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A global systematic review of the remote sensing vegetation indices

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ABSTRACT

Vegetation indices (VIs), with the advantages of being easy to understand, simple form, and robust, have emerged as a pivotal and widespread tool for monitoring and assessing vegetation health and dynamics. Decades of research have produced numerous VIs, broadening their use and impact across various fields, but possibly overwhelming users with too many options. This study conducted a bibliometric review of VI-related literature in the web of science (WOS) database since 1986, examining current trends and issues in data sources, geographic areas, eco-functional areas, applications, and technical methods. It also analyzed the correlation among 86 VIs from global satellite data and assessed the sensitivity of 16 VIs to different parameters using radiative transfer model simulations at leaf and canopy scales. This review revealed that (1) VI research accelerated since 1986, particularly after 2012, largely due to the availability of earth-observing satellite data and new VIs. (2) The central concern of VI is its sensitivity to vegetation parameters, with recent interest in complex terrain effects. (3) VI is difficult to distinguish structural and spectral information. Optimization of soil-adjusted vegetation indices (OSAVI) has the highest sensitivity to leaf area index (LAI), and Sentinel-2 red edge position (S2REP) has the highest sensitivity to chlorophyll among the 16 selected VIs. Overall, VI performance depends on band selection and formula, with an ideal VI balancing sensitivity to vegetation and interference resistance. VI Selection should be tailored to user needs, focusing on relevant vegetation parameters and the study area's conditions.

1. Introduction

Vegetation plays a crucial role in the Earth's ecosystems, influencing climate patterns, carbon cycling, and biodiversity. Understanding the current state and dynamics of vegetation is essential for addressing environmental challenges and managing natural resources effectively. In this context, vegetation indices (VIs), as simple mathematical combinations or reflectance conversions of two or more spectral bands, have emerged as valuable tools for monitoring the status and dynamics of vegetation across different spatial and temporal scales (Huete et al., 2002). They were designed to minimize the influence of confounding factors, including soil background, atmospheric conditions, and sensor characteristics, enabling researchers to focus on vegetation-specific information. VIs can be acquired at different scales, from handheld devices to tower and airborne sensors to satellite sensors, providing measurements ranging from fine to coarse (Pôças et al., 2020; Verrelst et al., 2015; Xue and Su, 2017).

The development of VIs can be traced back to the late 1960 s, when the simple ratio index (SR) was introduced as a proxy for estimating vegetation cover. Since then, a plethora of VIs have been proposed and tailored to address specific research questions and challenges, including VIs that are widely used in the characterization of vegetation greenness (e.g., normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI)), as well as more specialized VIs that capture specific vegetation properties (e.g., chlorophyll, leaf area index (LAI)) or account for the effect of non-vegetation confounding factors (e.g.,

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background, atmospheric, or terrain). Over the past decades, the scientific community has made significant efforts to evaluate and refine VIs, leading to a better understanding of their strengths, limitations, and applications. Previous studies have focused on assessing the performance of different VIs for characterizing vegetation parameters in different ecosystems and exploring their potential in various fields such as agriculture, ecology, forestry, and climate change studies (Carmona et al., 2015; Gao et al., 2024, 2023; Liu et al., 2021; Tangen et al., 2022; Yan et al., 2020). Additionally, with the advancement of remote sensing technologies and the availability of high-resolution satellite imagery, the VIs study has entered the era of big data, and its applications have been combined with data-driven techniques, such as machine learning, deep learning, and artificial intelligence, to achieve accurate monitoring and mapping of vegetation at regional and global scales (Ferchichi et al., 2022; Zhang et al., 2021).

VIs play an essential role in providing vegetation information and attract attention from ecological researchers as well as industrial communities around the world. Encouraged by important findings derived from VIs, a large amount of research has been devoted by the scientific community in the areas of development of new VI, evaluation of existing VIs, and their application in ecology over the past five decades. However, in the face of hundreds of VIs, how users can make a suitable choice according to their needs is a very important issue. In addition, due to the different performance of different VIs, the same study on the same area may lead to different conclusions. For example, the debate about "seasonality in the Amazon" has led to opposite conclusions based on EVI and NDVI (Morton et al., 2014; Saleska et al., 2016; Samanta et al., 2012). Past research in the VI field has inspired us and encouraged us, but also confused us. What findings have we made in the past few years of research in the VI field? What do these findings tell us about user choice and the future of VI research? Perhaps it is time to review past publications related to VIs and provide a comprehensive overview of research related to VIs from a user's perspective.

Many excellent reviews of VI studies exist, focusing on specific VI or applications in specific domains (specific information is summarized in Supplementary). For example, comprehensive evaluations of NDVI in ecological and environmental contexts elucidate its diverse applications, including animal ecology (Pettorelli et al., 2011), land degradation assessment (Yengoh et al., 2016), and time series reconstruction techniques (Li et al., 2021). Additionally, a substantial body of literature examines the role of VIs in agriculture, with a particular emphasis on precision agriculture (Giovos et al., 2021; Radočaj et al., 2023; Vélez et al., 2023), highlighting their pivotal contribution to enhancing agricultural productivity and sustainability. Moreover, several reviews provide an extensive historical overview and broad utilization of VI (Bannari et al., 1995; Glenn et al., 2008; Huete, 2014; Zeng et al., 2022). The findings from these VI reviews are both informative and significant. Nonetheless, given the substantial advancements in VI research in recent years (such as the introduction of kernel NDVI (kNDVI), improved evaluations of VI performance, the development and accessibility of hyperspectral data, and the integration of artificial intelligence), an updated *meta*-analysis review is warranted.

Bibliometrics is an effective research tool to summarize information on topics, current knowledge, knowledge gaps, and potential applications in a given research area. This paper systematically analyzes VI-related publications from the web of science (WOS) core library (Details of the methods are given in the Appendix), to grasp the overall development trend of the VI field by analyzing the authors, institutions, countries, as well as the research hotspots and cutting-edge changes. Moreover, this review examines the current status and key issues in VI studies, encompassing data sources, geographic regions, ecological functional zones, applications, and various technical methodologies, and also highlights factors affecting VI performance such as the atmosphere, background, sensors, and bi-directional effects.

To meet the increasing VI numbers and requirements of applications, the assessment of their performance has gradually become an integral part of the VI field (Gao et al., 2023; Leprieur et al., 1994; She et al., 2015; Wu et al., 2014, 2008; Xiao et al., 2003; Yan et al., 2020). Sensitivity analysis plays a crucial role in assessing the VIs' performance, which helps to identify the influential factors and guide the direction of VI optimization (Xiao et al., 2014; Zhang et al., 2023). It can be divided into two sorts: local approaches and global approaches. Global sensitivity analysis (GSA) evaluates the effects of individual parameters and their interactions and is commonly applied in complex mechanistic models like the extended fourier amplitude sensitivity test (EFAST) (Gu et al., 2016). Combining GSA with computer simulation provides a comprehensive and efficient strategy for evaluating the VI performance. This review used SIMLAB software to generate 4,950 sets of input parameters for the PROSPECT-D model (leaf-scale) (Féret et al., 2017), and 7,931 sets for general spectral vectors (GSV) model and the large-scale remote sensing data and image simulation framework (LESS) model (canopy-scale) (Qi et al., 2019) to construct a simulation dataset, and employed the EFAST method to evaluate the sensitivity of Sentinel-2 Multispectral Instrument (MSI) sensor band reflectance and 16 selected VIs to parameters at leaf and canopy scales.

The purpose of this review is to comprehensively understand VI from the perspective of users, to explore the way to select the most suitable VI according to practical application requirements, and to provide a scientific basis and guidance for the in-depth development of the VI field. Specifically, (1) trace the historical evolution of literature related to VI and evaluate global research interest and productivity; (2) explore several thematic clusters to examine research topics and concerns related to VI applications over the decades; (3) combine band utilization statistics, correlation analysis, and sensitivity analysis to discuss the applicability of different VIs. Finally, an outlook and potential future research directions are presented.

2. Current status of VI-related studies

This section outlines the historical trajectory of VI research since 1986, accompanied by a timeline of the emergence of satellite sensors and significant VIs since 1969, and assesses the global research interest and productivity in VI via bibliometric analytic frameworks from country, institution, and hematic developments perspectives.

2.1. Trend of publication outputs

The number of publications in the research field is highly correlated with the development of scholarly activity and interest, which represents the future trends and direction of this field (Shen et al., 2022). Fig. 1 shows the number of annual publications related to the VI study. The first relevant paper recorded in the WOS database was in 1986. Overall, the number of studies published annually on VIs has steadily increased during the recorded period and can be divided into four stages. In the initial stage (1986 – 2002), the VI studies did not receive extensive attention from academia, with fewer than 60 papers per year. Most of the studies during this period focused on event-based case studies using observations from Landsat (Irons et al., 2012), advanced very high resolution radiometer (AVHRR) (Politi et al., 2012), and satellite for earth observation (SPOT) (Maisongrande et al., 2004) which provided the longest temporal records of space-based observations. In the early-middle developmental stage (2003 – 2012), there was a significant expansion of annual publication numbers, which can be explained by the introduction of the important VI – EVI and the availability of moderate resolution imaging spectroradiometer (MODIS) data (Huete et al., 1994). After 2013, the number of papers increased rapidly with an average annual growth rate of 14.8 %, indicating that the VI research entered a booming development phase. The emergence of new satellite sensors with more spectral channels (i.e., Sentinel) and the proposal of new VIs (i.e., chlorophyll/carotenoid index (CCI), near-infrared reflectance of vegetation (NIRv), kernel normalized difference vegetation index (kNDVI)) have contributed to the prosperity of VI

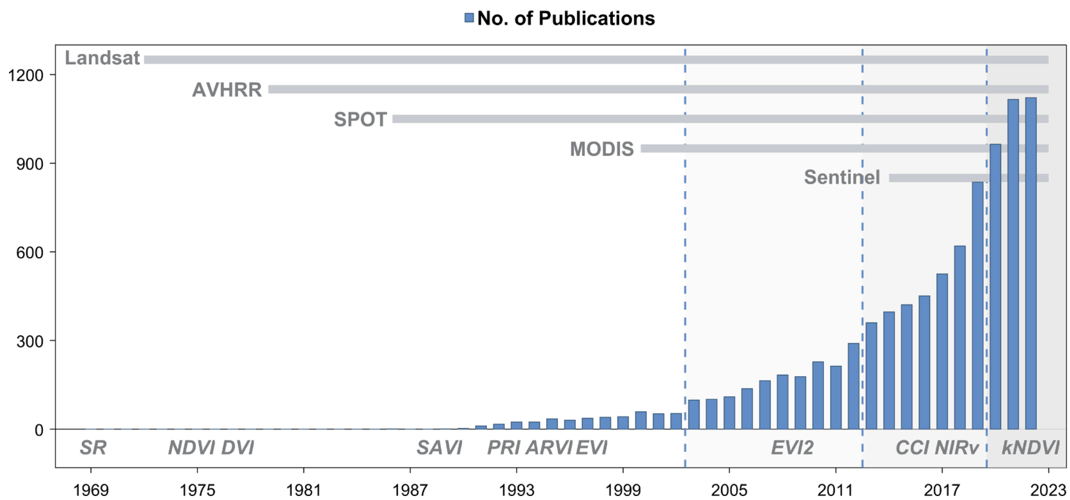

Fig. 1. Number of annually published papers on vegetation indices (VIs) studies from 1969 onwards and timeline of the primary use of satellite sensors and VIs. The reason for setting 1969 as the initial year was that the first VI was the simple ratio (SR) proposed by Carl F. Jordan in 1969 (Jordan, 1969). NDVI, normalized difference vegetation index (Rouse and Haas, 1974); DVI, difference vegetation index (Richardsons and Wiegand, 1977); SAVI, soil-adjusted vegetation index (Huete, 1988); PRI, photochemical reflectance index (Gamon et al., 1992); ARVI, Atmospherically Resistant Vegetation Index (Kaufman and Tanre., 1992); EVI, enhanced vegetation index (Huete, 1997); EVI2, two-band version of the enhanced vegetation index (Jiang et al., 2008); CCI, chlorophyll/carotenoid index (Gamon et al., 2016); NIRv, near-infrared reflectance of vegetation (Badgley et al., 2017); kNDVI, kernel normalized difference vegetation index (Camps-Valls et al., 2021).

research.

2.2. Country and institution distribution

The number of VI-related publications showed an obvious spatial distribution in regions (Fig. 2). Most VI studies were concentrated in the northern hemisphere, mainly in China (32.2 % of the worldwide research output) and the United States (28.5 %). Europe has also done well in VI research, especially in Germany, Spain, and Italy, with more than 400 publications. In the southern hemisphere, only Brazil and Australia have produced considerable outputs in the VI field (≥300 publications), probably due to their unique ecological environment and rich plant resources, as well as their economic and scientific base. Furthermore, the results clearly showed that the United States has the strongest cooperative relationships with China, Canada, Brazil, and Australia, which resulted in the highest number of co-authored articles. The Chinese academy of sciences (CAS), the university of CAS, and Beijing Normal University had the highest number and the highest intensity of collaboration (Fig. 3). It should be noted that due to the lack of specific information on collaborative projects, the results rely solely on the authors' affiliations and may not accurately reflect the true state of institutional and international cooperation. These findings should be considered as indicative rather than definitive.

2.3. Subjects and journals distribution

Analysis of journals and disciplines has been widely used to study the interdisciplinary structure of a given academic field, identify key relevant research areas, and provide recommendations for journal submissions (Xu et al., 2022). The top category is environmental science

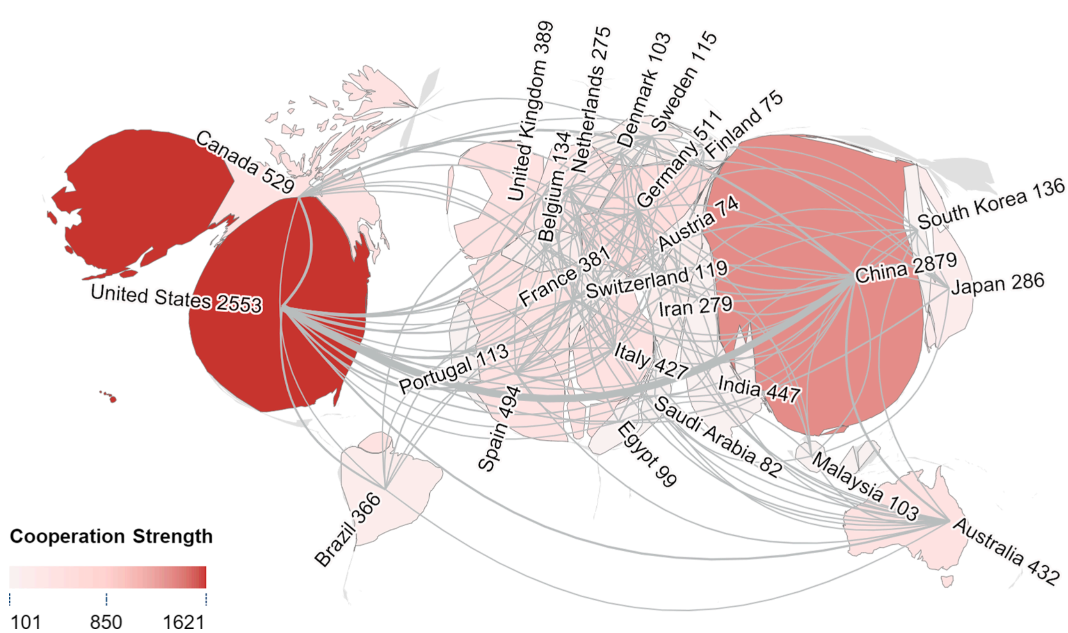

Fig. 2. Global distribution of the publication number and collaboration intensity in the VI field for the 25 most prolific countries. In this cartogram, the size of the regions represents the number of publications. The connecting lines number and the fill color of the regions indicate the strength of collaboration.

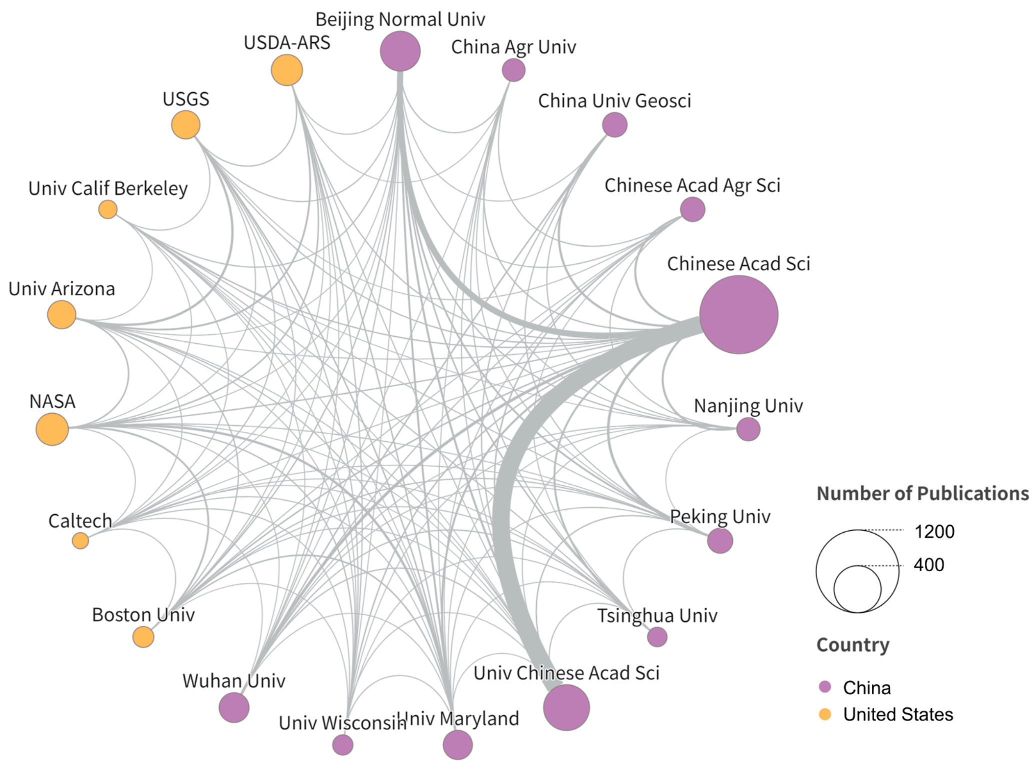

Fig. 3. Collaborative network of institutions with more than 40 publications. Each circle represents an individual unit as a whole, the size of the circle represents the publications number, the color represents the affiliated country, and the thickness of the line connecting the two circles is directly related to the strength of their collaboration.

(46.40 % of all publications), followed by remote sensing (35.87 %), image photogrammetry (34.01 %), geodiversity (10.76 %), and ecology (10.19 %). Other important disciplines include agronomy and geography.

Table 1 lists the top 15 journals with the most publications in the VI field, along with their CiteScore, impact factors (IF), and h-index. The CiteScore reflects the academic impact of a publication, and the h-index as well as the IF highlights the relative importance and academic influence of a journal in a related field (Wang et al., 2021). The top 15 journals with the highest article count accounted for 45 % of the total number of articles. "Remote Sensing" is the most productive journal with a total of 1,305 articles, much higher than the second place " Remote Sensing of Environment" with 529 articles, but its CiteScore is only one-third of that of the latter. "International Journal of Applied Earth Observation and Geoinformation" and "ISPRS Journal of Photogrammetry and Remote Sensing" also have a good overall performance with high CiteScore and publication counts. In addition, the high level of interest in the VI field, as seen in international multi-disciplinary natural science journals such as "Science of the Total Environment" and "Sustainability" indicates that the VI field is a cross-cutting discipline.

2.4. Research evolution analysis

As a high generalization of the paper content and label of disciplinary information, keywords can highly summarize and reveal the thematic features and research directions of publications (Wen et al., 2022). Keyword analyses (e.g., burst words detection, and co-occurrence analysis) are also the core for conducting bibliometrics in a specific field, which helps us to grasp the development of research hotspots better. Kleinberg's algorithm was employed as a burst detection approach to proficiently identify abrupt increases in word frequency and to detect fluctuations in keyword popularity over time (Kleinberg, 2002). Additionally, co-occurrence analysis reveals latent connections and thematic clusters within complex datasets by examining the frequency and patterns of concurrently occurring elements across various disciplines (Chen, 2017). Fig. 4 shows a time zone map of burst high-frequency keywords in the VIs studies from 1986 to 2022, which gives the researcher a quick overview of the topic evolution. In the initial period, most publications in the VIs field were accompanied by the emergence of new sensors and publicly available satellite sensor datasets, such as Landsat. Due to the limitations of satellite re-launch intervals and time accumulation of datasets, researchers mostly focused on spatial analysis. This was followed by the dramatic increase of academic interest in biochemical and physiological parameters retrieval based on VI, which has mainly undergone a shift from structural parameters (e.g., LAI, fractional vegetation cover (FVC), biomass) to biochemical parameters (fluorescence, light use efficiency (LUE)). With the increasing availability of earth observing system (EOS), researchers have also started to pay more attention to dynamic changes, involving topics of time series such as "phenology" and "climate change". In addition, the wavebands required for VI construction have gone through the classical broadband, such as red, near-infrared (NIR) band, to combined red-edge bands and shortwave-infrared (SWIR) bands that have great potential in vegetation mapping, and finally to the narrow contiguous band from hyperspectral imagery that contains a great deal of information. Machine learning is a topic that has received enormous attention in recent years, which facilitates the research and application of VIs (Johnson et al., 2016; Mountrakis et al., 2011; Rumpf et al., 2010). Besides, the advanced geographic information processing platform – google earth engine (GEE) dramatically reduces the cost and time to obtain satellite data and allows users to overcome computational limitations while exploring more comprehensive relationships between VIs and vegetation parameters at large scales (Kong et al., 2019; Tamiminia et al., 2020).

3. Cluster analysis of VI studies

This section explores thematic clustering in VI research by manually

Table 1
Top 15 journals for VI research papers (ranked by publication count).

No.	Journal	Counts	CiteScore	IF (In 2024)	H-index
1	Remote sensing	1305	7.9	5.0	81
2	Remote Sensing of Environment	529	24.8	13.5	238
3	International Journal of Remote Sensing	496	6.5	3.4	151
4	International Journal of Applied Earth Observation and Geoinformation	229	10.2	7.5	76
5	ISPRS Journal of Photogrammetry and Remote Sensing	180	19.2	12.7	110
6	Journal of Applied Remote Sensing	160	3.4	1.7	39
7	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	154	6.4	5.5	64
8	Agricultural and Forest Meteorology	143	10.7	6.2	144
9	Sensors	141	6.8	3.9	132
10	Ecological Indicators	122	10.3	6.9	97
11	Science of The Total Environment	119	16.8	9.8	205
12	IEEE Transactions on Geoscience and Remote Sensing	119	10.9	8.2	216
13	Computers and Electronics in Agriculture	118	13.6	8.3	96
14	Environmental monitoring and assessment	111	4.5	3.307	91
15	Sustainability	100	5	3.889	136

*Citation Score represents the cited times in the whole wos database. Impact Factor (IF) is a five-year IF from the journal Citation Reports of 2019. H-index is from google scholar metrics, which means there are h publications with at least citations in this journal, and it is not influenced by extreme values such as an average.

organizing keywords (Fig. 5), avoiding trivial terms, and discussing core themes such as data sources, geographic regions, eco-functional zones, applications, and other related technologies (Fig. 6), to provide a wide range of ideas and potential research topics for VI users.

3.1. Cluster 1 – data sources

The data used in the literature related to VIs are mainly from satellite sensors, airborne sensors, ground data, and model simulation data. Among the keywords involving data sources, satellite data have the largest share, which is due to the ability of satellite data to obtain terrestrial vegetation characteristics on a large scale. The most commonly used satellite sensors are shown in Fig. 7a.

Landsat series data (spatial resolution: 15, 30, 100 m; temporal resolution: 16 days; number of available bands and their ranges: 11 bands, 0.4um – 12.5um; available time: 1972 to present) and MODIS data (250, 500, 1000 m; 1 – 2 days; 36 bands; 0.4um – 14.4um; 1999 – present) are most commonly used because of their ability to provide long time-series data profiles and high revisit intervals for operational vegetation detection applications. In addition, the combination of MODIS and Landsat is often used to improve the radiometric and temporal resolution of the data (Potapov et al., 2008; Wu et al., 2016). The Sentinel satellites (10, 20, 60 m; 5 days; 13 spectral bands, 0.43um – 12.5um; 2015 – present) have received more focused attention in VI studies in recent years due to the improved spatial, temporal, and spectral (especially the introduction of the red-edge band) resolution, and the adoption of a free and open access policy (Frampton et al., 2013). Sentinel-2 MSI is designed to enable the continuation of SPOT and Landsat type data into the future. The NOAA AVHRR (1.1 km; < 1 day; 5 bands, 0.58 to 12.5 μm, 1981 – present) has provided a valuable accumulation of data for monitoring global changes, but has been used infrequently in recent years due to limitations in resolution and the sensor degradation (Kalluri et al., 2021). The WorldView-4 satellite (<1 day revisit frequency; 2016——2019) provides high-resolution images with 31 cm resolution in panchromatic mode and 1.24 cm resolution in multispectral mode and allows simultaneous acquisitions to eliminate time lags. Regrettably, however, on January 7, 2019, the WorldView-4 satellite was retired due to its control moment gyros failure (Guo et al., 2020). Most commonly used sensors are moderate to high-resolution multispectral sensors, with the exception of the Hyperion EO-1, which is a hyperspectral sensor. Compared to widely used multispectral platforms such as Landsat or Sentinel-2, Hyperion EO-1 (30 m; 16 days; 242 bands, 0.35——2.5um, 2000——2017) has a great potential to accurately retrieve vegetation parameters as it can detect more subtle differences in canopy reflectance than multispectral data (Bradter et al., 2020). The disadvantages of hyperspectral data are its limited availability, particularly at very high spatial resolutions, and the lower signal-to-noise ratio that may occur with narrow bandwidths (Thenkabail et al., 2014). The advanced microwave scanning radiometer for the earth observing system (AMSR-E) is a six-frequency dual-polarized total-power passive microwave spaceborne radiometer that observes water-related geophysical parameters, often in combination with VIs to support global change monitoring (Grant et al., 2016; Kawanishi et al., 2003). Overall, the Sentinel data may be the most promising for future applications due to its good overall performance, while the Hyperion EO-1 hyperspectral data have great potential for future VI research, especially in precision agriculture. Furthermore, the high resolution, multispectral, and rapid updating capabilities of regional satellite data, such as the Indian remote sensing (IRS) satellite series (1988 – present) (Ray et al., 2021) and China's Gaofen (2013 – present) and Ziyuan (2011 – present) series data (Dai et al., 2022; Yu et al., 2022), provide timely data for natural disaster prevention and control, climate change monitoring, and agricultural support. For example, India has completed nationwide land degradation mapping using IRS LISS-III data, identifying key areas affected by soil erosion and desertification, which provides an important basis for sustainable land management (Joshi et al., 2006).

Directly computed satellite-derived VIs without any bias or assumptions about land cover classes, soil types or climatic conditions help us to better understand the global distribution of vegetation types and their biophysical and structural properties, as well as spatial and temporal variability. Several global medium-resolution (10 m to 15 km) VI products have been generated in the past decades (Table 2). However, it should be noticed that the VI products generally include only two commonly used VI, i.e., NDVI and EVI, which are far from meeting practical needs. There is an urgent need to produce more VI products with high quality to support ecological research. The application performance of VIs has significant regional variability, with existing NDVI products showing excellent performance in temperate zones but failing to adequately capture vegetation dynamics in alpine and tropical regions (Fathollahi et al., 2024; Liu et al., 2023). Improvements in satellite sensor degradation, product continuity, and integrity are continually being explored to provide better-quality satellite products and thus better surface monitoring and decision-making.

3.2. Cluster 2 – geographic areas

We counted geographic study areas with specific geographic locations from keywords, and the results showed that the choice of the geographic area for research was closely related to its ecological value and scientific research resources and level (see Fig. 7b). There are 13 geographic regions mentioned more than 30 times, four of which are related to China, accounting for 55.63 % of the total number of times, i.e., 'China' (363), 'Qinghai-Tibet Plateau' (117), 'Loess Plateau' (60), 'Inner Mongolia' (57). The Qinghai-Tibet Plateau, known as the roof of the world, has become a hotspot for research on the vegetation dynamic

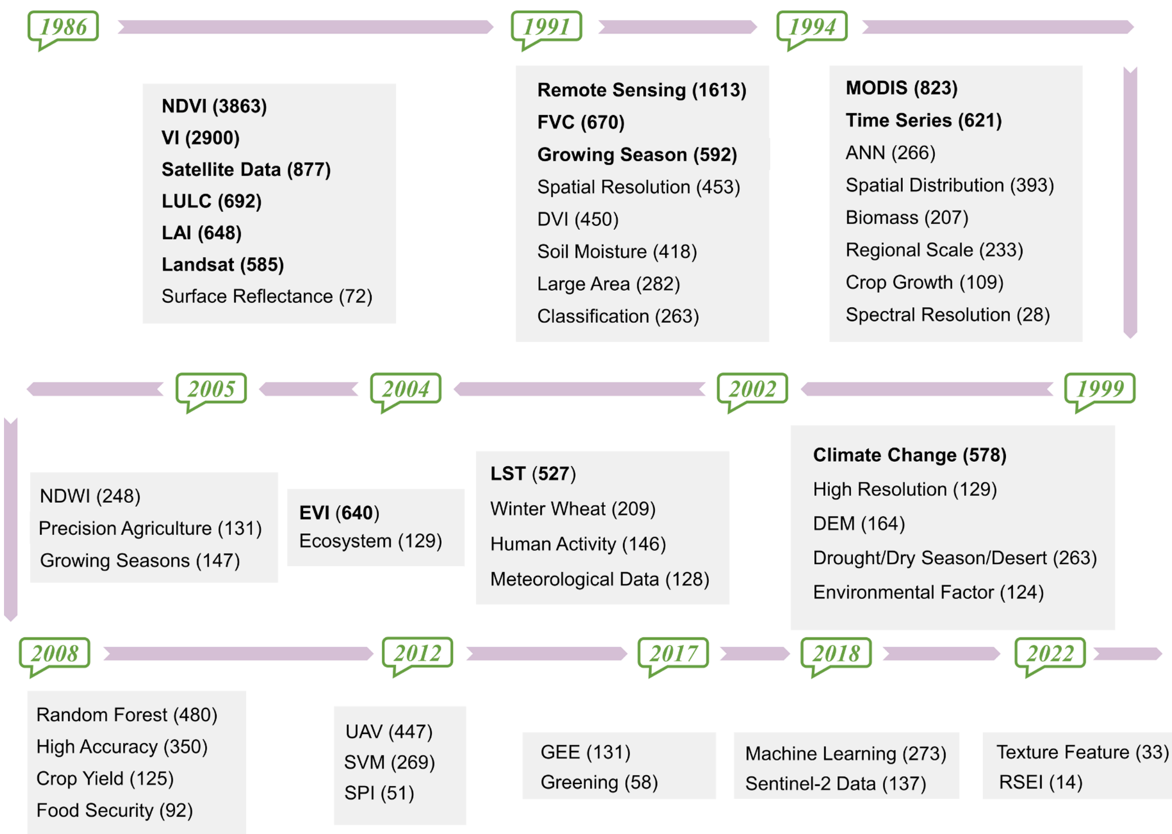

Fig. 4. Burst keywords related to VI studies and occurrence numbers from 1986 to 2022. The burst keywords were arranged in chronological order. Bold font represents super hot keywords with more than 500 occurrences. The purple color represents the year range of the burst keyword. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

response and has been extensively studied (Deng et al., 2022; Ma et al., 2018). The Loess Plateau of China is a typical area of land degradation due to soil erosion, and vegetation restoration is the most effective biological means to address the degradation of the Loess Plateau ecosystem. Large-scale afforestation will reduce streamflow in the semi-arid Loess Plateau lands of northern China and, to some extent, contribute to the recent drought in southwestern China (He et al., 2023; Jiang et al., 2019). Inner Mongolia is an important pastureland in China, part of the Eurasian temperate steppe zone, rich in grassland resources well as a hotspot for grass resource management and vegetation monitoring (Lyu et al., 2021; S. Wang et al., 2023). In addition, Africa and the United States have received considerable attention. The Central Great Plains of the United States is dominated by agricultural land, and its intensive management and continued transformation can rapidly change land cover patterns and affect climate, ecological processes, and the economy, so it often serves as a focal research platform for agricultural management (Wardlow et al., 2007; Zhou et al., 2017). The Boreal region refers to a vast expanse of coniferous forests, mire, and lakes circling the northern hemisphere, and it includes most of Sweden and Finland, all of Estonia, Latvia and Lithuania, and much of the Baltic Sea. Amazon rainforest, is a large tropical rainforest occupying the drainage basin of the Amazon river and its tributaries in northern South America and covering an area of 6,000,000 km^2. The Boreal region and the Amazon are typical study areas for coniferous and tropical rainforests, respectively (Jarvis and Linder, 2000; Saleska et al., 2016, 2007).

3.3. Cluster 3 – Eco-function areas

Each eco-functional zone represents a unique set of vegetation types or land cover types. Most of the keywords for VI-related research focused on vegetation and farmland, accounting for 48 % and 28 %, respectively (Fig. 7c). Among them, forests involved the most information on keywords, including 'tropical forests', 'Deciduous Forest', 'Boreal Forest', 'Forest', 'tree'. The focus on arid and semi-arid regions is also high, accounting for 13 % of all keywords for ecologically functional regions. It is worth noting that VI research's focus on areas that are not purely vegetated, such as wetland areas, has gradually increased in recent years (Taddeo et al., 2019; Tangen et al., 2022). This indicates a gradual shift of the scientific community's attention to the interactions among ecosystems.

3.4. Cluster 4 – vegetation parameters and VIs application

Based on the word cloud data (Fig. 5) provided for Cluster 4 – Application, we can see that the most frequent keywords include "Climate Change" (1312 times), "LAI" (1232 times), "Land Use/Land Cover (LULC)" (956 times), and "Yield Prediction" (794 times). These keywords reflect the application of VIs in climate change, vegetation parameters retrieval, land use/land cover, classification, and yield prediction. VI can be used as one of the indicators of climate change, and the response and adaptive capacity of vegetation to climate change can be assessed by monitoring the relationship between VIs and climate parameters (Huang et al., 2023; Peñuelas and Filella, 2001; Wohlfahrt et al., 2019; Zhang et al., 2004). Another important application of VIs is to obtain information on the spatial distribution of LULC and to monitor land cover change to support land management and planning (Feng et al., 2023; Lu et al., 2004). Classification and image interpretation are one of the important VI applications. Image classification is also the basis of LULC, which can identify different vegetation species and cover types based on remote sensing imagery to provide information for resource management and environmental monitoring (Foody, 2002). In

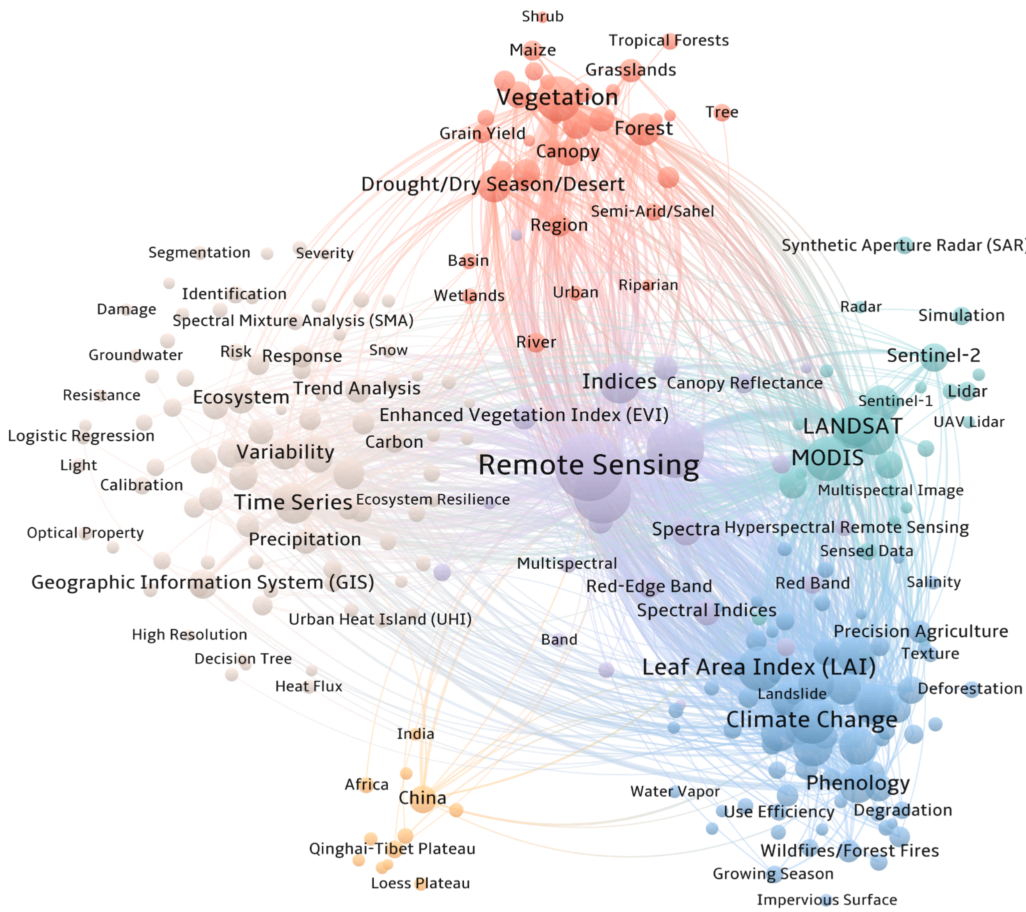

Fig. 5. Keyword clustering and co-occurrence network of all VI literature. The colors represent different clusters, and a total of 6 categories were found. The center part of the keywords (purple) is correlated with the VI establishment. The other 5 clusters are distributed around this center, namely cluster 1 – data sources, cluster 2 – geographic regions, cluster 3 – ecological functional regions, cluster 4 – applications, and cluster 5 – other relevant technologies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

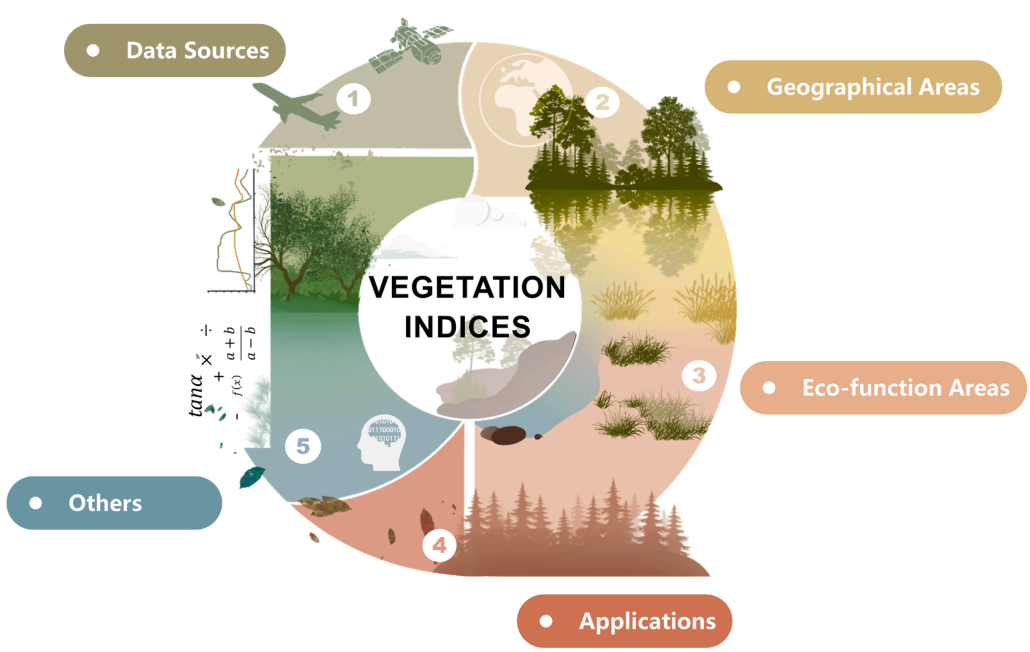

Fig. 6. Conceptual diagram of the VIs-related thematic cluster analysis.

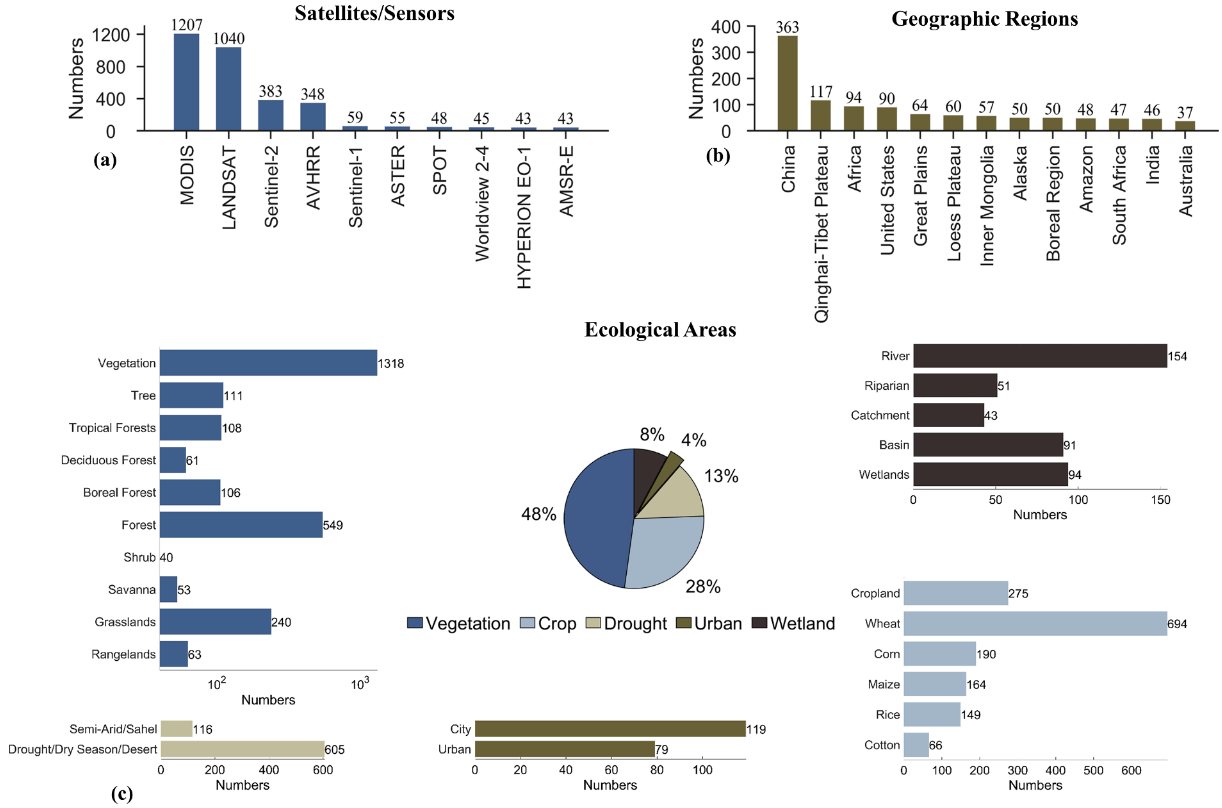

Fig. 7. Frequency statistics on (a) common sensors, (b) geographic regions, and (c) ecological functional areas extracted by keyword clustering of all VIs-related literature.

Table 2
Commonly used global VI products.

Sensors	Products	VI	Spatial-Temporal Resolution	Dates	Data Sources
NOAA-AVHRR	AVR13C1	NDVI	1 d, 0.05 deg	1981—	https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/N11_AVH13C1
	GIMMS		14 d, 1/12 deg	1981–2015	https://daac.ornl.gov/VEGETATION/guides/Global_Veg_Greenness_GIMMS_3G.html
	GVI		7 d, >=15 km	1982—	https://www.star.nesdis.noaa.gov/smcd/emb/vci/gvps/gvps_background.php
Landsat4/5-TM; Landsat7-ETM+	GWELDYR GWELDMO		yearly, 30 m monthly, 30 m	1984–2001	https://lpdaac.usgs.gov/products/gweldmov031/
SPOT-VGT	VGT-S10		10 d, 1 km	1998—	https://dataspace.copernicus.eu/spot-vegetation
PROBA-V	CGLS V3		10 d, 1 km	1999—	https://dataspace.copernicus.eu/proba-v
Terra/Aqua-MODIS	MOD/MYD13Q1	NDVI/EVI	16 d, 250 m	2000—	https://modis.gsfc.nasa.gov/data/dataprod/mod13.php
	MOD/MYD13A1		16 d, 500 m		
	MOD/MYD13A2		16 d, 1 km		
VIIRS	VNP13A1 VNP13A2 VNP13A3 VNP13C1 VNP13C2	NDVI/EVI/EVI2	16 d, 500 m 16 d, 1 km Monthly, 1 km 16-day, 0.05 deg Monthly, 0.05 deg	2011—	https://viirsland.gsfc.nasa.gov/Val/VI_Val.html
PROBA	PROBA-V	NDVI	10 d, 300 m	2016—	https://proba-v.vgt.vito.be/en
Sentinel-2	S2 L1C		5 d, 10 m	2015—	https://sentiwiki.copernicus.eu/web/s2-mission
Sentinel-3-OLCI	Sentinel 3-OLCI		11 d, 300 m	2020—	https://sentiwiki.copernicus.eu/web/s3-olci-instrument

addition, VI is sensitive to different characteristics of plant biophysical, biochemical, and physiological properties, and the most focused vegetation parameters include LAI, chlorophyll, FVC, net primary productivity (NPP), gross primary production (GPP), etc (Zeng et al., 2022).

3.5. Cluster 5 – other VI-related techniques

Other keywords related to VIs research include “Time Series” (829 times), “Variability” (529 times), “Soil Moisture” (468 times), and “Random Forest (RF)” (402 times). By analyzing the time series data of VIs, the seasonal and inter-annual patterns of vegetation changes can be revealed, and thus the response of vegetation to different environmental factors can be understood. The study of spatial variability is also crucial in revealing the ability of vegetation to respond and adapt to environmental changes. By analyzing the spatial and temporal variability of VIs, it is possible to understand the instability of vegetation growth and its sensitivity to external factors (Huang et al., 2020; Liu et al., 2022). In recent years, there has been an increasing interest in the use of artificial intelligence to extract vegetation parameters, with classification and regression using machine learning and deep learning being the main techniques used to process VI data. However, it is important to note that these techniques require large amounts of data and computational resources, as well as careful calibration and validation to ensure accuracy and reliability. Therefore, the use of these technical approaches must be balanced with other tools and prior knowledge to make informed decisions about vegetation status in dynamic and complex environments.

4. Discussion on VI selection

VI performance is co-determined by band selection and mathematical formula. The information characterized by the VI can be divided into two parts according to the design purpose, i.e., Remote-sensed VI = vegetation information + non-vegetation factors disturbance. Vegetation information includes vegetation biophysical (e.g., LAI, leaf angle distribution (LAD) and clumping index (CI)), biochemical (e.g., leaf water content, chlorophyll), energy and functional parameters (e.g., FPAR, GPP). Non-vegetative disturbances include sun-sensor geometry, scale effect, atmospheric effect, topography, and background conditions, etc (Fig. 8). Therefore, the assessment of VI performance is typically conducted in two dimensions: sensitivity to vegetation parameters and resistance to confounding factors. In response to public concerns over the past few decades, this section combined band utilization statistics, correlation analysis, GSA, and computer simulation to discuss the applicability of different VIs.

4.1. VI at different remote sensing resolutions

The spectral characteristics of leaves/vegetation are distinctly different from other features and are the basis for VI construction. Typically, leaves have low reflectance in the visible domain due to strong absorption of photosynthetic pigments by chlorophyll (two main absorption bands: 420–450 nm and 650–660 nm); high reflectance in the NIR band (700–1,300 nm), which is usually due to spongy mesophyll; and low reflectance in the SWIR region (1,300–2,500 nm), which is due to strong water absorption. In addition, other leaf biochemical characteristics, such as lignin, protein, and cellulose content, had less influence on the vegetation spectrum.

The 130 VIs selected in this study were constructed using the most NIR, red band, and green band (Fig. 9). The Aerosol band was less frequently used to construct VIs because it is mainly used for atmospheric correction and does not provide vegetation information directly. The combination of red and NIR was the most frequent, followed by the combination of green and red bands. The NIR bands mainly reflect structural parameters such as biomass, and vegetation cover, while the red and green bands mainly assess vegetation health status such as chlorophyll content. By using these bands in combination, more accurate vegetation information and more comprehensive analysis results can be obtained. In recent years, the red-edge band and the short-wave infrared band have also attracted the attention of researchers. The red-edge band is a specialized spectral band within the vegetation spectrum, recognized for its heightened sensitivity to variations in numerous

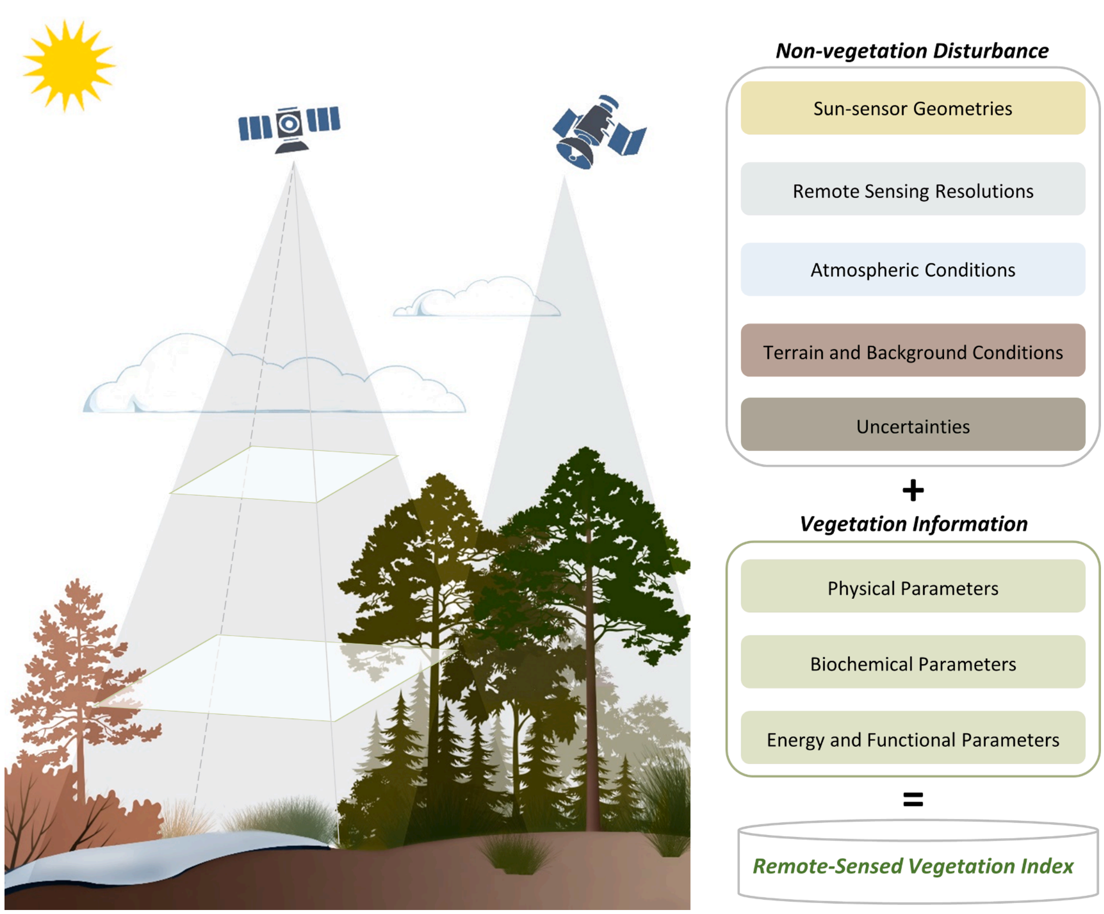

Fig. 8. The schematic view of concerns in the VIs application.

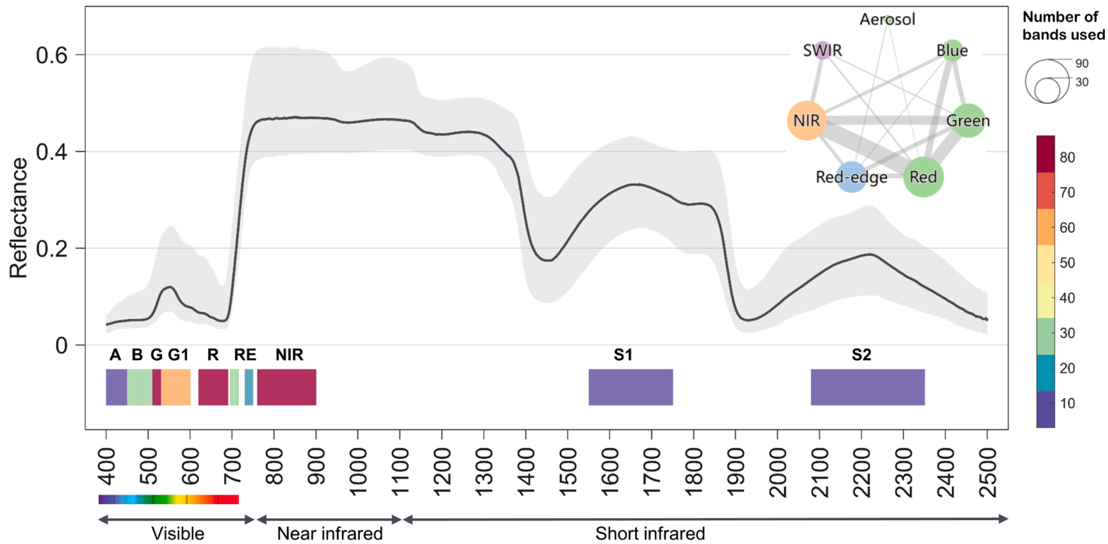

Fig. 9. Vegetation spectral characteristics and co-occurrence network of bands utilized by the 130 VIs. The black curves and gray shading are typical leaf spectra curves in the optical region, based on all data from the leaf optical properties experiment database (LOPEX93) (Hosgood and Jacquemoud, 1995). The colored bands above the x-axis represent the band counts utilized for VI establishment. The subplot in the upper right corner represents the occurrence and co-occurrence of the broadband attributed to the band utilization, the size represents the number of bands used, and the thickness of the connecting line represents the size of the co-occurrence count.

vegetation biophysical parameters, such as photosynthetic/non-photosynthetic FVC (Liu et al., 2022), LAI (Qiao et al., 2024) and chlorophyll content (Eitel et al., 2011), across a range of vegetation densities. It is frequently utilized in conjunction with the green, NIR, and red bands. The SWIR band provides important information on the physical and chemical properties of vegetation, such as vegetation moisture content and soil properties. By using these bands in combination, more accurate and comprehensive information on vegetation and better resistance to the influence of non-vegetation factors can be obtained. For example, atmospherically resistant vegetation index (ARVI) and EVI counteract atmospheric effects by introducing blue bands.

Different remote sensing resolutions (spectral, temporal, and spatial resolutions) need to be considered when selecting a suitable VI, which all play a significant role in the calculation and interpretation of VI. Spectral features involved in VI calculations include the number, location, and bandwidth of spectral bands. Increasing the number of spectral bands offers detailed information on surface vegetation, but the high correlation among neighboring bands leads to challenges in data processing and redundancy. Narrower bands enhance the VI's sensitivity to subtle changes, making them suitable for precision agriculture. However, they exhibit poor robustness, increase data processing complexity, and require higher capabilities from users. Bandwidth is one of the most important factors affecting the accuracy of VI retrieval for vegetation parameters. For instance, research has shown that when using VIs to retrieve LAI, narrow-band VI are more suitable for hyperspectral remote sensing data, while medium- and wide-band VI are more suitable for multispectral remote sensing data (Liang et al., 2020).

Temporal resolution is the time required for a sensor to revisit a previously imaged location and is critical in remote sensing of vegetation due to the daily, seasonal, and annual climatic cycle of vegetation growth. High temporal resolution data allows for more frequent updates of vegetation information, which helps to more accurately monitor changes in vegetation dynamics as well as short-term events such as droughts or pest outbreaks (Brown et al., 2008; Krawchuk et al., 2020). In addition, high temporal resolution data can provide more frequent clear-sky observations, which is especially important in tropical and coastal regions where persistent cloud cover and rainfall limit the frequency with which high quality images can be obtained (Nunes et al., 2022; Yang et al., 2017).

Spatial resolution refers to the smallest detectable unit of a sensor and is a function of sensor height, detector size, focal length, and system configuration. Suitable spatial resolution should satisfy detectability (i.e., detection of a target feature) and separability (i.e., the target feature can be distinguished from other features as a separate entity in the image) (Jensen, 1986; Unger Holtz, 2007). Higher spatial resolution can provide more detailed information on vegetation, which is especially important for analyzing vegetation changes at small scales. However, it also introduces some new problems, in particular shadows caused by topography and trees, and hyperspectral differences within the same land cover class. It is a challenge to fully utilize the rich spatial information available in fine spatial resolution data and to reduce the negative effects of redundant information.

In summary, high temporal, spectral, and spatial resolutions can provide finer vegetation information, but also increase the cost of data processing and storage. The users need to consider the temporal, spectral, and spatial resolutions in an integrated manner, and perform trade-offs and choices according to specific application needs and resource constraints.

4.2. VIs sensitivity to different spatio-temporal resolutions and application considerations

The advancement of remote sensing technology provides an abundant constellation of multi-platform, multi-sensor data, offering diverse spatio-temporal resolutions for vegetation analysis, as previously noted. While enabling extensive studies, the inherent variability in spatial grain and temporal frequency across datasets significantly modulates the calculation, interpretation, and sensitivity of VIs to vegetation properties and dynamics. Understanding how VI sensitivity is influenced by these characteristics is paramount for accurate monitoring and judicious data selection.

Spatial resolution primarily governs VI sensitivity through sub-pixel heterogeneity and scale-dependent effects. At coarser spatial resolutions (e.g., above 250 m for most medium-resolution sensors), intra-pixel signal averaging attenuates the vegetation component, thereby reducing sensitivity, particularly in complex landscapes (Bayle et al., 2021). Scale dependency complicates the cross-resolution transformation of VIs—vegetation parameter models transferability across resolutions due to non-linear aggregation effects (Deng et al., 2007), while ultra-high spatial resolution introduces distinct challenges, such as shadow and texture effects (He et al., 2016). Optimizing spatial resolution is therefore crucial for VI application, and existing studies indicate that resolutions finer than 100 m can effectively balance capturing landscape-scale vegetation variability while minimizing non-linear estimation biases (the loss of NDVI spatial variability) inherent in coarser data (Garrigues et al., 2006). Furthermore, fractal dimension estimation provides a quantitative framework to characterize the spatial complexity and heterogeneity of landscapes, yielding theoretical insights into scale dependency and informing the selection of optimal resolutions capable of resolving essential spatial patterns (Chockalingam and Mondal, 2017; Feng and Liu, 2015).

Temporal characteristics, notably observation frequency and compositing strategies, also profoundly influence VIs sensitivity (Jia et al., 2014; Zhao et al., 2022). High temporal resolution maximizes the potential for capturing rapid vegetation dynamics but necessitates robust methods to mitigate atmospheric contamination (Hashim et al., 2014). Standard synthesis techniques (e.g., 8/16-day MODIS synthesis) reduce noise but inevitably smooth out some of the true short-term fluctuations, potentially reducing the VIs sensitivity to transient events or ephemeral ecological events such as fire-driven deforestation (Kim et al., 2011; Sisheber et al., 2023). This calls for an urgent need to necessary trade-offs, such as date fusion algorithms, to balance the data quality with the ability to capture fine temporal detail, thereby enhancing the sensitivity of VI to monitor specific ecological events (Li et al., 2024). Besides, this limitation simultaneously motivates the development of innovative approaches to extract more specific ecological insights from these readily available, temporally integrated datasets. For instance, Singh et al. developed a deciduousness metric using 16-day composite MODIS NDVI data to assess leaf-fall patterns and their sensitivity to rainfall, showing that specialized metrics can enhance the use of time-integrated VI data for specific monitoring (Singh et al., 2020). Techniques such as time-series principal components in conjunction with fractal dimension measures to quantify the complexity of VI time series and demonstrably improve land cover discrimination in challenging mixed-pixel environments where magnitude-based approaches alone prove inadequate (Chockalingam and Mondal, 2017).

Overall, higher-level applications of VI demand a deep understanding of how their sensitivity is affected by spatial resolution and temporal characteristics. Combining remote sensing dataset attributes (resolutions, quality, available bands) and research methods (e.g., fusion, compositing strategy) with the inherent scale (temporal and spatial) and heterogeneity of the target ecological processes or parameters under investigation is crucial.

4.3. Information decomposition of spectral reflectance and VIs

The objective of the VI design is to enhance the detection of specific vegetation parameters of interest while minimizing the influence of extraneous factors. To identify the spectral bands and VIs that exhibit the highest sensitivity to the target parameters and the lowest sensitivity to confounding variables, the EFAST was employed to evaluate the

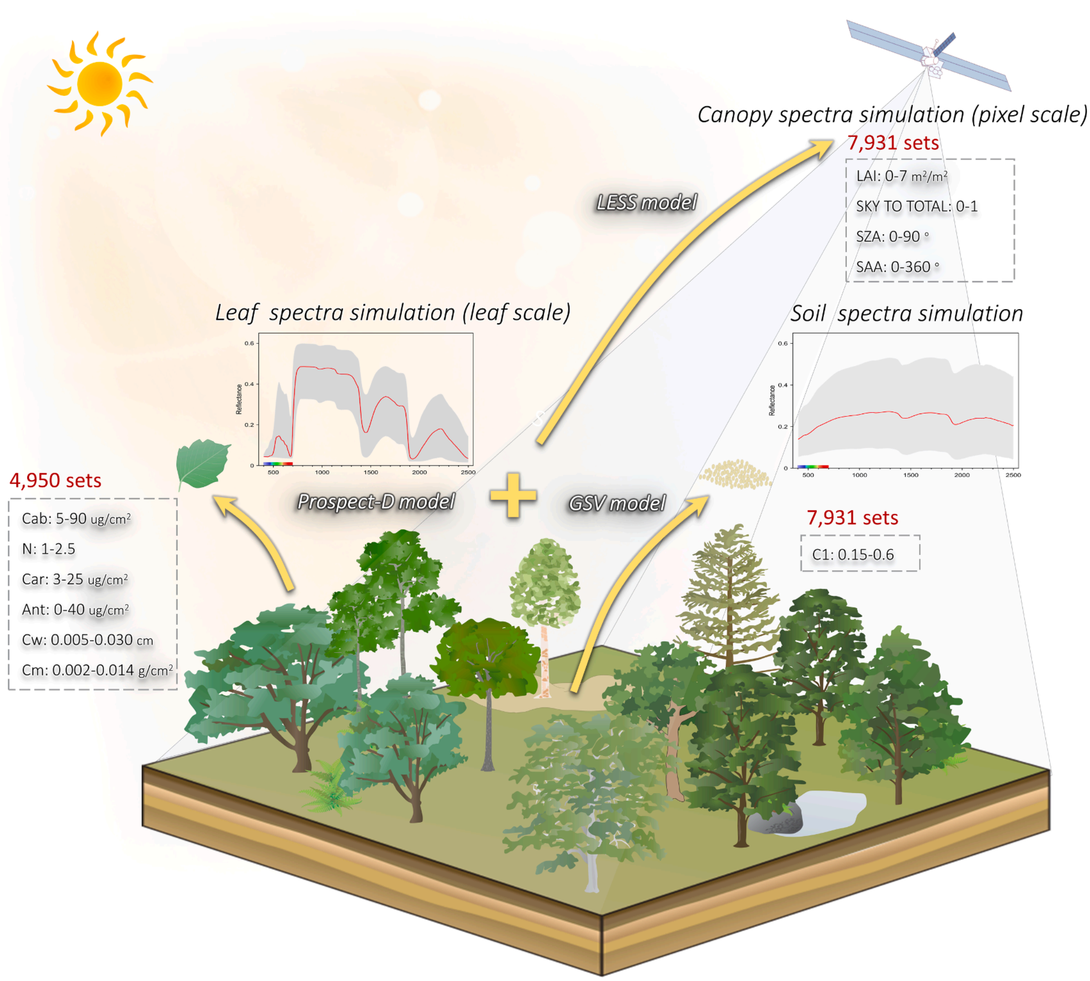

Fig. 10. Conceptual diagram of sensitivity analysis based on radiative transfer modeling. PROSPECT-D model was used to simulate 4950 sets of leaf spectra and GSV model was used to simulate 7931 sets of soil spectra. Soil and leaf spectra were used as inputs to the LESS model to simulate 7931 canopy spectra. Specific parameter information is shown in Table C1.

sensitivity of Sentinel-2 MSI 10 bands reflectance and selected 16 VIs to parameters at leaf scale and canopy scale based on radiative transfer models simulation (detailed experiment information and parameter settings can be found in Appendix C). Fig. 10 illustrates the simulation experiment diagram for sensitivity analysis of Sentinel-2 spectral reflectance and VIs at the leaf scale and canopy scale. The leaf structural parameter N exerts an influence on all bands, particularly exhibiting the highest sensitivity (>85 %) in the red-edge 2, red-edge 3 bands, and the NIR band. This is primarily associated with the multiple scattering effects of photons in the NIR domain. The leaf water content (Cw) contributes approximately 30–45 % of the sensitivity in the SWIR bands, making SWIR frequently utilized for constructing VIs that detect vegetation water content. Chlorophyll $a + \mathrm{b}$ (Cab) is sensitive to visible and the red edge domain, especially the red and red edge 1 bands. Furthermore, the aerosol band is significantly influenced by the coupling effects between parameters, with similar sensitivity magnitudes across all parameters. This indicates that aerosol bands are not suitable for vegetation parameter retrieval due to the complexity caused by the interaction of multiple parameters. Compared to the leaf scale, the interaction of parameters has a greater impact on the sensitivity analysis of canopy reflectance (Fig. 11), accounting for about 20 %. The influence of internal leaf parameters becomes smaller, with LAI contributing the greatest sensitivity (60–70 %) to canopy reflectance in the visible domain, followed by dry matter (C1) and solar zenith angle, collectively contributing about 10 % of the sensitivity (Gao et al., 2024). This also explains why VIs designed to retrieve leaf chlorophyll content find it difficult to fully resist the influence of canopy structure. The SWIR band still shows a certain sensitivity to Cw, but due to the influence of the canopy structure parameter and soil background, the sensitivity decreases significantly.

Compared to the band reflectance at the canopy level, all VIs have reduced the interference from the soil background to a certain extent (Fig. 11(d)). The majority of the selected VIs exhibit a high sensitivity to the structural parameter—LAI. S2REP demonstrates a significant sensitivity of approximately 85 % to Cab within simulated scenarios where LAI ranges from 0 to 7. However, some VIs, such as green normalized difference vegetation index (GNDVI) and chlorophyll index of green (CIG), which were originally designed for leaf chlorophyll retrieval, show greater sensitivity to anthocyanins than to Cab. This increased sensitivity to anthocyanins is suspected to result from the introduction of green bands that are particularly influenced by anthocyanins. Additionally, structure-related VIs like infrared percentage vegetation index (IPVI) and NIRv display high sensitivity to LAI in simulated scenarios. Nevertheless, the saturation effect of VIs with increasing LAI cannot be ignored.

4.4. Global spatial correlations of existing VIs

Correlations between 83 broadband VIs worldwide in August 2020 were calculated based on MODIS MCD43A4 reflectance data to explore similarities and differences between VIs. As can be seen from Fig. 12 (a), there are positive correlations between most VIs, but the relationship between some indices and the rest of the indices shows a strong negative correlation, such as red chromatic coordinate (RCC), which is determined by its mathematical form, decreasing with vegetation increase. Overall, the 83 VIs can be grouped into three broad categories labeled on the heat map. Among all VIs, GRVI and CIG, green–red normalized difference vegetation index (GRNDVI) and NormNIR, IPVI and transformed vegetation index (TVI), modified chlorophyll absorption reflectance index1 (MCARI1) and modified triangular vegetation index1 (MTVI1), MCARI2 and MTVI2, modified green red vegetation index (MGRVI) and normalized green red difference index (NGRDI), and

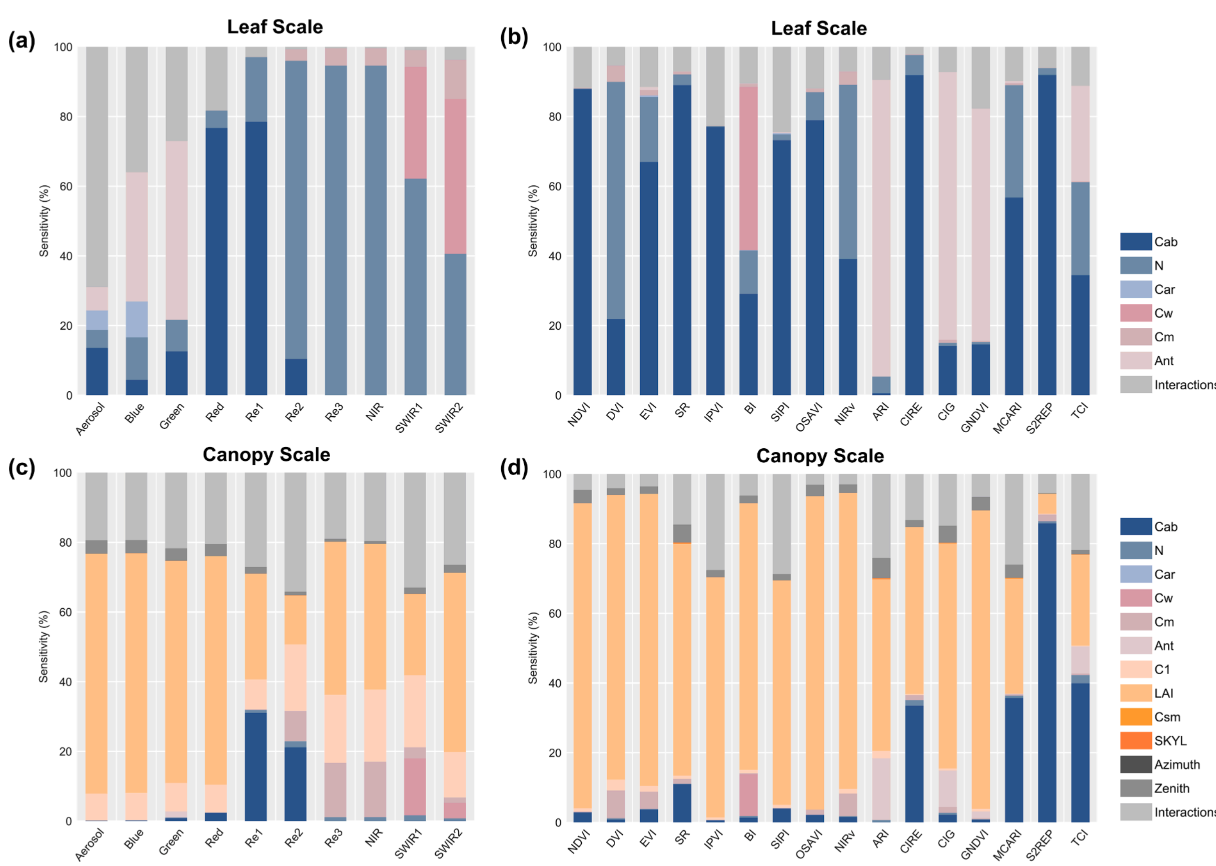

Fig. 11. GSA of Sentinel-2 MSI bands and VIs to the parameters at leaf and canopy scale based on the EFAST method. The explanation of each model parameter can be found in Table C1.

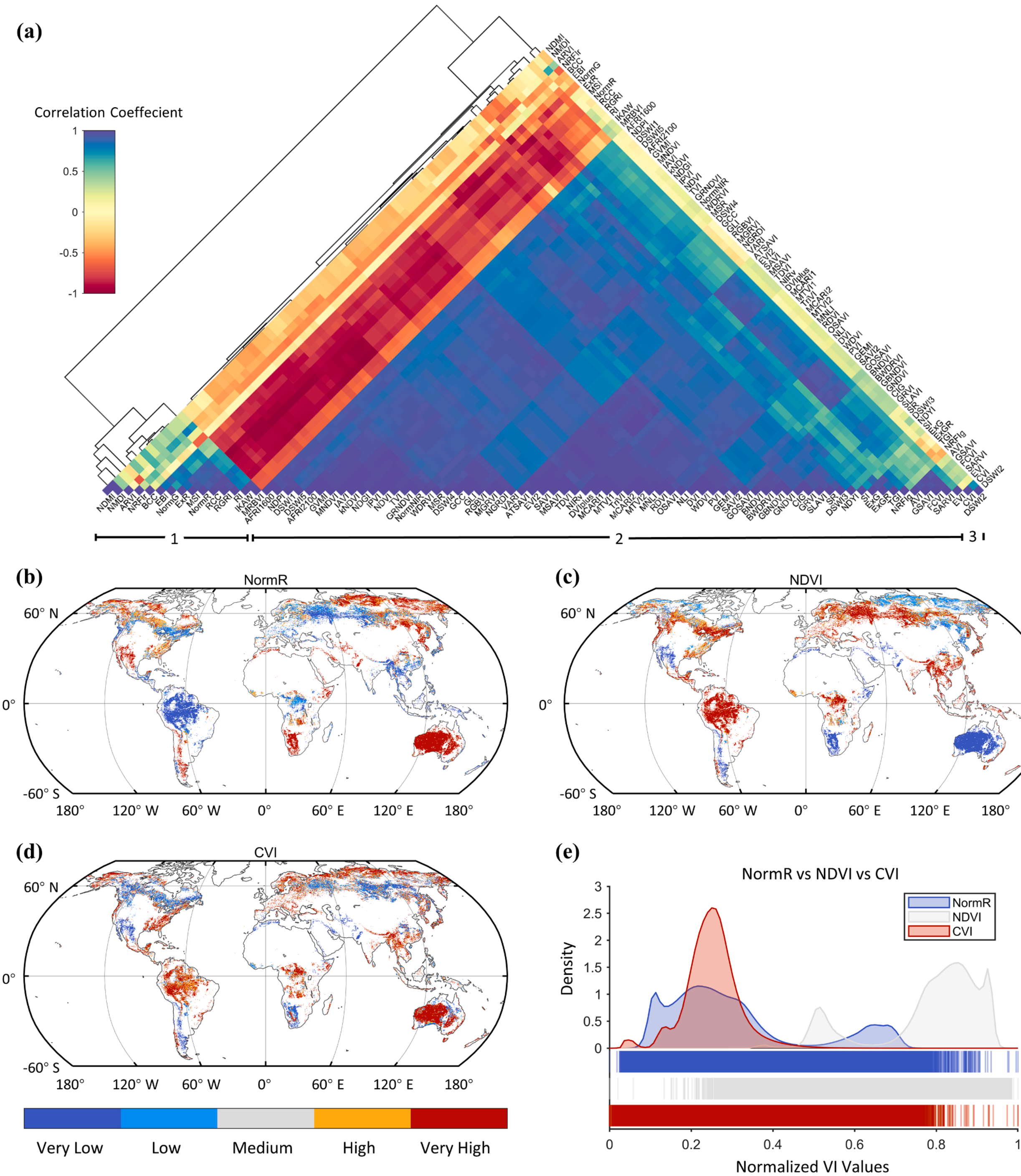

Fig. 12. (a) Global spatial correlation of 83 vegetation indices obtained in August 2020 from MODIS reflectance data. (b) Median composition values of NormR, (c) NDVI and (d) CVI in 2020. (e) Comparison of the global distribution of NormR, NDVI and CVI values. Please note that these results are only applicable to MODIS sensors, and results from other sensors may vary due to different band settings and atmospheric correction algorithms of different sensors.

difference vegetation index (DVI) and perpendicular vegetation index (PVI) and wide dynamic range vegetation index (WDVI) have the highest correlation. This suggests that there is a strong similarity in the performance of these indices in detecting vegetation and that they can be interchanged when applied.

It is worth noting that EVI, which is verified to have excellent performance in vegetation detection, has correlations below 0.7 with most indices, and the highest correlation with its substitute, EVI2, at only 0.73. We conjecture that this may be due to the fixed parameters (i.e., $L = 1$, $C1 = 6$, $C2 = 7.5$, and $G = 2.5$) and the fact that EVI has a combined resistance to both atmosphere and soil. Although there have been detailed evaluations of EVI with LAI and NDVI for different regions and vegetation types, and concluded that the fixed parameters of EVI can be used globally with good performance in most regions (Huete et al., 2002). However, due to the complexity of the environment, e.g., soil and atmospheric disturbances, fixed parameter settings on small-scale studies may have an impact on the EVI results. On the contrary, the correlation between EVI2 and the other VIs is very strong, so we further hypothesize that the blue band is responsible for the low correlation between EVI and other VIs. This result is specific to MODIS sensors and is not generalizable because different sensors use different band configurations and atmospheric correction algorithms. In addition, differences in temporal, spatial, and spectral resolution of different sensors can also affect the performance of these indices, as discussed in the previous section.

We subsequently selected representative VIs from the three categories: NormR, NDVI, and CVI. Notably, the performance of these three VIs exhibits variability. For instance, in the Amazon region, NormR is observed to be low, whereas both NDVI and CVI are high. Conversely, in Australia, both NormR and CVI are elevated, while NDVI is low. This discrepancy can be attributed to the distinct information encapsulated by each VI. NDVI is typically employed to assess overall vegetation growth, whereas CVI demonstrates heightened sensitivity to chlorophyll content. The appropriate utilization of VIs can enhance our comprehension of global vegetation dynamics, like in Australia, where vegetation is sparse but has high chlorophyll levels.

4.5. Selection of appropriate VI

The selection of the optimal VI should combine the ability to accurately portray vegetation and improve resistance to non-vegetation disturbances. These issues were taken into account by the researchers when constructing the VIs. We extracted and clustered the keywords for these 130 literatures, and categorized the VI concerns in the form of bar charts (Fig. 12). It is imperative to prioritize vegetation sensitivity when constructing and selecting VIs. The sensitivity of different VIs to different vegetation parameters varies, for example, NDVI is suitable for fraction of absorbed photosynthetically active radiation (FPAR) inversion, physiological reflectance index (PRI) is suitable for detecting pigment changes, NIRv is suitable for detecting GPP, and kNDVI is suitable for solar-induced chlorophyll fluorescence (SIF) inversion. Moreover, the characteristics of different regions and vegetation types need to be considered, e.g., in tropical rainforests, vegetation is typically dense, so NDVI is not recommended because it is easily saturated. Therefore, when choosing a VI, it is important to first identify the vegetation parameters of interest and have a general judgment of the vegetation type and growing status in the study area.

After determining some VIs that can be sufficiently sensitive to the vegetation parameters of interest, non-vegetation factors such as illumination conditions, sensor properties, sun-sensor geometries, atmospheric effects, topography, background conditions, etc., and others should also be scrutinized next (Fig. 13). The research is also more concerned with the bidirectional reflectance distribution function (BRDF) effect, which involves factors such as the incidence angle of the sun, the observation angle of the sensor, and the surface properties of the landscape features. These factors collectively determine the distribution of light reflections on the surface feature, which has an important impact on the acquisition and interpretation of remote sensing data. For instance, rugged terrain distorts optical remote sensing observations and subsequently impacts biophysical and biochemical parameters retrieval by VIs over mountainous areas (Li et al., 2023). Owing to its complexity, VIs research has continued to pay attention to the BRDF effect in recent years. Concerns about both the atmosphere and soil are relatively early, and more attention has been paid to soils. The mechanisms of how the atmosphere and soil affect the VIs results have also been more thoroughly studied. For example, in the densely vegetated Amazon region, researchers should consider atmospheric effects much more than subsurface effects, and an atmospherically resistant index such as EVI is recommended. Whereas in sparsely vegetated areas such as savannas and shrublands that are more sensitive to the soil background, soil-resistant indices such as SAVI and DVI are recommended.

Overall, selecting an appropriate VI requires a thorough understanding of the specific vegetation parameters of interest, as well as a comprehensive assessment of the vegetation types and growth conditions in the study area. For instance, NDVI is particularly effective in temperate regions and arid environments, such as the grasslands of the Tibetan Plateau (Liu et al., 2022). In contrast, EVI and NIRv are better suited for resisting saturation effects and are more appropriate for use in tropical forests (Merrick et al., 2021; Rowland et al., 2014; Wang et al., 2023). Additionally, the topography-adjusted vegetation index (TAVI) excels in monitoring forest dynamics and effectively mitigates the impact of terrain shading on vegetation monitoring (Xie et al., 2023; Yang et al., 2022).

5. Conclusions and future work

Vegetation index (VI), with concise mathematical form and clear meaning, is a powerful tool for vegetation monitoring. In this article, we

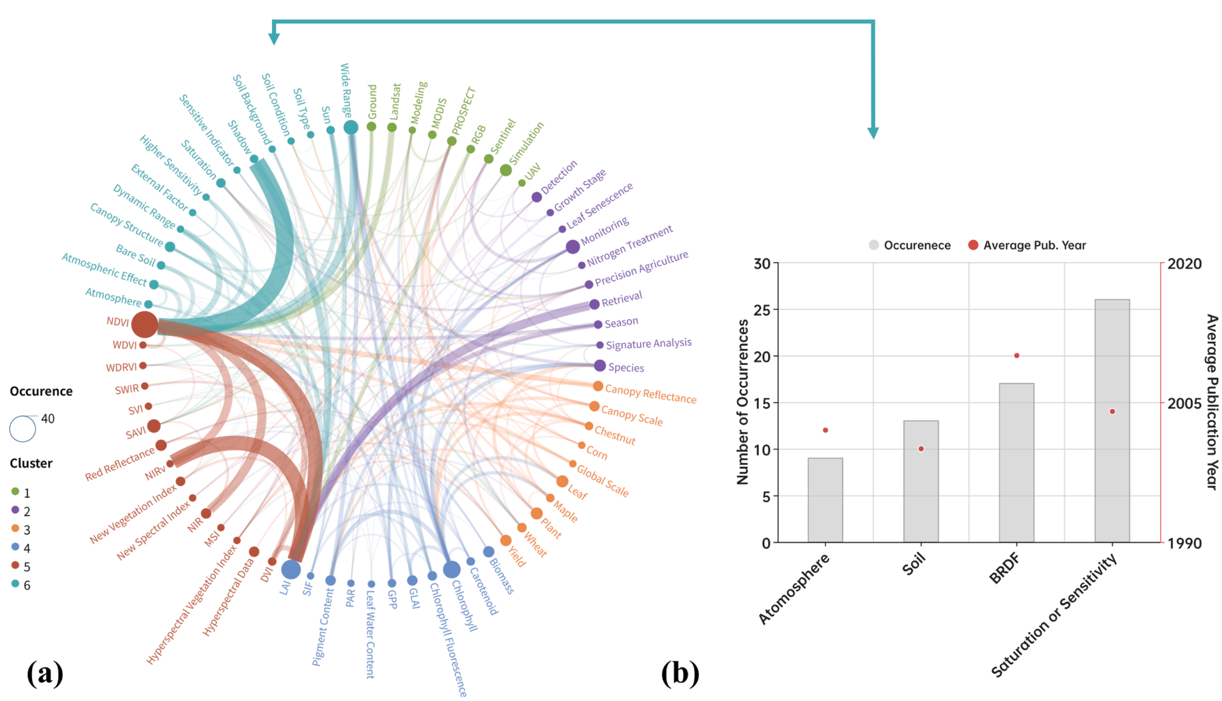

Fig. 13. (a) Keyword clustering and co-occurrence network of VIs construction literature. (b) Concerns summary in VI construction.

use bibliometric methods to review the VI-related literature in the web of science (WOS) database since the beginning of the record. The results show that the publication of VI-related papers has shown an overall trend of continuous growth, especially since 2012. Publications from the United States and China far outnumber those from other countries. The United States is the most active country in terms of international cooperation in the VI field, with a wide and unrivaled influence. The Chinese Academy of Sciences has the highest number of institutional publications. In addition, the VI field involves many disciplines such as environmental science, remote sensing, image photogrammetry, geodiversity, and ecology. Fostering collaboration between institutions and countries can contribute to the continued progress of this field. Next, based on the results of keyword clustering, we briefly summarize the use of data sources, study areas, application development, and other related technical approaches in VI research over the past decades. Besides, we selected a lot of existing VIs for band utilization statistics, correlation analysis, and literature review. We found that most of the VIs are combined around the near-infrared, red, and green bands, and in recent years more attention has begun to be paid to the red-edge and shortwave infrared bands. Spatial correlation analysis of VI images globally shows the similarities and differences among the different VIs.

This review analyzes the longest span of literature related to VIs, and the results are representative, but some limitations remain. Limitations in the analytical tools and data selection process may affect the accuracy and comprehensiveness of the results in this paper, e.g., the subject search may miss some publications that did not contain search terms in the title, abstract, or keywords. In addition, the WOS database has incomplete data records and errors in the details of some older literature. We also made some adjustments to the visualization, such as manually merging some of the full and abbreviated keywords.

This review helps to provide the research community with a scientific basis and guidance to better grasp the development of the VI field and inspires future work in VI construction. In the future development of VI, the focus should be on improving their applicability and further resisting the influence of non-vegetation factors. For instance, researchers should continue to work on the BRDF effect and pay more attention to the VI performance on mountainous, heterogeneous surfaces. In addition, it is important to ensure the consistency of performance when the same VI is applied to different sensors. The systematic assessment of different VIs based on simulation and satellite datasets and making the results truly serve and guide ecological applications is an ongoing priority program. Good robustness and accuracy will attract more researchers to use VIs, thus better promoting their improvement and development. We are confident that with the continuous development, VI will take on an increasing role in surface vegetation monitoring and even terrestrial ecosystem monitoring in the future.

Statement:

In this study, we utilized the Grammarly tool (https://www.grammarly.com) exclusively for grammar checking and style improvement to ensure the formal and academic tone of the manuscript. It is important to note that all content generation and summarization were conducted independently by the author team without the use of any other artificial intelligence (AI) or machine learning (ML) tools.

CRediT authorship contribution statement

Kai Yan: Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition. **Si Gao:** Writing - original draft, Writing - review & editing, Conceptualization, Methodology, Visualization. **Guangjian Yan:** Supervision, Resources. **Xuanlong Ma:** Writing – review & editing, Supervision. **Xiuzhi Chen:** Writing – review & editing, Supervision. **Peng Zhu:** Writing – review & editing, Supervision. **Jinhua Li:** Writing – review & editing, Methodology. **Sicong Gao:** Writing – review & editing, Supervision. **Jean-Philippe Gastellu-Etchegorry:** Supervision, Resources, Conceptualization. **Ranga B. Myneni:** Supervision, Resources, Conceptualization. **Qiao Wang:** Supervision, Resources, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Bibliometric data collection

In this study, we selected the core collection of the Web of Science (WOS) database – SCI-EXPANDED for the literature search, which was considered the most comprehensive scientific database containing the most relevant and influential journal (Mongeon and Paul-Hus, 2016; Tao et al., 2020). The search terms included: TS (Topic)= ("vegetation index" OR "vegetation indices") AND TS= "remote sensing" OR "RS". The query was limited to articles and reviews as document types and English language. While ensuring the comprehensiveness of the data, initial literature search results were de-duplicated and irrelevant literature was manually identified and excluded. We finally obtained 8,943 literatures highly relevant to the topic, containing 190 reviews and 8,753 articles. The time frame spans nearly 30 years, which allows for a more typical analysis of the structure and trends in the VI field.

VIs are known to generally achieve vegetation condition assessment by using chlorophyll absorption bands and canopy structural features, and along this line, many VIs have been created over time and the total number of indices has steadily increased. To analyze the status of this existing VIs literature, we analyzed 127 VIs from the vegetation domain of awesome spectral indices (ASI) (See detailed VIs formula and definitions in Supplementary Table S2 and S3), a collection of standardized catalogs for earth system research (Montero et al., 2023), and three commonly used VIs, CCI, PRI, and PVI, for a total of 128 VI-constructed papers.

Appendix B. Literature analysis methods

To gain a comprehensive understanding of the scientific knowledge and trends in the VI field, we combined bibliometric methods with web analytic and data visualization techniques to analyze the relevant literature. Data were imported into VOSviewer (downloaded from https://www.vosviewer.com) and Citespace software (https://cluster.cis.drexel.edu/~cchen/citespace/download/) to perform collaborative network analysis on countries, institutions, and authors, a subject category analysis, a reference co-citation analysis, and a keyword analysis. After identifying high-frequency keywords, the related topics were clustered around data sources, geographic regions, ecological regions, applications, and other related technologies.

Burst detection is a methodological approach utilized to identify abrupt increases in the frequency of specific terms within a data stream, which often serves as an indicator of emerging research hotspots, technological advancements, or significant societal events. In CiteSpace, Kleinberg's framework is employed as burst detection algorithm to detect burst words by analyzing the frequency of terms in the titles and abstracts of pertinent scholarly articles (Kleinberg, 2002). This algorithm identifies keywords that exhibit a substantial increase in frequency over a defined temporal interval, designating them as "bursting" keywords. Such bursting keywords are reflective of the latest developments and emerging trends within a research domain, thereby enabling researchers to swiftly grasp the evolving dynamics of their respective fields.

Co-occurrence analysis constitutes a foundational methodology in data analysis and information science, serving as a potent instrument for elucidating key relationships within complex systems and extensive datasets. This analytical technique examines the frequency and patterns of simultaneous occurrences of various elements—such as words, terms, or concepts—within a dataset. It finds extensive application across diverse disciplines, including bibliometrics, text mining, and web analytics, to uncover meaningful associations and trends. By identifying these co-occurring relationships, researchers can uncover hidden connections, thematic clusters, and underlying structures (Chen, 2017). For instance, in literary analysis, examining keyword co-occurrences can illuminate research hotspots and emerging topics, whereas in social network analysis, such co-occurrences can reveal connections among different participants or entities.

It should be noted that bibliometric analyses based on author affiliations have limitations when assessing international cooperation and institutional collaboration. While authors with multiple affiliations may suggest potential connections between different institutions or countries, such affiliations do not necessarily imply actual collaborative research activities. For instance, authors may list multiple institutions due to personal affiliations such as part-time positions, visiting scholar roles, or honorary appointments, without any substantive research collaboration occurring between these institutions. Additionally, factors such as geographical distance, differences in institutional types, and the specificity of research fields can influence the authenticity and depth of multi-institutional collaborations. Therefore, relying solely on affiliation data may overestimate or misinterpret the extent of international cooperation.

Appendix C. Global sensitivity analysis of spectral reflectance and VIs

The purpose of the VI design is to amplify the contribution of vegetation parameters of interest while suppressing the impact of other factors. To select the bands and vegetation indices that are most sensitive to the target parameters and least sensitive to interfering parameters, we analyzed the sensitivity of VIs and Sentinel-2 MSI bands reflectance to various parameters at both leaf and canopy scales based on radiative transfer models. The experimental process consists of three parts: parameter generation, spectral simulation, and sensitivity analysis. Firstly, we utilized SIMLAB software to generate 4,950 sets of input parameters for the PROSPECT-D model (leaf-scale) (Féret et al., 2017) and 7,931 sets for the LESS model (canopy-scale) (Qi et al., 2019). The parameter values are detailed in Table C1, with parameter ranges set based on the LOPEX93 database (Hosgood and Jacquemoud, 1995) and (Gitelson et al., 2009). Secondly, we simulated the reflectance spectra for leaves and canopies using the PROSPECT-D and LESS models, resulting in a total of 12,881 spectra. The spectral range spanned from 400 to 2500 nm with a 1 nm interval. In the 3D simulation, trees were randomly distributed, with parameters as described in Table A2, without considering atmospheric effects. Lastly, we employed the extended fourier amplitude sensitivity test (EFAST) method to evaluate the sensitivity of Sentinel-2 band reflectance and selected VIs to parameters at leaf and canopy scales. The EFAST method is a quantitative global sensitivity analysis (GSA) technique known for its high computational efficiency and robust stability, accounting for the effects of parameter interactions on model outputs (Gu et al., 2016). A total of 16 VIs were selected for this study, including classic VIs such as NDVI, DVI, EVI, and SR, as well as chlorophyll-related indices (SIPI, CIRE, CIG, GNDVI, MCARI, S2REP, TCI), structure-related indices (IPVI, NIRv), and anthocyanin-related indices (ARI), and soil-adjusted indices (OSAVI2) and soil-indices (BI).

Table C1
Ranges of input parameters in PROSPECT-D and LESS models.

Parameters (Abbreviation, unit)		Values
PROSPECT-D	Chlorophyll (Cab, ug/cm^2)	5:90
	Structural Coefficient (N, −)	1:2.5
	Carotenoids (Car, ug/cm^2)	3:25
	Brown Pigment Content	Fixed at 0
	Anthocyanin (Ant, ug/cm^2)	0:40
	Water Thickness (Cw, cm)	0.005:0.030
	Dry Matter (Cm, g/cm^2)	0.002:0.014
GSV	C1 (dry soil coefficient1)	0.15:0.6
LESS	Leaf Area Index (LAI, m^2 m^{-2})	0:0.14451:7
	Cm (soil moisture coefficient)	Fixed at −0.1
	Ratio to diffuse to total incident radiation (SKY TO TOTAL)	0:1
	Solar zenith angle	0:90
	Solar azimuth angle	0:360

*a:b:c format indicates a range of values from a to c, in increments of b.
*a:b format indicates a range of values from a to b.

Table C2
Single tree model parameter.

Broadleaved tree parameter	Values
Trunk Height(m)	6
Crown shape	ellipsoid
Crown height(m)	9.2
Crown Diameter(m)	4
DBH (m)	0.2
Leaf Volume Density	0.75

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2025.104560.

Data availability

Data will be made available on request.

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