) These bottlenecks are particularly pronounced when addressing complex surface conditions and nonlinear spatiotemporal relationships. With advancements in deep learning technology, its capabilities for hierarchical feature extraction and complex pattern mining offer a new paradigm for remote sensing data analysis.(5)

In the domain of vegetation index dynamic modeling, deep learning methods have undergone a technological evolution: from the basic feature representation of multilayer perceptrons (MLPs),(6) to the spatial pattern interpretation by convolutional neural networks (CNNs),(7) and then to the modeling of temporal dependencies using recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM).(8) In recent years, the Transformer architecture, leveraging self-attention mechanisms, has further overcome the bottleneck in modeling long-range spatiotemporal dependencies, providing more efficient solutions for complex tasks such as vegetation phenology prediction. Concurrently, by constructing cascaded hybrid models (e.g., CNN-LSTM architectures)(9,10) and employing feature coupling strategies, such as convolutional long short-term memory (ConvLSTM) fusion architectures,(11) researchers have achieved the synergistic optimization of spatiotemporal features and multimodal information fusion. These advancements have demonstrated broader technological adaptability in cross-domain applications such as crop yield prediction and ecosystem carbon sink assessment.

Focusing on the multidimensional applications at the intersection of vegetation indices and deep learning, existing technical reviews primarily discuss methodological innovations and validation in specific contexts. However, review papers that systematically reveal the interdisciplinary development trajectory and multidomain prediction potential from scientometric perspectives, such as author relationships and co-citation analysis, are relatively scarce. In recent years, as research combining vegetation indices and deep learning has advanced, several review papers have summarized this field from various perspectives.(12–20) These studies are primarily focused on two dimensions: the evolution of technical methods and validation in specific application scenarios. At the technical method level, Saki *et al.*(16) provided an in-depth analysis of the evolution from foundational models to Transformer architectures in precision agriculture data fusion, while Shang *et al.*(17) systematically outlined the overall progress and challenges of AI in remote sensing; however, both studies remain heavily focused on algorithmic architecture iteration and technical bottleneck analysis. At the application scenario level, Mahmoud and Mohammed(18) investigated innovations in deep learning for time-series forecasting but did not sufficiently explore the cross-domain application value from the perspective of vegetation indices; Van Klompenburg *et al.*(19) evaluated the performance of deep learning in crop yield prediction, emphasizing the importance of vegetation indices in the agricultural domain, but did not extend this analysis to other key areas such as ecological conservation and water resource management. Furthermore, Stepchenko *et al.*,[20] by comparing various time-series forecasting methods [e.g., regression analysis, Markov chains, and artificial neural networks (ANNs)], explored the application of *NDVI* in short-term vegetation prediction, but did not provide a comprehensive summary of the diversity and applicability of vegetation indices in broader contexts. These limitations prevent existing reviews from comprehensively reflecting the overall characteristics of the field intersecting vegetation indices and deep learning, as well as its integrated application potential in multidomain prediction.

Scientometrics is one approach to the quantitative study of academic literature and science policy, aiming to reveal patterns and trends in scientific research through statistical and data mining techniques.[21] Fortunato *et al.*[22] defined it as the study based on large-scale scientific data that explores universal patterns and domain-specific characteristics (such as evolutionary patterns, system structures, and working mechanisms). Therefore, in the exploration of research directions and literature analysis, employing scientometric methods can facilitate a better understanding of research themes, trends, and knowledge structures.

To address the current research gap, in this study, we focus on both the application of deep learning for vegetation index prediction across multiple domains and a scientometric evaluation. We collected relevant literature from the Web of Science database and utilized the CiteSpace software (version 6.4.R1) to conduct the scientometric analysis. By constructing author co-citation networks, journal co-citation networks, keyword co-occurrence networks, and country collaboration networks, we systematically reveal the research history, development trajectory, and future trends of this field. The results of this analysis not only identify the core research themes at the intersection of vegetation indices and deep learning but also offer valuable guidance for researchers seeking a comprehensive understanding of the field's knowledge structure and development directions.

The remainder of this paper is structured as follows. In Sect. 2, we introduce the background information related to the application of deep learning for vegetation index prediction across multiple domains. In Sect. 3, we briefly describe the scientometric analysis methods adopted in this study. The scientometric results are analyzed and discussed in Sect. 4. In Sect. 5, we conclude the paper.

2. Background Knowledge

In this section, we systematically review the characteristics of deep learning in vegetation index prediction from a background knowledge perspective. This section is organized into four subsections for discussion. In Sect. 2.1, we introduce data acquisition methods; in Sect. 2.2, we review fundamental deep learning models; in Sect. 2.3, we explore the form of integrated models; and in Sect. 2.4, we analyze their practical applications across multiple domains. This structural arrangement is aimed at sequentially presenting the technical background and interdisciplinary potential of deep learning in vegetation index prediction, from data preparation to model characteristics, architectural forms, and practical applications.

2.1 Data acquisition

A vegetation index is a broad term referring to metrics derived from combinations of remote sensing spectral bands to quantify vegetation characteristics. One of the earliest vegetation indices is the ratio vegetation index (*RVI*), proposed by Jordan.[23] The difference vegetation index (*DVI*) was subsequently proposed by Richardson and Wiegand.[24] While these indices are highly sensitive to vegetation cover in areas with dense green vegetation, they are also susceptible to atmospheric conditions, requiring atmospheric correction to obtain accurate results.

The *NDVI* was proposed by Rouse *et al.*[2] and its calculation formula is

$$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}. \tag{1}$$

NDVI is widely used owing to its ability to normalize the effects of lighting and atmospheric conditions, providing a more stable measure of vegetation cover. Its value ranges from −1 to 1, with higher values indicating denser and healthier vegetation. Compared with *RVI* and *DVI*, *NDVI* is less sensitive to background interference. In addition, there are other vegetation indices, such as the *EVI*,[3] which is also commonly used to quantify vegetation characteristics. Its calculation formula is

$$EVI = 2.5 \times \frac{R_{NIR} - R_{Red}}{R_{NIR} + 6 \times R_{Red} - 7.5 \times R_{Blue} + 1}. \tag{2}$$

NDVI is typically obtained from the visible and near-infrared bands of remote sensing imagery. Table 1 lists some data sources that can be used to calculate *NDVI*, including satellite and sensor types, resolution, band information, and data acquisition platforms.

In addition to calculating *NDVI* using the aforementioned data, most *NDVI* predictions directly utilize *NDVI* products. Table 2 shows several commonly used *NDVI* data sources that can be directly accessed, including their temporal coverage, spatial resolution, and data acquisition platforms.

Table 1
Overview of remote sensing data sources for *NDVI* calculation.

Satellite/Sensor	Resolution	Band information	Data platform
Landsat series	30 m (Multispectral)	Red: Band 4; NIR: Band 5	USGS EarthExplorer
MODIS	250 m–1 km	Red: Band 1; NIR: Band 2	NASA Earthdata Search
Sentinel-2	10 m (Multispectral)	Red: Band 4; NIR: Band 8	Copernicus Open Access Hub
NOAA AVHRR	1.1 km	Red: Band 1; NIR: Band 2	NOAA CLASS
VIIRS	375–750 m	Red: I1; NIR: I2	NASA Earthdata

Table 2
Several directly accessible *NDVI* data sources.

Data source	Coverage time	Spatial resolution	Data platform
Landsat *NDVI*	1984–2024	30 m	USGS EarthExplorer
MODIS *NDVI*	2000–present	250 m–1 km	NASA Earthdata Search
NOAA CDR *NDVI*	1981–present	0.05°	NOAA CLASS
PKU GIMMS *NDVI*	1982–2022	1/12°	Google Earth Engine

2.2 Fundamental deep learning models

2.2.1 MLPs

MLPs are a fundamental class of deep learning models composed of an input layer, one or more hidden layers, and an output layer, with fully connected neurons facilitating information transmission between layers. Owing to their simple architecture and strong nonlinear mapping capability, MLPs are widely used in vegetation-index-based prediction tasks. In existing studies, various fully connected network variants have been referred to by different terminologies, including backpropagation neural network and deep neural network. Additionally, some models are labeled as ANNs but, in practice, consist solely of fully connected structures, making them inherently part of the MLP framework. Therefore, in this review, we collectively categorize these fully connected models as MLPs to facilitate a more systematic discussion of their applications in vegetation-index-based predictions.

MLPs and their variants are primarily applied in agriculture for vegetation-index-based prediction methods. Researchers have utilized these models in combination with vegetation indices derived from satellite remote sensing data to predict cotton lint yield,(25) estimate maize biomass,(26) and integrate multimodal unmanned aerial vehicle (UAV) data for soybean yield prediction.(27) Beyond agricultural applications, MLPs have also been employed for broader vegetation index prediction tasks, particularly forecasting *NDVI* itself. Some studies have used ANNs to predict *NDVI* by incorporating environmental factors such as temperature, precipitation, and soil moisture.(28) Others have leveraged precipitation data and combined ANNs with nonlinear autoregressive networks with exogenous inputs to model the spatiotemporal dynamics of *NDVI*.(29) Additionally, MLPs have been applied to predict interannual variations in agricultural productivity, demonstrating their potential in vegetation index modeling.(14) These studies highlight that, across various application scenarios, MLPs can effectively capture the dynamic characteristics of vegetation indices compared with traditional machine learning methods, providing a reliable baseline for prediction tasks.

However, despite the success of MLPs in vegetation index prediction, their inherent structural limitations constrain further optimization and broader applicability. Owing to their fully connected architecture, MLPs lack structural constraints, making it difficult to effectively capture the spatial relationships within vegetation index data. In vegetation-index-based prediction tasks, the ability to account for spatial information is a key factor affecting model performance. Unlike CNNs, which can leverage the geographic dependencies of spatial neighborhood information, MLPs struggle to process data with strong spatial attributes, limiting their effectiveness in such scenarios. At the same time, MLPs exhibit shortcomings in time series modeling. While existing approaches perform short-term forecasting by providing multiple time steps as parallel inputs, MLPs treat each time step as an independent feature and lack the ability to model long-term dependencies. This makes them ineffective at capturing dynamic temporal changes in vegetation index data. Vegetation index variations are often affected by long-term factors such as seasonality, climate trends, and land use changes, which require historical dependencies to be accurately modeled. Unlike RNNs or Transformers, MLPs are unable to establish effective historical dependencies, potentially reducing prediction accuracy. Furthermore, MLPs employ a fixed number of neurons and layers in fully connected computations, leading to a large number of model parameters. This increases the risk of overfitting, particularly when dealing with limited or noisy data. Compared with other deep learning architectures specifically designed to directly model spatial or temporal dependencies, MLPs require additional feature engineering to compensate for their deficiencies in handling spatial and temporal information. Therefore, while MLPs remain applicable and have been widely used in vegetation index prediction, their limitations in complex spatiotemporal modeling often necessitate integration with other models to enhance predictive performance.

2.2.2 CNNs

CNNs are deep learning models specifically designed to process data with an explicit Euclidean structure. Their core mechanism lies in convolution operations, where kernels slide over input data (such as sequences, images, or volumetric data) to extract spatial features through local receptive fields. This approach reduces the number of model parameters and improves computational efficiency. However, traditional CNNs face challenges as network depth increases, including gradient-related issues and fixed receptive fields that limit the extraction of long-range dependencies. In vegetation-index-based prediction tasks, conventional CNNs are typically designed for relatively simple classification and regression problems. For instance, Yang *et al.*[30] developed a CNN model based on UAV imagery to extract key features of rice growth for phenological classification, supporting precision agriculture. Recently, Li[31] proposed a novel deep convolutional classifier specifically for *NDVI* image recognition, further demonstrating the enduring effectiveness of optimized CNN architectures in vegetation feature extraction and classification tasks. Similarly, Khaki *et al.*[32] introduced YieldNet for simultaneous maize and soybean yield prediction, demonstrating that integrating remote sensing data with deep learning models significantly improves yield prediction accuracy. Additionally, Nomura and Oki[33] applied CNNs to downscale MODIS *NDVI* by incorporating high-resolution synthetic aperture radar (SAR) data, enhancing *NDVI*'s spatial resolution. These results demonstrate the advantages of CNNs in processing spatial features from multisource remote sensing data.

To address the limitations of traditional CNNs in capturing multiscale features and preventing information loss in deep networks, researchers have introduced architectural enhancements to build deeper and more robust CNNs, such as ResNet[34] and DenseNet.[35]

These improvements mitigate gradient vanishing issues in deep CNNs while enhancing feature reuse, thereby improving training stability and enabling better extraction of complex high-dimensional spatial features. As a result, these advanced CNN architectures have been widely applied in vegetation-index-based remote sensing prediction tasks. For instance, Diykh *et al.*(36) proposed a deep DenseNet model based on empirical curve transformation to achieve high-accuracy *NDVI* estimation using only RGB bands, even in the absence of the NIR band in UAV imagery. Similarly, Han *et al.*(37) developed the residual dense block *NDVI* reconstruction network, which integrates residual learning and dense blocks to significantly enhance *NDVI* reconstruction accuracy by combining SAR and optical imagery. Beyond traditional CNNs and their improved variants, end-to-end semantic segmentation models have also played a crucial role in vegetation-index-based prediction tasks. The aim of semantic segmentation is to classify input data at the pixel level, allowing for the detailed capture of different regions. For example, Sahin *et al.*(38) designed a U-Net enhanced with conditional random fields for multispectral remote-sensing-based segmentation of weeds and crops. He *et al.*(39) introduced FA-HRNet, a model incorporating a novel fusion attention mechanism to improve vegetation segmentation accuracy. Furthermore, addressing high-dimensional data processing, Nițu *et al.*(40) investigated the efficacy of *NDVI* and other vegetation indices as features for crop recognition and segmentation in hyperspectral data, confirming that multi-index features can significantly enhance segmentation performance in complex spectral environments. Notably, although these models were originally designed for semantic segmentation tasks, they can be adapted for spatial regression tasks with appropriate modifications. For example, Roßberg and Schmitt(41) proposed a globally applicable U-Net-based approach to estimate *NDVI* from SAR backscatter data. By integrating SAR data with digital surface models and land use information, their method significantly improved *NDVI* estimation accuracy.

Additionally, in vegetation-index-based time-series prediction tasks, temporal convolutional networks (TCNs) have emerged as a viable solution. Unlike RNNs, which rely on recurrent structures, or Transformers, which encode temporal positions explicitly, TCNs utilize one-dimensional causal convolutions to capture long-range dependencies in sequential data. When applied to vegetation index time-series prediction, TCN-based models can stack multiple convolutional layers to model the dynamic variations of time-series data at deeper levels. For instance, Rhif and co-workers(42,43) developed TCN-based frameworks for vegetation-related predictions in nonstationary time series. Their approach effectively captured long-term dependencies and variation trends within vegetation index time series, providing a stable and efficient solution for modeling growth conditions and vegetation pattern changes.

Overall, CNNs excel in processing data with well-defined spatial structures and have been widely applied in vegetation-index-based spatial regression, semantic segmentation, and time-series modeling tasks. This effectiveness stems from their convolutional operations, which differ from the feature extraction approaches used by RNNs and Transformers for temporal or spatial data processing. Given these differences, researchers have also explored various alternative modeling approaches for vegetation index prediction tasks, aiming to understand their distinct characteristics and advantages across different applications.

2.2.3 RNNs

RNNs are a class of neural networks designed for sequential data processing, where information is passed between cells at different time steps. At each time step, a cell receives the current input along with the hidden state from the previous step and updates the hidden state through specific operations to encode historical information. The simplest and most fundamental form of RNN is the simple RNN (SRNN), also known as the fully connected RNN. Its structure and computation are highly similar to those of the Elman network,[44] which is considered the ancestor of almost all modern RNN variants. Marsetič and Kanjir[45] utilized an SRNN model to analyze PlanetScope time-series data and predict vegetation behavior. Their results demonstrated that RNNs can effectively capture the dynamic changes in vegetation growth, highlighting their potential for processing vegetation index time-series data.

To address the inherent gradient issues of SRNN and effectively capture long-term dependencies in sequences, Hochreiter and Schmidhuber[46] introduced the LSTM neural network model. By incorporating forget gates, input gates, and output gates, this gating mechanism allows LSTM to selectively retain and update long-term information, mitigating information loss that can occur with increasing time steps, thus improving the handling of long-term dependencies. Researchers have utilized LSTM to predict the dynamic *NDVI* of vegetation.[47–49] By analyzing *NDVI* time series data, these researchers demonstrated the effectiveness of LSTM in capturing long-term dynamic changes in vegetation and successfully managing long-term dependencies within *NDVI* data, thereby enhancing prediction accuracy. Building on this, to more precisely capture cyclic growth characteristics, Zhao *et al.*[50] proposed a Seasonal LSTM model for predicting winter wheat *NDVI*, further refining the model's ability to parse seasonal patterns within the time series. Wang *et al.*[51] applied an attention-enhanced LSTM model using features from peak *NDVI* images to predict soybean yields throughout the growing season, achieving satisfactory prediction accuracy. For tasks requiring contextual information, bidirectional LSTM (Bi-LSTM) processes sequences in both forward and backward directions, enabling the capture of bidirectional dependencies. Studies indicate that Bi-LSTM outperforms LSTM in feature extraction for time-series vegetation indices,[52–54] making them more effective for *NDVI* prediction tasks and yield forecasting.

Gated recurrent units (GRUs)[55] feature a simplified structure compared with LSTM and are also designed to address the gradient issues inherent in traditional RNNs. GRUs introduce a reset gate and combine the forget gate and input gate into an update gate, resulting in greater computational efficiency. In existing research, GRU models have primarily been applied in the agricultural sector. For example, Bi *et al.*[56] developed a GRU-based model to predict soybean sudden death syndrome during the growing season, demonstrating the effectiveness of the GRU method with overall test accuracy. Boukhris *et al.*[57] utilized a GRU model to accurately predict wheat yields by integrating time-series remote sensing data and sensor data, outperforming other compared machine learning algorithms. Similar to Bi-LSTM, Bi-GRU can also capture bidirectional dependencies. Khodadadi *et al.*[58] employed a Bi-GRU in conjunction with a deep attention network for *NDVI* prediction, showcasing the potential of Bi-GRU in predicting vegetation dynamics in arid regions.

Despite significant progress in the use of RNNs for processing time-series vegetation index data, these networks face challenges owing to their recurrent computation approach. This necessitates a stepwise handling of sequential data, making efficient parallel computation difficult and negatively impacting training speed and computational efficiency. Although the gating mechanisms in improved RNNs help mitigate gradient issues, they still struggle to effectively model long-range dependencies. In applications such as vegetation index prediction, this limitation may hinder the model's ability to capture long-term *NDVI* change trends. Consequently, in recent years, researchers have begun to explore new sequence modeling methods to further enhance the representation capabilities of time-series data.

2.2.4 Transformers

In contrast to RNNs, which rely on hidden states to sequentially transmit information, Transformers employ a fundamentally different modeling approach based entirely on attention mechanisms.(59) Unlike traditional RNN recurrent structures, Transformers can process input data in parallel, significantly enhancing efficiency. The Transformer architecture consists of an encoder and a decoder; however, in practical applications, not all tasks require the full encoder-decoder structure. For long sequence modeling, the commonly used variant is Informer, which features a sparse attention mechanism that substantially reduces computational complexity while maintaining predictive accuracy.(60) Existing studies have demonstrated that Transformer-based models can focus on global patterns within the entire time series data, allowing for the more accurate modeling of long-term trends in vegetation indices. For instance, researchers have utilized Informer models to predict *NDVI* using meteorological factors in specific study areas.(61,62) The results indicate that the Informer model exhibits excellent predictive performance, contributing to sustainable and efficient agricultural production. Furthermore, with advancements in self-supervised learning, Faran *et al.*(63) proposed a self-supervised Transformer framework specifically for the long-term prediction of Landsat *NDVI* time series, further validating the potential of such models in capturing complex temporal dynamics, thereby contributing to sustainable and efficient agricultural production.

In addition to their applications in time-series modeling, Vision Transformers (ViTs)(64) and their variants, such as Swin Transformer,(65) have been widely used in vegetation-index-related prediction tasks. Compared with traditional CNN architectures, ViTs can capture long-range feature relationships more comprehensively, enabling them to perform better in complex land cover environments. For instance, Karim *et al.*(66) proposed a ViT-based model for detecting cropland abandonment, with experimental results demonstrating that the ViT model outperforms baseline methods. Moreover, incorporating various vegetation indices into the model further enhances monitoring performance. Marjani *et al.*(67) developed a ViT-based model for wetland mapping, achieving improved classification accuracy by integrating spatiotemporal information from remote sensing data and vegetation indices.

Although research on Transformers in vegetation index prediction tasks is relatively limited, existing studies have already demonstrated their significant advantages in handling long sequence dependencies and complex pattern recognition. However, owing to their complex structure and large number of parameters, these models can be prone to overfitting on smaller datasets. Additionally, the high computational cost associated with Transformers limits their applicability in resource-constrained environments. To address these issues, researchers have begun to explore combinations of transformers with other model architectures to improve prediction accuracy while reducing computational complexity. For instance, Olamofe *et al.*(68) innovatively combined reservoir computing with pretrained language models for *NDVI* prediction, achieving a balance between model efficiency and accuracy. This multimodel combination method maintains the strengths of different models while achieving a balance among computational efficiency, predictive accuracy, and generalization ability. In the next section, we will discuss the application of combined models in vegetation index prediction and explore their applicability and optimization directions in practical tasks.

2.3 Form of integrated model

2.3.1 Cascade connection or branch parallel

In vegetation index prediction tasks, researchers have proposed various combination model architectures in recent years to fully leverage the strengths of different models. Two common approaches are cascade connections and branch parallel structures. Cascade connections involve the use of the output of one model as the input to another, allowing the features extracted by the preceding model to be further processed by the subsequent model. This enables feature extraction through multiple pathways. It is important to note that when basic CNNs, RNNs, or Transformers are applied to classification or single-value regression problems, they often require the use of MLPs for dimensionality reduction at the output stage. This type of model combination is essential for completing the tasks, but it is relatively straightforward. Therefore, it will not be included in the discussion in this section.

In existing research on cascade models, researchers often extract spatial features using CNNs and then input these features into RNNs or Transformers for temporal modeling. This approach allows temporal modeling to take spatial features into account, thereby improving accuracy. For instance, Sun *et al.*(69) constructed a CNN-LSTM model for predicting county-level soybean yields in the continental United States at the end of the season and within the season, showing that this model outperformed models that used CNNs or LSTMs alone. Ghazaryan *et al.*(70) utilized a 3DCNN-LSTM model with multisource data to estimate the yields of various crops, achieving high regression accuracy. Muriga *et al.*(71) proposed a cascade model combining CNN and LSTM for drought spatiotemporal prediction, demonstrating that drought indices calculated from *NDVI* are more suitable for long-term forecasting. Reddy *et al.*(72) employed a CNN-LSTM model for classifying cotton water stress, achieving higher accuracy than baseline models, thereby effectively supporting precision agriculture. Additionally, some studies have utilized different model structures to extract features from the temporal dimension of the data, optimizing performance in modeling both local and long-term dependencies. For example, Gao *et al.*(73) developed a CNN-LSTM model for predicting *NDVI* after time series decomposition, and the comparative results indicated that the combined model outperformed the individual

CNN and LSTM models. Vătășoiu and Faur[74] similarly employed a CNN-LSTM cascade structure for *NDVI* trend prediction in environmental monitoring applications. Dey *et al.*[75] applied spatiotemporal *NDVI* prediction to rice crop yield estimation. Wang *et al.*[76] estimated wheat yields using a cascade CNN-GRU model based on multiple temporal vegetation indices, with experimental results showing that the model combining CNNs outperformed the use of GRU alone. Furthermore, Kalmani *et al.*[77] introduced attention layers and skip connections into the CNN-LSTM cascade structure, further optimizing feature transmission and focusing capabilities, and achieved improved performance in crop yield prediction.

The branch parallel structure involves multiple modules composed of different model architectures that process the same or different input data in parallel. The outputs of each branch are then fused at the final stage to obtain a more comprehensive feature representation. This combination approach effectively leverages the complementary characteristics of different model structures and data sources, enhancing the model's generalization performance and predictive effectiveness. For example, Wang *et al.*[8] developed a parallel model combining LSTM and CNN for winter wheat yield prediction, where the model separately processes the dynamic and static features of the land, resulting in high prediction accuracy. He *et al.*[78] proposed a parallel model combining multiscale CNN and GRU for landslide susceptibility mapping, demonstrating that the combined model outperformed both individual models and machine learning benchmark models. Zhao *et al.*[79] utilized a CNN-BiGRU parallel model along with Shapley additive explanations analysis to explore the individual and combined effects of factors contributing to the susceptibility and contextual drivers of terrorist attacks and armed conflicts, yielding results with strong interpretability.

The aforementioned cascade connection and branch parallel structure models combine multiple architectures in different ways to leverage their strengths in extracting features across various spatial and temporal dimensions. However, these methods typically involve combinations of independent modules without improvements to the fundamental structure of the deep learning models. In recent years, researchers have begun to focus on how to integrate spatial and temporal features within the internal structure of the models, allowing them to simultaneously model spatial and temporal dependencies within a local receptive field. This approach has led to the emergence of models that deeply couple different structures. The introduction of these models has expanded the modeling approach from traditional methods that separately extract features for sequences and spatial data to spatiotemporal joint modeling. This provides a more comprehensive capability for feature extraction tasks involving time-series vegetation index raster data. In the next section, we will specifically highlight the applications of these spatiotemporal fusion models in vegetation-index-based prediction.

2.3.2 Coupling and fusion structure

To enhance the model's ability to utilize spatiotemporal data from vegetation indices, researchers have increasingly employed a more tightly coupled architecture to integrate spatial and temporal information within the model, enabling more comprehensive spatiotemporal feature modeling. A typical representative of this approach is the ConvLSTM, which was initially proposed by Shi *et al.*(80) Unlike traditional LSTMs, ConvLSTM incorporates convolution operations in all gate structures and state update processes, allowing the model to directly encode spatial structural information within the hidden states. This innovation enables ConvLSTM to jointly model spatiotemporal data effectively. As a result, ConvLSTM has demonstrated exceptional performance in tasks involving time-series vegetation indices and meteorological data modeling, providing a new perspective for analyzing complex spatiotemporal sequence data.

Most existing research based on ConvLSTM was primarily focused on the spatiotemporal changes of future vegetation.(81–84) In these studies, the ConvLSTM model was utilized to capture the spatiotemporal dependencies in time-series vegetation indices, significantly improving modeling accuracy compared with traditional point-based benchmark prediction methods. Feng and Zong(85) further applied the spatiotemporal feature extraction capability of ConvLSTM to large-scale crop image recognition tasks, improving model performance through the introduction of the coordinate attention mechanism. However, owing to the high computational complexity of ConvLSTM, the temporary spatiotemporal feature maps generated during computation tend to be large in size and high in dimensionality. This can lead to issues such as feature redundancy and gradient vanishing. To address this challenge, some researchers have introduced attention mechanisms in the spatiotemporal feature extraction phase of the model to enhance the focus on critical spatiotemporal features, further optimizing spatiotemporal modeling and prediction performance.(86–88) Notably, in current methods where ConvLSTM is applied for vegetation index modeling while integrating attention mechanisms, the gated dimensions of the attention mechanisms only include spatial and channel dimensions, without incorporating attention to the temporal dimension. Additionally, Zhang *et al.*(89) developed a model based on convolutional GRU (ConvGRU) for *NDVI* spatiotemporal prediction. Compared with ConvLSTM, ConvGRU is more lightweight and requires fewer computational resources, with results indicating that ConvGRU can achieve performance comparable to that of ConvLSTM.

By examining the aforementioned studies on the spatiotemporal modeling of vegetation indices, it is evident that these models exhibit significant advantages in vegetation prediction tasks. This success can be attributed to their ability to effectively ensure the joint constraints of spatiotemporal information, resulting in predictions that not only possess high numerical accuracy but also exhibit greater coherence and rationality in spatial distribution. However, these models also face challenges such as high computational complexity, large parameter counts, and substantial hardware requirements. Particularly when larger spatial dimensions or longer time sequences are input, the increase in the shape of spatiotemporal feature maps exacerbates the consumption of computational resources. Additionally, compared with the combination models based on cascade or parallel structures discussed in the previous section, ConvLSTM-based model architectures tend to be more rigid, making it difficult to flexibly adapt to different types of feature extraction methods. Moreover, their deep integration with structures such as Transformers poses significant challenges. These potential issues may, to some extent, limit the scalability and applicability of such models in various scenarios.

2.4 Application fields

The application fields of vegetation indices combined with deep learning technology have diversified across multiple domains. On the basis of 176 records initially retrieved from the Web of Science database using the search strategy described in Sect. 3.1, we manually classified each study into one primary application category in accordance with its main research objective. The resulting distribution is shown in Table 3, with the major domains including agricultural management, vegetation monitoring, disaster and climate analysis, and land and resource management. In agricultural production, the integration of vegetation indices with deep learning technology has significantly enhanced the precision and efficiency of crop management. Among these applications, crop yield prediction has received the most attention, with statistical analysis revealing that it accounts for 23.86% of the collected application cases, highlighting the critical value of this technology in supporting agricultural production decisions.(27,90,91) Additionally, this technology has been widely applied to the early warning of plant diseases(92) and the precise identification of crops versus weeds,(38) providing effective support for refined farmland management. In vegetation ecological monitoring, deep learning models have achieved more precise *NDVI* trend prediction by integrating historical observation data and climatic factors, offering scientific guidance for ecological conservation planning.(28,93) Meanwhile, by analyzing multisource satellite remote sensing data, this technology can accurately estimate the biomass and biophysical parameters of various vegetation types, including forests and grasslands,(26,94–97) providing essential data support for vegetation–environment interaction studies, ecosystem service assessments, and regional carbon cycle analysis.(98)

In the field of disaster and meteorological analysis, the integration of vegetation indices with deep learning technology provides new technical approaches for disaster risk assessment and postdisaster impact analysis. By comparatively analyzing the spatiotemporal variation characteristics of vegetation indices before and after disasters, deep learning models can rapidly and accurately evaluate the extent and spatial distribution of natural disaster impacts on vegetation. Currently, this technology has been successfully applied to various disaster scenarios, including forest fire risk prediction and burned area extent detection,(99–102) early

Table 3
Frequency and proportion analysis of cross-disciplinary applications of vegetation indices.

Research domain	Application	Frequency	Proportion (%)
Agricultural management	Crop yield prediction	42	23.86
	Plant disease detection	8	4.55
	Weed Identification	2	1.14
Vegetation monitoring	*NDVI* prediction	47	26.70
	Vegetation dynamics monitoring	27	15.34
	Biomass estimation	1	0.57
Disaster and climate analysis	Disaster assessment	23	13.07
	Drought monitoring and ecological water use	8	4.55
	Surface temperature prediction	7	3.98
Land and resource management	Land cover classification	7	3.98
	Soil parameter assessment	3	1.70
	Ecological economic evaluation	1	0.57

monitoring and warning of agricultural drought,(103–106) surface temperature change prediction, and climate–vegetation coupling relationship analysis.(107) In the domain of land and resource management, deep learning technology also plays an important role, primarily applied to the precise classification of land cover types,(108) rapid assessment of key parameters such as soil moisture and nutrients,(109,110) and comprehensive evaluation of ecological-economic values,(111) providing new technical means for precision agriculture development and sustainable regional resource management. In summary, these diverse application cases fully demonstrate the broad adaptability and significant practical value of combining vegetation indices with deep learning technology in interdisciplinary research.

3. Methodology

3.1 Data collection

To systematically review the research progression and future forecasting trends of vegetation indices combined with deep learning methods, we conducted a literature search in the Web of Science database, with the timeframe set from 2015 to 2025. The retrieval strategy employed an advanced search expression: TI = (forecast* OR predict*) AND TS = (*NDVI* OR *EVI* OR "Normalized Difference Vegetation Index" OR "Enhanced Vegetation Index" OR "vegeta* index" OR "vegetation dynamic*") AND TS = ("deep learning"). Additionally, filters were applied to limit the language to English and the content to full records and citations. The search yielded a total of 176 records. These records were used for the application-domain classification and descriptive analysis presented in Table 3. For the subsequent CiteSpace analysis, the retrieved records were further screened for suitability in bibliometric network analysis. As a result, 3 nonstandard records were excluded, and 173 publications were finally retained for analysis. To elucidate the dynamic changes in this field over the past decade, we calculated the annual publication counts from 2015 to 2025. The results indicate a steady upward trend (see Fig. 1), with the number of publications increasing from one in 2015 to 47 in 2025. This trend suggests that the interdisciplinary study of vegetation indices and deep learning is emerging as a critical direction in the integration of remote sensing technology and artificial intelligence, providing a robust data foundation for subsequent bibliometric analysis. Note that we relied

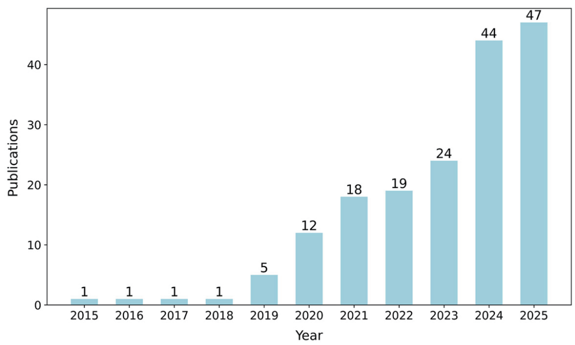

Fig. 1. (Color online) Statistical data on the number of papers published annually from 2015 to 2025.

solely on the Web of Science database for literature retrieval. Although this is widely recognized as an authoritative source in scientometric research, relevant studies indexed in other databases such as Scopus or Google Scholar may not be captured, which represents a limitation of the current analysis.

3.2 CiteSpace tool for scientometric analysis

To systematically analyze the applications of deep learning in multidomain predictions using vegetation indices and their knowledge network patterns, in this study, we employed CiteSpace (version 6.4.R1) for bibliometric analysis. By constructing an author co-citation network, a journal co-citation network, a keyword co-occurrence network, and a national collaboration network, we aim to uncover the core authors, key journals, research hotspots, and cross-regional collaboration relationships in the field of vegetation indices. CiteSpace is an efficient network analysis and visualization tool that supports the construction of various knowledge networks, making it well-suited for revealing knowledge distribution and interdisciplinary integration trends in vegetation index research.

A co-citation network refers to the relationship between two publications that are both cited in the reference list of another publication. In this study, we utilized CiteSpace to construct an author co-citation network and a journal co-citation network, with nodes representing cited authors and cited journals, respectively, and the connecting lines between nodes indicating co-citation relationships. Through the analysis of these networks, we aim to identify the core authors and key journals in vegetation index research, revealing the knowledge flow and interdisciplinary collaboration patterns within the field of deep-learning-based predictions.

A co-occurrence network refers to a collaborative relationship established between different countries or keywords on the basis of their simultaneous occurrence within the same paper. In this study, we employed CiteSpace to construct a country collaboration network and a keyword co-occurrence network, where nodes represent collaborating countries and keywords, respectively. The size of each node reflects the frequency of published papers, while the connecting lines between nodes and their thickness indicate the collaborative relationships and their strength (measured by co-occurrence frequency). Through the analysis of these networks, we aim to reveal international collaboration patterns and research hotspots in vegetation index studies. To further quantify the collaboration strength within the country collaboration network and the keyword co-occurrence network, we utilized CiteSpace to calculate the degree of association between nodes using cosine similarity. The formula is presented as

$$\cos\left(C_{ij}, S_i, S_j\right) = \frac{C_{ij}}{\sqrt{S_i S_j}}. \tag{3}$$

Specifically, S_i represents the frequency of node i, S_j represents the frequency of node j, and C_{ij} denotes the co-occurrence frequency of S_i and S_j. By applying cosine similarity, we can measure the collaboration strength between different countries and the degree of association between keywords in vegetation index research, thereby elucidating international collaboration patterns and research hotspots within the field of deep-learning-based predictions.

In this study, we used CiteSpace to employ betweenness centrality, citation frequency, and citation burst as quantitative indicators to characterize the knowledge network in vegetation index research. Betweenness centrality measures the proportion of shortest paths in the network that pass through a given node (with scores ranging from 0 to 1); a higher score indicates greater influence of the node (e.g., an author or journal), which is visually represented in CiteSpace by the thickness of the node's ring. Citation frequency reflects the number of times a node is cited within a specific time period, with larger nodes signifying stronger influence in the vegetation index domain, and the temporal citation patterns are displayed through the colors of concentric rings. Citation burst detects sudden increases in a node's citation frequency, calculated on the basis of Kleinberg's(112) method, with the parameter γ set to 1 to balance the consideration of all nodes, thereby identifying emerging trends in vegetation index research. These metrics facilitate the revelation of core authors, key journals, and research dynamics in the field of vegetation index studies within the context of deep-learning-based predictions, providing theoretical support for its applications in multidomain forecasting.

Additionally, we conducted a cluster analysis on the author co-citation network and the journal co-citation network to delineate the scope, research hotspots, and trends within the vegetation index domain. The cluster analysis in CiteSpace primarily employs the spectral clustering method, which groups data points into clusters on the basis of their co-occurrence relationships. Specifically, this method first defines an affinity matrix that describes the similarity between pairs of data points on the basis of a given sample dataset. Subsequently, the eigenvectors of this matrix are computed, and the data points are clustered on the basis of these eigenvectors. In this study, we labeled the resulting clusters with a set of representative terms for interpretability. These terms were extracted from noun phrases (e.g., titles, abstracts, and keywords) in the documents using the log-likelihood ratio (*LLR*) algorithm provided by CiteSpace. For a cluster C_j, the eigenvector V_{ij} is composed of the frequency (α), concentration (β), and dispersion (γ) of the word ω_i. Cluster labels were generated by calculating the *LLR* for each word, with the formula presented as

$$LLR = \log \frac{p(C_j \mid V_{ij})}{p(\overline{C_j} \mid V_{ij})}. \tag{4}$$

Here, $p(C_j|V_{ij})$ and $p(\overline{C}_j|V_{ij})$ represent the density functions of the word V_{ij} in cluster C_j and its complement $\overline{C}_j$, respectively. Words with high *LLR* values are selected as cluster labels to represent the core themes in vegetation index research. To evaluate the quality of the clustering, modularity (i.e., the Q value) and silhouette value (i.e., the S value) were used as key metrics. Network modularity measures the extent to which a network can be divided into distinct components or modules, providing a reference for the overall clarity of a given network decomposition. A higher Q value indicates tighter connections within clusters and sparser connections with other clusters. The silhouette value (S value, ranging from −1 to 1) indicates the homogeneity of nodes within a cluster, with a higher S value signifying better clustering quality.

In this study, a Q value greater than 0.3 and an S value greater than 0.7 were considered ideal thresholds, indicating a significant community structure in the network and high confidence in the clustering results.

4. Results and Discussion

4.1 Co-citation of authors

We applied CiteSpace to conduct an author co-citation network analysis, identifying core researchers who have made significant contributions to the application of *NDVI* in multidomain deep learning. The analysis spans from 2015 to 2025, focusing on the top ten authors within each annual time slice (a quantity commonly selected in most studies for network construction). Owing to limitations in the Web of Science database, such as incomplete records, unrecognizable or missing author information, and privacy protection clauses, some author data were not provided. Consequently, we excluded anonymous authors from the analysis.

As shown in Fig. 2, the author co-citation network consists of 489 nodes and 1260 links. Nodes represent individual authors, and a link between two nodes is formed when both authors are cited by the same publication, indicating a co-citation relationship. Each color corresponds to a specific time slice (i.e., one year), and the concentric rings of different colors reflect the temporal evolution of the authors' co-citation patterns.

In Fig. 2, the larger the node size, the higher the citation frequency of the author. Authors with higher citation frequencies can be regarded as core figures in the *NDVI* research field. The data shows that Sepp Hochreiter from Johannes Kepler University Linz in Austria has the highest citation frequency in each time segment, reaching 34 citations, with his node having the largest radius in the entire network. He is followed by Aya Ferchichi from the University of Manouba in Tunisia and Yann LeCun from New York University and Facebook AI Research, with 30 and 18 citations, respectively. This indicates that their publications in the field of *NDVI* prediction are more popular and widely recognized by other scholars in related fields. Notably, a review of their research interests listed on Google Scholar reveals that these authors all exhibit a strong interest in AI, and neural networks.

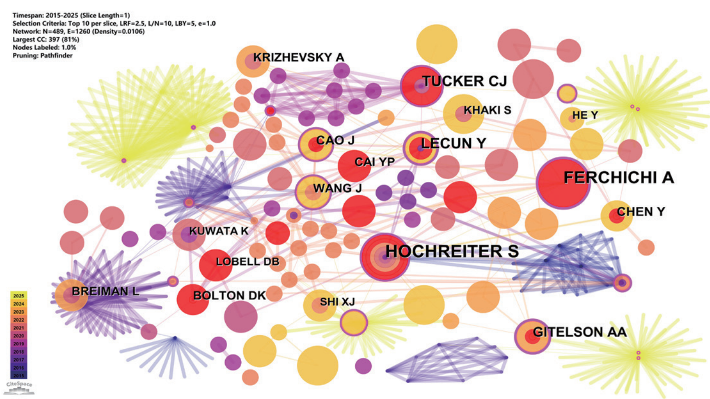

Fig. 2. (Color online) Visualization of the merged network of author co-citation network analysis for the years 2015 to 2025.

Table 4 lists the top five core authors ranked on the basis of the betweenness centrality metric. The data shows that Anatoly Gitelson from the Israel Institute of Technology leads with a betweenness centrality value of 0.31. As a renowned scholar in the field of remote sensing, his current research focuses on the remote sensing monitoring of aquatic and terrestrial environments, particularly the application and development of the *NDVI*. Serving as an intermediary, he established the shortest paths between pairs of authors and has played a critical role in connecting all authors and building the *NDVI* prediction research network since the start of his active research. In recent years, Aya Ferchichi from the University of Manouba in Tunisia has also gained increasing attention. Her research involves deep learning and the optimization of *NDVI* prediction algorithms, and her work has been widely cited and recognized in the academic community. Overall, authors with high betweenness centrality are considered key drivers of collaboration and interdisciplinary research in the *NDVI* field.

In Fig. 2, scholar nodes with significant citation burst characteristics are marked with red bold circles, where the thickness of the ring is positively correlated with the duration of the burst. Table 5 lists the top five scholars in descending order of burst strength. Tunisian scholar Aya Ferchichi leads the ranking with a burst strength of 12.45, significantly ahead of other researchers, revealing that her research achievements have continuously attracted attention from the academic community in recent years and triggered a high frequency of citations. Following her are Sepp Hochreiter, Douglas K. Bolton, and Yaping Cai, with burst strength values of 6.21, 5.37, and 5.22, respectively. These scholars exhibit similar temporal patterns of citation bursts, indicating that the research attention in this field continues to rise and has become a frontier direction collectively focused on by scholars across multiple disciplines.

We conducted a clustering analysis of the author community in the application of *NDVI* in multidomain deep learning to identify groups of authors with similar academic influence and collaboration relationships. As shown in Fig. 3, the network exhibits seven distinct clusters, each representing different research directions and collaboration networks within the field of *NDVI* prediction. The weighted average silhouette value (*S*) of the network is 0.9127, indicating a high

Table 4
Top five core authors based on the betweenness centrality metric from 2015 to 2025.

Author	Full name	Betweenness centrality	Average year
GITELSON AA	Anatoly Gitelson	0.31	2020
FERCHICHI A	Aya Ferchichi	0.25	2022
AERTS JCJH	Jeroen C. J. H. Aerts	0.24	2025
AHMADLOU M	M. Ahmadlou	0.24	2025
LECUN Y	Yann LeCun	0.23	2018

Table 5
Top five core authors based on citation burst strength from 2015 to 2025.

Author	Full name	Citation burst	Begin (year)
FERCHICHI A	Aya Ferchichi	12.45	2023
HOCHREITER S	Sepp Hochreiter	6.21	2023
BOLTON DK	Douglas K. Bolton	5.37	2018
CAI YP	Yaping Cai	5.22	2020
LOBELL DB	David B. Lobell	4.52	2019

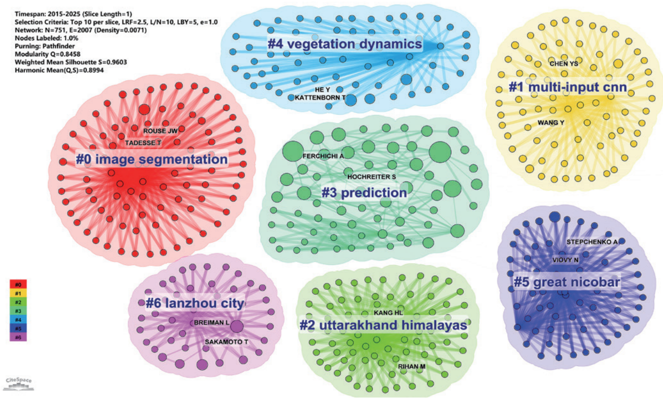

Fig. 3. (Color online) Clustering analysis results of the co-citation network of authors from 2015 to 2025.

level of internal consistency within the clusters. The modularity (Q) value of 0.7707 reflects a strong degree of modular structure in the network division. Both metrics suggest that the clustering results are highly reliable. These clusters reveal the academic collaboration networks across various research directions in this field, providing valuable insights into the knowledge structure and collaboration patterns of *NDVI* applications in multidomain deep learning.

Table 6 shows detailed information about these clusters, arranged in descending order by the number of samples included. The silhouette value (S value), average publication year, and labels generated by the *LLR* method are also provided for each cluster to interpret the clustering results. All S values exceed 0.7, indicating that grouping similar research topics into a single cluster is reasonable. For example, Cluster #0, with an average year of 2017 and comprising 93 samples, is the largest cluster. Its S value of 0.947 suggests an extremely high degree of similarity among the samples within this cluster. The themes of this cluster encompass research areas such as image segmentation, agricultural robotics, precision agriculture, zcndvi (standardized score of seasonally cumulative normalized difference vegetation index), and convolutional neural networks. In contrast, Cluster #1, with an average year of 2024 and containing 84 samples, has an S value of 0.981, indicating even greater similarity. This cluster primarily focuses on research directions such as multi-input convolutional neural networks (multi-input CNN), Sentinel-1 SAR data, single-input convolutional neural networks (single-input CNN), and optical imagery. These clusters reflect the evolution of the field from early applications in image processing and agriculture (Cluster #0) to more advanced deep learning techniques and disaster prediction applications (Cluster #1), highlighting the diversification of research topics and technological advancements over time. Labels such as “convolutional neural network”, “long short-term memory”, and “multi-input cnn” also reflect the growing methodological diversity of the field.

4.2 Co-citation of journals

The journal co-citation network is a network structure used to analyze and visualize the citation exchanges and relationships between journals. In this network, each journal is represented as a node, and the citation relationships between journals are depicted as links connecting the nodes. As shown in Fig. 4, the journal co-citation network consists of 118 nodes

Table 6
Summary of clustering in the authors' co-citation network.

Cluster ID	Size	Silhouette	Mean (year)	Label (*LLR*)
0	93	0.947	2017	image segmentation; agrobotic; precision farming; zcndvi; convolutional neural network
1	84	0.981	2024	multi-input cnn; mapping; sentinel-1 sar; single-input cnn; optical images
2	81	1	2025	uttarakhand himalayas; partial dependence plots (pdp); influencing factors; flash flood; early warning system
3	66	0.825	2019	prediction; climate change impact; geospatial discovery; yield prediction; google earth engine (gee)
4	65	0.943	2024	vegetation dynamics; spatiotemporal prediction; semantic segmentation; the stl-emd-informer model; normalized difference vegetation index (ndvi)
5	62	0.981	2017	great nicobar; LSTM; time series; neural networks; normalized difference vegetation index
6	43	0.933	2017	lanzhou city; 3d-cnn; spectral statistics; gru; grapevine vein-clearing virus (gvcv)

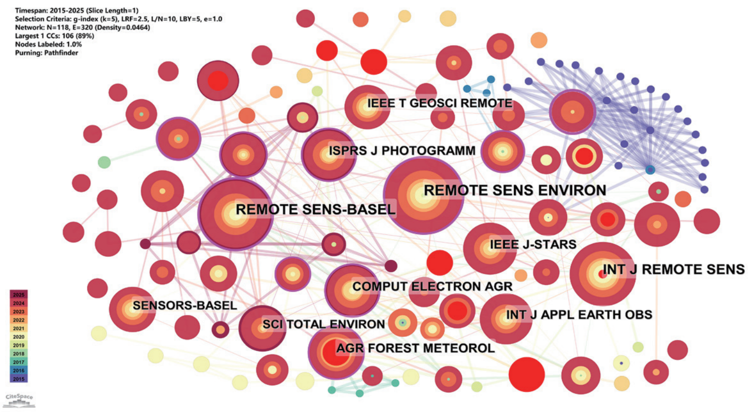

Fig. 4. (Color online) Visualization of journal co-citation network for the years 2015 to 2025.

and 320 links. The larger the node size, the greater the number of publications that the journal has in the field related to *NDVI* prediction. Table 7 lists information on the top five journals ranked by publication frequency, including journal name, latest impact factor, publication frequency, and average publication year. It can be observed that Remote Sensing of Environment, the journal with the largest node radius, has the highest publication frequency at 111 articles, with an average publication year of 2015. Following closely behind, *NDVI*-prediction-related literature is primarily published in journals such as Remote Sensing and International Journal of Remote Sensing, all of which have high impact factors and belong to categories such as remote sensing and ecological environments.

As shown in Fig. 4, the outermost purple ring around each node represents the betweenness centrality of a journal. The thicker the purple ring, the higher the journal's betweenness centrality. The purple ring appears only when the betweenness centrality exceeds 0.1. Table 8 lists the top six journals ranked by betweenness centrality in the co-citation network, including their abbreviated names, full names, impact factors, betweenness centrality scores, and average publication years. The journals arXiv, Remote Sensing, and Remote Sensing of Environment have betweenness centrality scores of 0.46, 0.36, and 0.32, respectively, playing intermediary

Table 7
Top five journals sorted by frequency of publications for the years 2015 to 2025.

Abbreviation	Full name	Impact factor (2024–2025)	Frequency of publications	Average year
REMOTE SENS ENVIRON	Remote Sensing of Environment	11.4	111	2015
REMOTE SENS-BASEL	Remote Sensing	4.1	96	2018
INT J REMOTE SENS	International Journal of Remote Sensing	2.6	81	2015
IEEE J-STARS	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	5.3	54	2015
ISPRS J PHOTOGRAMM	ISPRS Journal of Photogrammetry and Remote Sensing	12.2	52	2015

Table 8
Top six journals based on betweenness centrality for the years 2015 to 2025.

Abbreviation	Full name	Impact factor (2024–2025)	Betweenness centrality	Average year
ARXIV	arXiv	N/A	0.46	2015
REMOTE SENS-BASEL	Remote Sensing	4.1	0.36	2018
REMOTE SENS ENVIRON	Remote Sensing of Environment	11.4	0.32	2015
J HYDROL	Journal of Hydrology	6.3	0.24	2018
AGR FOREST METEOROL	Agricultural and Forest Meteorology	5.7	0.14	2017
COMPUT ELECTRON AGR	Computers and Electronics in Agriculture	8.9	0.13	2019

roles in the *NDVI* field from 2015 to 2018 by connecting journals with co-citation relationships. In recent years, Journal of Hydrology and Computers and Electronics in Agriculture, with betweenness centrality scores of 0.24 and 0.13, respectively, have attracted attention, emerging as core journals in the *NDVI* field and facilitating interdisciplinary collaboration and knowledge exchange.

When the number of citations for a journal increases rapidly within a specific time period, the journal is considered to exhibit a strong citation burst. As shown in Table 9, the journal Field Crops Research has the strongest citation burst, with a value of 9.32, lasting for three years from 2019 to 2021. Several well-known and high-impact-factor journals also experienced significant citation bursts, such as Science and Geophysical Research Letters, which saw bursts between 2018 and 2020, demonstrating that top-tier research in the *NDVI* field during these periods was widely recognized and frequently cited by the academic community. The journal AAAI Conference on Artificial Intelligence recorded the longest citation burst, spanning four years from 2018 to 2021, during which its publications related to *NDVI* prediction were cited at a frequency exceeding peer expectations.

To identify journal groups with high homogeneity, we conducted a clustering analysis on the journal co-citation network. As shown in Fig. 5, the network was divided into seven clusters, each represented by a distinct color. The modularity Q value is 0.5671, and the weighted mean

Table 9
Top five journals ranked by citation burst strength for the years 2015 to 2025.

Abbreviation	Full name	Impact factor (2024–2025)	Burst	Begin year	End year
FIELD CROP RES	Field Crops Research	6.4	9.32	2019	2021
AAAI CONF ARTIF INTE	AAAI Conference on Artificial Intelligence	N/A	5.1	2018	2021
INT J REMOTE SENS	International Journal of Remote Sensing	2.6	4.76	2018	2019
SCIENCE	Science	45.8	4.06	2018	2020
GEOPHYS RES LETT	Geophysical Research Letters	4.6	3.21	2018	2020

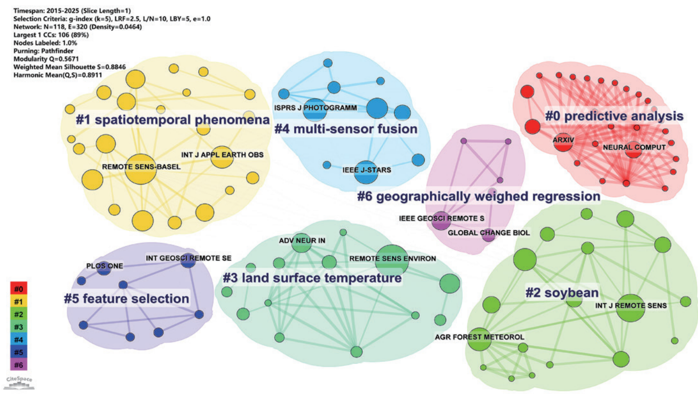

Fig. 5. (Color online) Clusters of the journal co-citation network for the years 2015 to 2025.

silhouette value S is 0.8846, both of which fall within the ideal range. These results indicate that the clustering analysis is reliable and aligns with expectations, facilitating a deeper understanding of the academic structure of *NDVI* prediction research for scholars.

Table 10 lists detailed information about seven clusters, including the number of journals, S value, average publication year, and labels generated by the *LLR* method. Cluster #0 is the largest, comprising 27 journals with an average year of 2015, labeled as “predictive analysis” and “satellite image time series (SITS)”, focusing on the application of predictive analysis and satellite imagery time series in *NDVI* research. Clusters #1, #2, and #3 are similar in size, containing 23, 18, and 14 journals, with average years of 2020, 2018, and 2021, and they focus on “spatiotemporal phenomena”, “soybean”, and “land surface temperature”, respectively. Cluster #4 includes 10 journals, with an S value of 0.872 and an average year of 2019, addressing the application of “multisensor fusion” in *NDVI* prediction. Cluster #6 is the smallest, with only six journals, but it has an S value of 0.919 and an average year of 2016, indicating high homogeneity; its label highlights a focus on “geographically weighted regression” and wheat yield prediction.

4.3 Co-occurrence of keywords

Keywords serve as an effective means to summarize the themes of a publication. To investigate the associations and developmental trends of research themes in the field of *NDVI*

Table 10
Largest seven clusters in the journal co-citation network.

Cluster ID	Size	Silhouette	Mean (Year)	Label (*LLR*)
0	27	0.96	2015	predictive analysis; satellite image time series (sits); autoencoders; convlstm neural networks; unmanned aerial vehicles
1	23	0.838	2020	spatiotemporal phenomena; vegetation mapping; crop yield; modis; yield estimation
2	18	0.77	2018	soybean; LSTM; crop damage; google earth engine; rice-yield estimation
3	14	0.94	2021	land surface temperature; lstm; yield prediction; urban hot spots; moderate resolution imaging spectroradiometer
4	10	0.872	2019	multisensor fusion; sentinel-2 ndvi ; crop mapping; deeplabv3+; late/early stage computation
5	8	0.916	2020	feature selection; gated recurrent unit; soybean breeding; soybean disease; disease detection
6	6	0.919	2016	geographically weighed regression; wheat yield; explainable AI (xai); LSTM; indian wheat belt

prediction, we conducted a co-occurrence network analysis of the top 10 keywords each year from 2015 to 2025. As shown in Fig. 6, the network comprises 173 nodes and 509 links ($N = 173$, $E = 509$, Density = 0.039). Nodes represent keywords, and a link between two nodes indicates a co-occurrence relationship when the keywords appear together in the same document. The size of a node reflects the frequency of the keyword's use across all publications, while its color denotes the year of the keyword's first appearance. As observed in Fig. 6, the nodes for "remote sensing" and "deep learning" hold the highest prominence in the network, signifying in which we noted their status as core research themes in *NDVI* prediction. This is consistent with the discussion in Sect. 4.2, in which we noted that remote sensing and deep learning methods are widely applied in existing studies for *NDVI* prediction and related analyses. Furthermore, nodes such as "time series", "machine learning", "convolutional neural network", and "vegetation index" are also notably prominent, underscoring the importance of these techniques in *NDVI* prediction. The network also highlights keywords such as "winter wheat" and "satellite", indicating a focus on specific crops and data sources in *NDVI* prediction research. Overall, this co-occurrence network reveals that the research hotspots in the *NDVI* prediction field predominantly center on remote sensing technologies, deep learning methods, and time series analysis, closely linked to practical applications in agriculture and environmental monitoring.

Table 11 shows the top five keywords with the highest betweenness centrality scores in the field of *NDVI* prediction. A higher betweenness centrality score indicates that these keywords play a significant role in the research. They serve as intermediaries in constructing the keyword co-occurrence network, suggesting that these keywords are not only frequently used but also widely recognized in *NDVI* prediction studies. Additionally, these influential nodes, emerging in different years, illustrate the evolution of research hotspots in the *NDVI* prediction field. For example, the node representing "deep learning" has a notably higher betweenness centrality score than others, a trend that began in 2015 and has continued to shape subsequent research. This signifies the transition of deep learning techniques in *NDVI* prediction from an emerging tool to a pivotal method, significantly enhancing spatiotemporal data analysis and model accuracy.

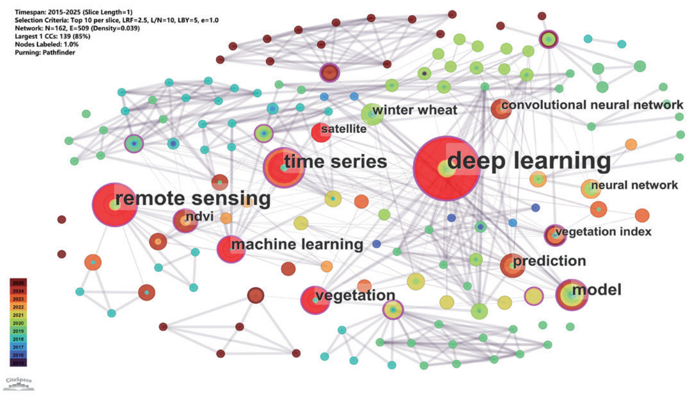

Fig. 6. (Color online) Visualization of keyword co-occurrence networks for the years 2015 to 2025.

Table 11
Top five keywords based on betweenness centrality for the years 2015 to 2025.

Keywords	Betweenness centrality	Average year
deep learning	0.32	2015
classification	0.3	2018
time series	0.29	2016
index	0.24	2024
model	0.18	2017

Table 12 shows the top six keywords with the highest citation burst strength in the field of *NDVI* prediction from 2015 to 2025, where citation bursts reflect the concentration of research hotspots in specific periods. Analysis of the trends reveals that from 2020 to 2022, research was primarily focused on time series analysis and the application of satellite data, highlighting the emphasis on data processing and acquisition in *NDVI* prediction. However, from 2022 to 2025, the research hotspots shifted significantly toward the dominance of deep learning and remote sensing technologies, indicating a pattern of evolution in the *NDVI* prediction field from foundational data applications to more complex, technology-driven approaches. This trend aligns with the prominent positions of the “deep learning” and “remote sensing” keywords in Fig. 6, suggesting that deep learning is driving the advanced development of *NDVI* prediction research. These keyword co-occurrence and burst patterns further support the technical review presented in Sect. 2. In particular, the prominence of terms such as “deep learning”, “time series”, and “convolutional neural network”, together with the recent burst of “deep learning” and “remote sensing”, suggests that the field has gradually evolved from earlier time-series- and data-oriented prediction studies toward more advanced and integrated spatiotemporal modeling frameworks.

4.4 Collaborative country networks

In this section, we constructed a national collaboration network to analyze and visualize the cooperation patterns among countries worldwide in the field of *NDVI* prediction from 2015 to

Table 12
Top six keywords sorted by citation burst from the years 2015 to 2025.

Keywords	Burst	Begin (year)	End (year)
deep learning	9.72	2023	2025
remote sensing	5.29	2023	2025
time series	2.83	2020	2022
machine learning	2.6	2022	2025
vegetation	2.6	2023	2025
satellite	2.5	2021	2023

2025. Country information was extracted from author affiliations, resulting in a network comprising 62 nodes and 98 edges, where nodes represent countries, edges indicate cooperative relationships between countries, and node size reflects the frequency of publications by each country in the *NDVI* prediction domain. Concentric rings of different colors around the nodes illustrate the temporal patterns of *NDVI* prediction-related publications by each country from 2015 to 2025, while the color of the connecting lines corresponds to the year of the first collaboration between countries. The thickness of the outermost purple ring signifies the importance of a country's interwoven relationships within the collaboration network, with thick purple rings indicating higher betweenness centrality, highlighting their critical intermediary role in connecting countries in *NDVI* prediction research.

As shown in Fig. 7, China has the largest node radius, with a publication frequency of 58, accounting for 25.22% of the total publications (see Table 13), demonstrating China's dominant position in *NDVI* prediction research as a primary contributor. The United States ranks second, with a publication frequency of 34, representing 14.78%. India, Iran, and Germany follow with publication frequencies of 11, 10, and 10, corresponding to 4.78, 4.35, and 4.35% of the total, respectively. Table 13 also reveals that the average publication years for China and the United States are earlier (2018 and 2015, respectively), while Iran and Germany's publications are concentrated in later years (2019 and 2020), reflecting differences in the timing of *NDVI* prediction research activity across countries. The contributions of these nations have collectively advanced global research progress in the *NDVI* prediction field.

Table 14 shows the top five countries with the highest betweenness centrality. From the table, it can be inferred that since 2018, China has become a key hub in the collaboration network connecting other countries, with the highest betweenness centrality of 0.5, followed closely by the United States. Countries with high betweenness centrality also tend to have high degree centrality, such as China and the United States, with degree centralities of 13 and 12, respectively, indicating their extensive scope of collaboration. The betweenness centrality and average years of Saudi Arabia (2024), Canada (2019), and Iran (2019) suggest an increase in their collaboration activity in later years. Through extensive international cooperation, these countries have made significant contributions to global research exchange in the field of *NDVI* prediction.

To investigate the development trends of *NDVI*-prediction-related research over the past decade, we conducted a citation burst analysis for countries, revealing that China exhibited the strongest citation burst, with this analysis considering all nodes in the collaborative country network. The analysis includes strength scores as well as start and end years. The burst (i.e., a

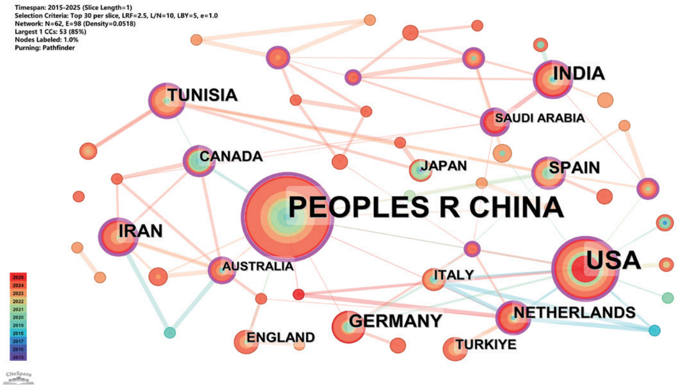

Fig. 7. (Color online) Visualization of national collaboration network for the years 2015 to 2025.

Table 13
Top five countries ranked by publication frequency for the years 2015 to 2025.

Country	Publication frequency	Proportion	Average year
PEOPLES R CHINA	58	0.2522	2018
USA	34	0.1478	2015
INDIA	11	0.0478	2016
IRAN	10	0.0435	2019
GERMANY	10	0.0435	2020

Table 14
Top five countries ranked by betweenness centrality for the years 2015 to 2025.

Country	Betweenness centrality	Degree centrality	Average year
PEOPLES R CHINA	0.5	13	2018
USA	0.3	12	2015
SAUDI ARABIA	0.29	6	2024
CANADA	0.28	6	2019
IRAN	0.27	6	2019

sudden increase in citation counts) lasted for five years, from 2015 to 2020, achieving a score of 2.08. This indicates that *NDVI*-prediction-related research conducted in China during these years garnered widespread attention from researchers. This pattern also suggests that the expansion of vegetation index prediction research across application domains has been accompanied by increasingly international collaboration.

5. Conclusions

The interdisciplinary research on vegetation indices and deep learning has made remarkable progress in recent years, offering efficient solutions for predictive tasks across multiple domains, including ecological monitoring, agricultural forecasting, and disaster assessment. Through a technical review and bibliometric analysis, we elucidated the evolutionary trends in this field, from methodological innovation to interdisciplinary applications, underscoring its vast potential in multidomain practices. On the technical front, deep learning models such as MLPs, CNNs, RNNs, and Transformers have demonstrated their unique strengths in vegetation index prediction, particularly excelling in cascaded, parallel frameworks, and coupled fusion structures, thereby providing critical support for enhancing prediction accuracy and adapting to diverse domain-specific scenarios.

From a bibliometric perspective, CiteSpace analysis revealed the emergence of a core group of authors and key journals in this field. Ferchichi's citation burst strength (12.45) signals a rapidly growing research front, whereas Gitelson's highest betweenness centrality (0.31) highlights his bridging role between the remote sensing and deep learning communities. Remote Sensing of Environment remains the foundational journal (111 co-citations), whereas the rising centralities of Journal of Hydrology and Computers and Electronics in Agriculture reflect an expanding interdisciplinary scope. Keyword burst detection indicates a transition from data-oriented themes such as "time series" (burst period 2020–2022) to technology-driven topics led by "deep learning" (burst strength 9.72, 2023–2025). China leads in both publication volume (25.22%) and betweenness centrality (0.5), with Saudi Arabia and Canada emerging as increasingly active collaborators.

Future research should focus on exploring the potential of emerging architectures (e.g., Transformer-based models) in capturing complex *NDVI* spatiotemporal dynamics, strengthening cross-disciplinary collaboration, and fostering broader international partnerships to promote applications in ecological conservation, agricultural optimization, and disaster management. Nevertheless, we relied exclusively on the Web of Science Core Collection, which may have limited the completeness of the dataset; future studies may incorporate Scopus and other databases to achieve broader literature coverage.

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Author contributions

Shuzhao Wu: Methodology, Software, Data curation, Formal analysis, Writing – original draft, Visualization, Writing – review & editing. Changfeng Jing: Conceptualization, Resources, Supervision, Funding Acquisition, Writing – review & editing. Sheng Yao: Conceptualization, Methodology, Formal analysis, Writing – original draft. Ziyi Zhou: Data curation, Software, Visualization, Formal analysis, Writing – review & editing. Gaoran Xu: Formal analysis, Writing – review & editing. Ying Xiao: Formal analysis, Writing – review & editing. Jiaxing Dong: Formal analysis, Writing – review & editing.

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