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Review

Earth Observation-Based Rice Mapping Studies in Vietnamese Mekong Delta Compared to Global Context: A Bibliometric Analysis

Anuva Chowdhury [1], Surajit Ghosh [2,*] and Bunyod Holmatov [2]

1 Department of Remote Sensing, Birla Institute of Technology Mesra, Ranchi 835215, Jharkhand, India
2 International Water Management Institute, 127 Sunil Mawatha, Battaramulla, Colombo 10120, Sri Lanka
* Correspondence: s.ghosh@cgiar.org

Abstract: A bibliometric study on mapping the rice cropping systems in VMD is crucial for understanding the trend of EO-based rice mapping and how remote sensing technologies are essential to address the food security issue in the region. This article presents an overview of Earth observation (EO)-based rice mapping strategies since 1979, prioritizing the scope of data, approaches, and techniques derived from 3700 research articles worldwide and contrasting them with the Vietnamese Mekong Delta (VMD). Various quantitative analyses were conducted through bibliometric analysis using the VOS viewer and Scopus database. Optical images, particularly the Landsat (~16%) and MODIS (~12%) time series datasets, were the most commonly utilized globally. MODIS data (~31%) had the highest share in the VMD context, followed by Landsat data (~19%), while Sentinel series (~13% for global and ~16% for VMD) data became more popular in recent years. Research on rice mapping using UAVs has been gradually creeping into rice mapping research globally, but a gap is yet to be filled in the VMD. The most widely used approaches for rice mapping globally were Random Forest, Support Vector Machine, and Principal Component Analysis. Spectral indices like EVI, NDVI, and RVI were commonly used for rice mapping and monitoring. The findings underscore the critical role of EO-based rice mapping studies in the VMD in addressing sustainability and food security challenges.

Keywords: Earth observation; rice mapping; Scopus; Vietnamese Mekong Delta; bibliometric analysis

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1. Introduction

The global population is anticipated to surge to nearly 9.8 billion by 2050 (UN-DESA 2017), with Asia contributing 54.34% to the world's population (UN World Population Prospects 2019), demanding additional food production. Rice, a staple crop for more than half the world's population [1], is cultivated in over 100 countries. Countries that produce and consume rice testify to the fact that rice is grown in a range of habitats, from tropical to temperate, with varying water regimes and topographic circumstances. From the driest deserts to the world's most humid locations, rice is produced everywhere. It is grown at Al Hasa Oasis, Saudi Arabia, where annual rainfall is less than 100 mm, and along the Arakan coast in Myanmar, where the growing season has an average of more than 5100 mm of rainfall. The areas are considerably different in temperature, such as in Otaru, Japan, which averages 17 °C, whereas the Upper Sind region of Pakistan experiences 33 °C [2]. Furthermore, more than 110,000 kinds of rice are cultivated, each with a unique quality and nutritional makeup [3]. Rice provides 80% of the energy needs of almost 2 billion people in Asia alone. It mainly comprises 80% carbohydrates, 7–8% protein, 3% fat, and 3% fibre [4]. In 2012, 11.5% of the world's cultivable land was covered by paddy fields. About 19% of the world's daily calories come from rice, which was consumed annually at an average of 65 kg per person between 2010 and 2011 [5] (IRRI, AfricaRice and CIAT 2010). Despite a sizable worldwide rice cultivation area and rising rice production in many nations, the overall demand frequently exceeds the supply [1]. Additionally, it is anticipated that the world will consume 873 million tonnes of rice in 2030 [6]. In the global context, rice must be given the utmost consideration due to its significance as a staple food for more than 90% of the population in underprivileged and developing nations; its contribution to Sustainable Goal target 2—Zero Hunger; and its significance in international trade [3].

Mapping rice cropping systems is crucial and has been increasingly explored using Earth observation (EO) data to estimate the area under cultivation, yield, seasonality, and many more [7–10]. The widespread geographical coverage and freely available EO data with increased spatial and temporal resolution are a boon for studying the different perspectives of rice cultivation, from phenology to yield assessment. Depending upon the availability of the data sources, paddy mapping strategies are classified into three parts. Using optical satellite-based methods based on local to global scales, rice cultivating areas can be mapped using the Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC); Medium-Resolution Imaging Spectrometer (MERIS); Moderate-Resolution Imaging Spectroradiometer (MODIS); Landsat series comprising TM, ETM, and OLI; hyperspectral datasets; AHVRR; and Sentinel-2 dataset time series. Secondly, microwave- or radar-based satellite data using Sentinel-1, RADARSAT, Envisat, etc., can be used. Thirdly, a fusion or combination of both optical and microwave datasets can be used for rice mapping [11]. A number of published studies have had difficulties identifying and classifying paddy rice pixels in varied environments due to commonly employed coarse spatial (MODIS, 500 m) and low-temporal-resolution (Landsat, 16 days) data [12–14]. Since paddy rice fields in South and Southeast Asia are small due to land fragmentation, applying MODIS leads to low classification accuracy attributed to mixed pixels incorporating several crops [15]. However, employing Sentinel-2 data, which have higher revisit frequency and greater spectral and radiometric resolution, could increase the precision of classification by capturing spatial variety in agricultural management practices [16]. The ability to estimate phenological events is further enhanced by data derived from time series analysis of EO data [17,18], such as the Normalized Difference Vegetation Index (NDVI) [19], the Enhanced Vegetation Index (EVI) [20], the Normalized Difference Land Surface Water Index (LSWI) [21], the Normalized Difference Water Index (NDWI) [22], the Normalized Difference Flood Index [23], and other indices. Recently, machine learning and deep learning techniques in EO-based rice mapping have significantly increased [18,24,25]. Google Earth Engine (GEE), a cloud-based repository for satellite imagery and processing tools, has grown due to its potential for handling sizable-volume datasets and its capability to visualize, process, and analyse big data. Recently, these index-based studies have been approached using the GEE platform for mapping and monitoring rice using time series and phenology-based algorithms of vegetation indices [26], and due to their advantages of cloud computing and rapid monitoring they are being widely explored [27,28]. An effective literature analysis technique would be beneficial to support upcoming studies, summarize historical evolution, and uncover hotspots. Bibliometric analysis incorporates an interdisciplinary combination of computing, facts, and data; has robust quantitative functions; offers a thorough and systematic statistical appraisal of the literature from many domains; and effectively describes the general trajectory of a subject's or field's development [29]. The bibliometric analysis tool has been used in studies related to the physiology and management of rice [30–32] and perennial staple crops [33]; studies on the application of fertilizers in rice farming [34]; rice cultivation and irrigation exposure [35]; the review on top-cited papers in global rice research [36] (rice cultivation and the impacts of climate change [37]; trends and research features on greenhouse gas emissions from rice production [38]; research trends in rice remote sensing [39]; and research on rice cultivation and its interconnection with greenhouse gases [40]. The application of bibliometric analysis on EO-based rice mapping focusing on the Vietnamese Mekong Delta (VMD) has not been attempted. The Mekong Delta is Vietnam's most significant agricultural and aquaculture production zone, producing 50% of the nation's rice, 80% of the nation's fruit, and 60% of the country's fish (International Centre for Environmental Management 2012). In 2019, the VMD represented 54.46% of the country's rice cultivation area, making it the primary rice-producing region (General Statistics Office—GSO 2018). Thus, this investigation tried to dig deep into rice mapping and excavate the annual trend in the literature of applying EO data in rice research through a Scopus-listed keyword co-occurrence analysis using the bibliometric method. The VMD stands out as a critical area in regions where rice is vital to the economy and food security. This article presents a comprehensive bibliometric analysis that aims to unravel the role of EO-based rice mapping studies in the VMD compared to global studies. The analysis seeks to shed light on the contributions of these studies to sustainability and food security in the region.

2. Materials and Methods

2.1. Study Area

Vietnam heavily relies on rice production in the Mekong River Delta for its food supply and national economy. Considered one of the most fertile agricultural regions globally, Vietnam is the world's second-largest rice exporter and the seventh-largest rice consumer. Rice cultivation in Vietnam follows three distinct cropping seasons: winter–spring (December to March), summer–autumn (April to August), and autumn–winter (September to November). Farmers typically sow on either irrigated or non-irrigated fields in the autumn–winter season, from mid-July to the end of August [41]. These different seasons allow for continuous rice production throughout the year. Three ecosystems within the country's geographic regions influence Vietnam's rice-growing culture. The northern delta, characterized by a tropical monsoon climate, experiences cold winters and relies on rainfed and flood-tolerant rice varieties. On the other hand, the highlands of the north cultivate upland rice varieties due to their specific conditions. Finally, the southern delta, i.e., the VMD, dominates rice cultivation in Vietnam and benefits from a warm and humid climate year-round, accompanied by abundant sunshine (Figure 1).

Figure 1. Study area.

2.2. Data

Scopus (https://www.scopus.com, accessed on 1 October 2023), a repository for scientific publications, is one of the most extensive global collections of abstracts and citations from the peer-reviewed literature from Elsevier Group. Scopus' preview database was exclusively selected primarily for two reasons, i.e., it has a sizable collection of topnotch-quality scientific research publications and a widespread reputation in academia for conserving high-quality, peer-reviewed investigations and articles, and the catalogue of bibliometric output produced by the directory makes text mining and bibliometric analyses convenient [42]. The information search was carried out considering a few criteria set by the author based on the perception and the requirement of the analysis. The filtered data could then be exported from the web repository of Scopus (1979 to 2022) in CSV format for analysis.

2.3. Method

A keyword plays a vital role in capturing the core idea of a study, and a cluster of keywords together conveys the essence and outline of the study [43]. Thus, keywords are used to depict research boundaries and forecast upcoming trends, since keywords are a viable way to describe research hotspots. The domain or subject matter that is most intimately correlated to the issue covered in the author's study is typically listed along with several keywords. It is also typical for reviewers, and editors in particular, to augment such material with additional keywords gleaned from databases in accordance with the publication's topic content. In this vein, the unified keywords (Table S1) used for text mining were Rice, Paddy, Remote Sensing, Geospatial, Mapping, Earth observation, and GEE to study the various remote sensing applications using the preview of rice mapping and monitoring studies. These particular keywords were used in the search engine so that the body of literature in the form of articles, reviews, conference papers, letters, conference reviews, book chapters, editorials, data papers, errata, notes, short surveys, books, and reports, with the specific words or various combinations within the title, abstracts, and keywords, could be extracted for use in the study. Using these keywords mentioned above in the search tab of the Scopus database, 3700 papers on the themes were considered initially. By specifying the export type "complete records and cited references", the data were downloaded and saved in CSV format. They were then imported into the VOS viewer for citation analysis. Utilizing the Scopus database (bibliometric data), network and overlay visualizations were made using the VOS viewer to spot co-occurrences and concentrations of articles. The VOS viewer (version 1.6.18, 2022, Leiden University, Leiden, The Netherlands) is used to build and display bibliometric networks. These networks can be created using citations, co-authorship, or bibliographic coupling (Figure 2).

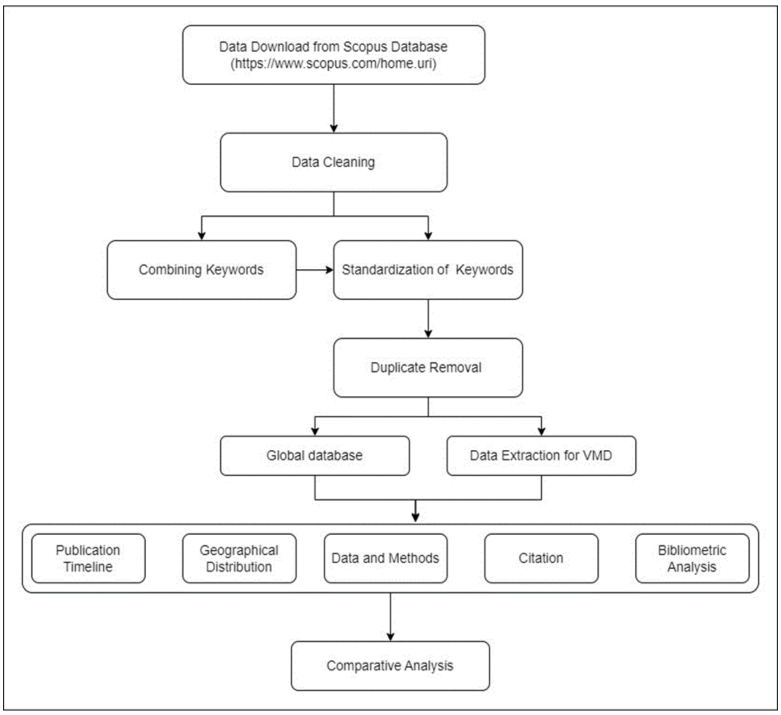

Figure 2. Methodology flowchart.

3. Results and Discussion

3.1. Publication History

Rice cultivation is extensively practiced in Southeast Asia, with India, China, Bangladesh, Thailand, Indonesia, and Vietnam being the top producers. These countries are also the major contributors to scientific research on rice mapping using remote sensing techniques. The Vietnamese Mekong Delta has shown a significant increase in research on rice mapping using EO data in recent years. The application of EO data for rice mapping gained momentum in the 1980s and has since seen substantial growth.

The scientific and academic research on rice mapping across the globe started in 1974 (4) and gradually showed an increasing trend. The breakthrough in the number of publications occurred in 2005 (77), with the highest number of articles published in 2020 (350) (Figure 3).

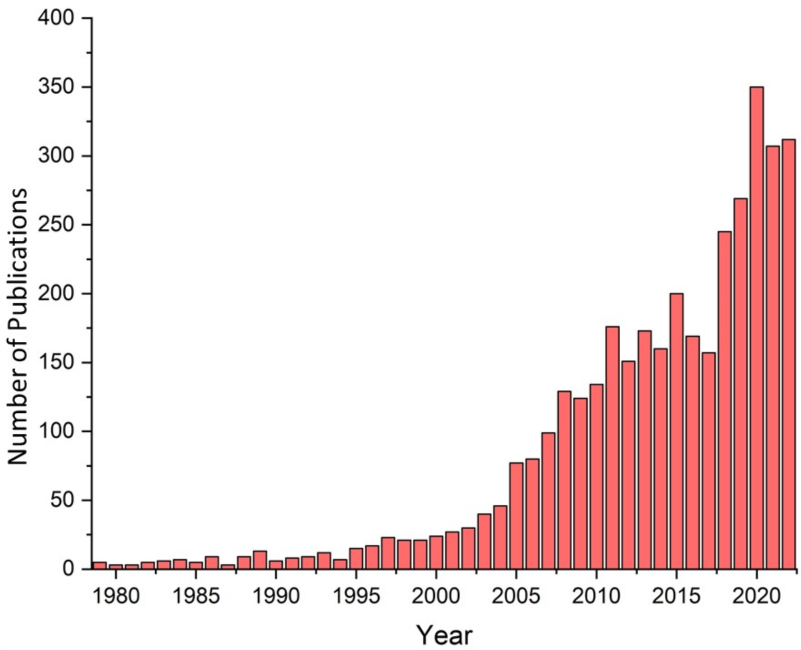

Figure 3. Year-wise publication globally.

The scientific investigation of rice mapping in the VMD started in 1997 and gradually showed an increasing trend. The peak number of publications per year was in 2018 and 2021 (10), followed by 2020 (8), 2012, 2013, and 2022 (7) (Figure 4). Japan was the first country to carry out rice research, in "On the seasonal winds in autumn over Kawagishi village, the valley of tenryū", in the *Journal of Agricultural Meteorology* in 1953. The first paper based on the direct implication of rice mapping using EO data was "Temporal Study on Paddy (Rice) Using X-Band Scatterometer" in a conference proceeding in the *Proceedings of the International Symposium on Remote Sensing of Environment* published in 1979 in India. The first few papers on rice cultivation in the VMD, "Landcover classification over the Mekong River Delta using ERS and RADARSAT SAR images" and "Application of multitemporal ERS SAR in delineating rice cropping systems in the Mekong River Delta" were published in the conference proceeding of the International Geoscience and Remote Sensing Symposium (IGARSS). The first paper to be published in China based on rice monitoring using EO data, named "Regional paddy monitoring system using NOAA HRPT data", was published in 1989 in *Digest—International Geoscience and Remote Sensing Symposium (IGARSS)*. The first publication in Bangladesh was published in 1990 in the conference proceeding Proceedings of the International Symposium on Remote Sensing of Environment. The dominant leap in the research of rice mapping using remote sensing techniques started in 1980, and this has substantially increased in the last decade. Before these years, the number of publications was limited to one per year, with most of the years without any and lacking direct implications of EO data analysis.

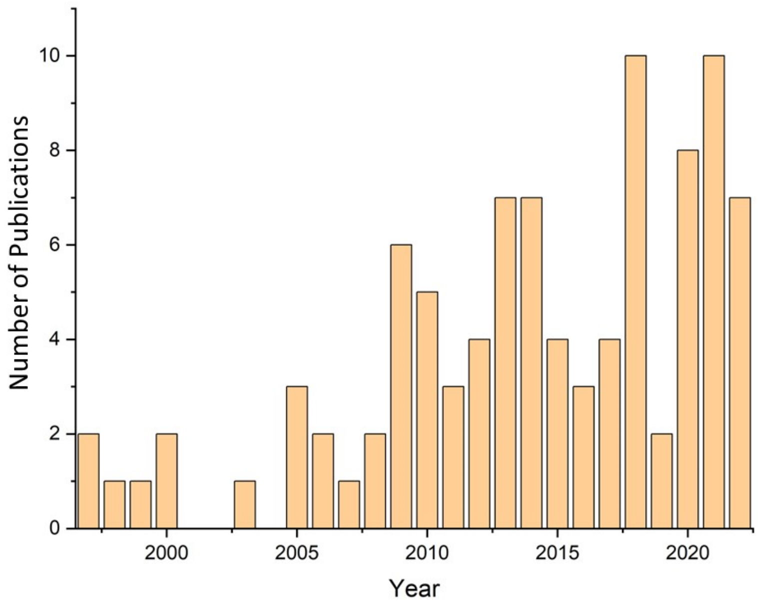

Figure 4. Year-wise publication in the Vietnamese Mekong Delta.

3.2. Country-Wise Publication

Rice cultivation is extensively practiced in Southeast Asia due to its favourable climate. Bangladesh, Cambodia, China, India, Indonesia, Iran, Japan, Laos, Malaysia, Myanmar, Nepal, North Korea, Pakistan, Philippines, South Korea, Sri Lanka, Taiwan, Thailand, and Vietnam are the leading rice farming areas. India, China, Bangladesh, Thailand, Indonesia, and Vietnam fall under the top six rice-producing countries (FAO 2023, https://www.fao.org/faostat/en/#home, accessed on 1 October 2023). Global rice mapping research using EO data is spread over the southeastern and eastern zones, where the areas under cultivation and harvesting are high. Consequently, China, India, Japan, Indonesia, Vietnam (Mekong Delta Region), and Bangladesh are the major countries using remote sensing techniques for rice research (Figure 5). It is clear from the Scopus database that the chief rice-producing nations are the major contributors to the scientific investigation of rice mapping using remote sensing techniques. There are several exceptions, such as Japan, which ranks twelfth in rice production yet third in the amount of scientific research. However, Bangladesh, the third-largest rice producer, only provides 4% of the EO-based rice mapping repository. These areas are predominated by two or three cropping seasons. Vietnam, being an exception, has five cropping seasons for rice cultivation. China, Bangladesh, and Indonesia have three rice cropping seasons, whereas India, Thailand, Philippines, Myanmar (Burma), and others have only two dominant rice cropping seasons. (Source: https://ipad.fas.usda.gov/cropexplorer/cropview/commodityView.aspx?cropid=0422110, accessed on 1 October 2023). India is one of the largest producers of rice, followed by China and Bangladesh. The leading exporters are Japan, China, Myanmar, and Vietnam. China, the second producer and exporter of rice, ranks first in scientific investigations of rice mapping through remote sensing techniques. India, the largest producer and the ninth-largest exporter, does not lag in research and development as it has the second-highest number of scientific publications in this domain. Vietnam holds the sixth position in scientific research for rice mapping using remote sensing techniques and is the fifth-largest producer globally. Consequently, Bangladesh, the third-largest producer and fifth-largest exporter has around 1.8% of research articles on rice mapping using EO data.

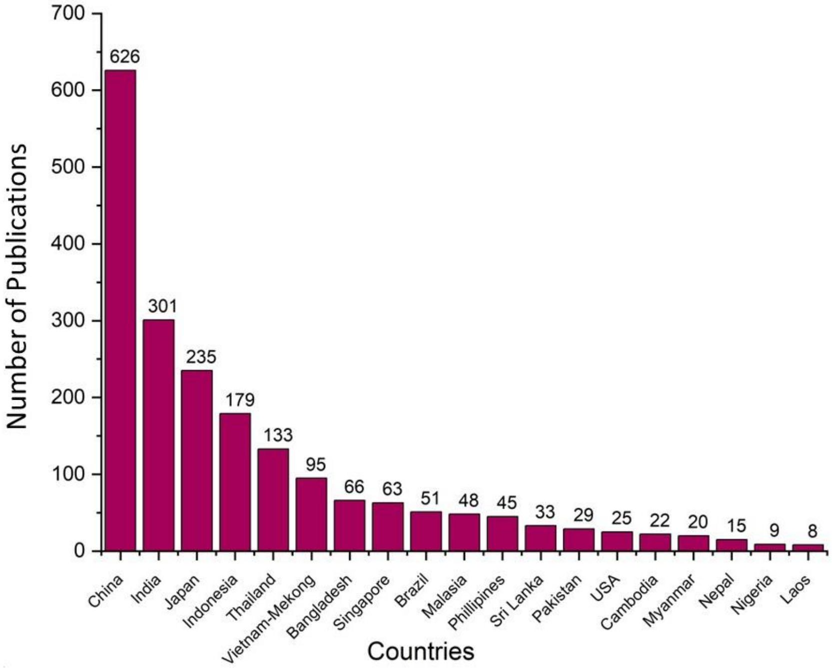

Figure 5. Country-wise publication.

Thus, research on rice mapping using EO data is prominent in major rice-producing countries like China, India, and Vietnam. These countries also have multiple cropping seasons for rice cultivation. Other significant rice producers like Bangladesh also contribute to research but to a lesser extent. Remote sensing techniques are vital in monitoring and managing rice cultivation, supporting sustainable agriculture in these regions.

3.3. EO Data and Methods Used in the Publications

Different sensors and satellites mounted on airborne and spaceborne platforms can constantly capture and monitor the Earth's surface to gather a wide range of data. These images are used in agricultural studies to monitor the transplanting, growth, and harvesting phases; detect anomalies; estimate yield; and map the extent of cultivation. Several approaches, such as Support Vector Machine (SVM) [44], Random Forest (RF) [45,46], time series analysis [47,48], and phenological indices [49], have been developed to map rice-producing regions worldwide (Table 1).

Table 1. Approach/method used in the publications.

Approaches/Platform	Number of Publications	
	Global	**Mekong**
Random Forest	168	24
Linear Mixture Model	7	2
Empirical Mode Decomposition	13	6
Semiautomatic Hierarchical Clustering Algorithm	17	1
Isodata	18	2
Time series analysis	33	22
Principal Component Analysis	50	3
Support Vector Machine	165	4
GEE	89	3

The highest application of MODIS satellite data is seen in the VMD region, followed by the Landsat time series satellite data (Table 2). Contrarily, from a global perspective, Landsat time series data represent a larger share than MODIS data. Thus, it is understood that the optical datasets predominate in rice mapping using EO datasets. The advancement in geospatial domains, with liberated and open data policies from the United States Geological Survey (USGS) providing Sentinel 2 MSI datasets and Copernicus Open Access Hub of the European Union providing Sentinel-1 datasets, radar images hold a significant position in the study of rice mapping using EO data. The Sentinel-1 sensor, with its cloud-penetrating property, is more famous for mapping and monitoring rice cultivation. The application of HJ-1A/B (CCD1/2) is limited globally, but no application is found in the VMD. AVHRR hyperspectral images are used in only two publications that focused on the study of VMD, whereas there is no application in the global domain. Commercial satellite data such as SPOT, Terrasar-X, and Radarsat have also occupied a place in studying rice mapping using remote sensing techniques.

Table 2. Earth observation (EO) satellite sensors' characteristics and related publications.

Satellite/Sensor	Spatial Resolution (m)	Temporal Resolution (Days)	Number of Publications		Accessibility
			Global	Mekong	
Landsat (OLI/ETM/TM)	30 m	16	578	18	Open Access
Sentinel-1	5–40	12	323	12	Open Access
Sentinel-2 (MSI)	10–20	5	164	3	Open Access
Modis (Terra/Aqua)	250–1000	1–2	448	29	Open Access
UAV			191	0	Commercial
HJ-1A/B (CCD1/2)	30	2–4	10	0	Open Access
SPOT (HRV (SPOT1-3) VGT (SPOT-4) HRG/HRS/VGT(SPOT-5))	1000	1	181	7	Commercial
COSMO-SkyMed (SAR)	3–15 m	16	12	1	Commercial
TerraSAR-X (SAR)	3–10 m	11	31	5	Commercial
ENVISAT (ASAR)			53	6	Open Access
RADARSAT-1 (SAR)	10–100 m	24	18	1	Commercial
RADARSAT-2 (SAR)	3–100 m	24	62	2	Commercial
ALOS-2 (PALSAR-2)	25 m	14	12	2	Commercial
AVHRR			0	2	Open Access
Total			3700	94	

Note: ASAR—Advanced Synthetic Aperture Radar; CCD—Charge-Coupled Device; ETM+—Enhanced Thematic Mapper Plus; HRG—High-Resolution Geometric Imaging Instrument; HRS—High-Resolution Stereoscopic Imaging Instrument; HRV—High-Resolution Visible; MODIS—Moderate Resolution Imaging Spectroradiometer; MSI—Multispectral Instrument; OLI—Operational Land Imager; SAR—Synthetic Aperture Radar; SPOT—Satellite pour l'Observation de la Terre; TM—Thematic Mapper; UAV—Unmanned Aerial Vehicle; VGT—VEGETATION.

Landsat and MODIS are the most frequently used optical remote sensing satellites for rice mapping. Radar data, namely Sentinel-1 and TerrasAR-X, have often been employed in recent studies [50,51]. Some of the literature using satellite-based remote sensing techniques in rice mapping, such as Liew (1998) [52], used Synthetic Aperture Radar (SAR) imagery from the multitemporal ERS-2 satellite to map and delineate regions in the VMD that were cultivated with various types of rice crops. Sakamoto et al. (2009) [53] provide a strategy for assessing spatiotemporal changes in the farming systems of the VMD based on MODIS time series imagery. In the context of the VMD, rice mapping using Landsat data contributes to approximately 19%, whereas MODIS data contribute 31%, giving MODIS the lion's share of the available research in this area. A total of 89 scientific publications have used GEE for rice mapping across the globe, whereas a mere share of only three publications using GEE have focused on the VMD. The top three approaches or methods for global rice mapping are RF, SVM, and time series analysis. In the VMD region, Random Forest is also the top-applied approach, followed by time series analysis and Empirical Mode Decomposition. In recent years, Unmanned Aerial Vehicles (UAVs) [54] have emerged as a low-cost alternative in sensing technology mapping and monitoring natural resources. The first application of UAVs in vigour mapping based on the Normalized Differentiated Vegetation Index (NDVI), studied in Italy, proved highly appropriate for precision agriculture in medium-sized farms [55]. Using UAVs in rice is critical for classification, assessing phenological behaviour, yield estimation, and activating many researchers to create a global, national, and regional rice database [56].

Traditional machine learning techniques such as RF, SVM, and time series analysis have been widely used. Newer approaches with these methods and the GEE platform have given a new dimension to studying EO-based rice mapping. The application of UAVs in rice mapping, used for crop health detection, yield estimation, and vegetation vigour mapping, is gradually gaining global relevance. However, UAV research in rice mapping in the VMD has yet to be started, providing further avenues for research exploration.

The phenological indices-based assessment of rice mapping using time series EO data is widely practiced worldwide for scientific investigations. Among the various vegetation indices, EVI holds the lion's share in studying rice mapping using EO data globally and in the VMD. NDVI is the second-highest method applied as a phenological index for global rice mapping, but contrarily, it is the third-highest method for VMD after the RVI. NSWI and LSWI are two indices that are used comparatively more for rice mapping in the VMD than in the global perspective (Figure 6). Thus, EVI, NDVI, and RVI are the top three applied indices for monitoring and mapping rice cultivation.

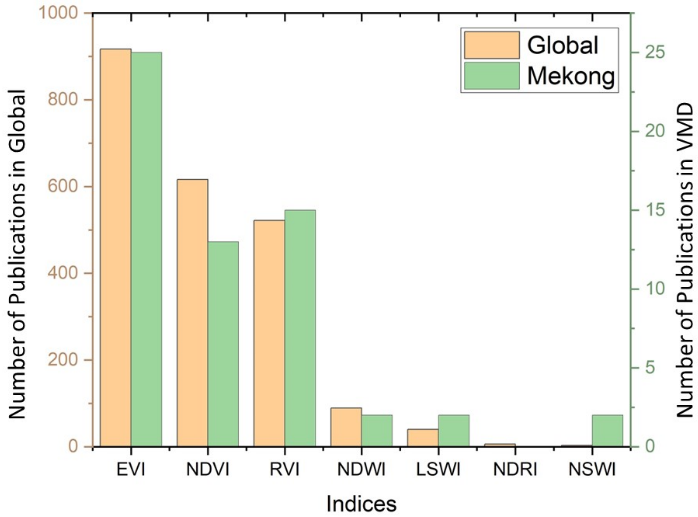

Figure 6. Comparison of phenological indices.

Therefore, remote sensing plays a crucial role in rice mapping globally, with prominent use in major rice-producing countries like China, India, and Vietnam. Different sensors and satellites, including MODIS, Landsat, and Sentinel-1, are widely employed for capturing Earth surface data. Optical datasets are predominant in rice mapping using EO data, but radar data from sensors like Sentinel-1 and TerraSAR-X are gaining relevance. Traditional machine learning techniques like Random Forest and Support Vector Machine are commonly used, while newer approaches with the application of these methods on the GEE platform are opening new possibilities. UAVs are also emerging as a low-cost alternative for monitoring rice crops. Phenological index-based assessment, particularly with EVI, NDVI, and RVI, is extensively used for rice mapping globally. The VMD region has shown significant research interest in this field, and there is further potential for exploration, especially in UAV research.

3.4. Publication Outlets and Citations

The top four highest cited papers in the study of rice mapping over the VMD are "Remote sensing of rice crop areas" [57], "Mapping rice paddy extent and intensification in the Vetnamese Mekong River Delta with dense time stacks of Landsat data" [58], "Mapping the irrigated rice cropping patterns of the Mekong Delta, Vietnam, through hyper-temporal spot NDVI image analysis" [59], and "Mapping rice cropping systems in Vietnam using an NDVI-based time-series similarity measurement based on DTW distance" [19]. The highest citations, above 100, are in the journals *Proceedings of the National Academy of Sciences of the United States of America*, *International Journal of Remote Sensing*, and *Remote Sensing of Environment*. Five articles have between 80 and 100 citations in the journals of *Remote Sensing*, *Science of the Total Environment*, *Environment*, *Development and Sustainability*, *Landscape* and *Urban Planning*, and *IEEE Transactions on Geoscience and Remote Sensing*. On the other hand, 34 articles pertinent to rice mapping using EO data were found without any citations. Those papers mainly belong to conference proceeding articles. The top five highest articles globally are "Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s" [60], with a cite score of over 1000; "Spatial and temporal patterns of China's cropland during 1990–2000: An analysis based on Landsat TM data" [61]; "A crop phenology detection method using time-series MODIS data" [62]; "Mapping paddy rice agriculture in southern China using multi-temporal MODIS images" [63]; and "Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images" [64], which has a citation score of above 600. The highest cited paper was published in the *Journal of Geographical Sciences* and *Remote Sensing of Environment*. Out of the total list of publications globally, only 83 articles show a cite score above 100, followed by 46 between 80 and 100 citations. There are around 600 articles with a cite score ranging between 10 and 30. More than 1100 articles without citations were related to symposiums, conference proceedings, and journal articles (Figure 7).

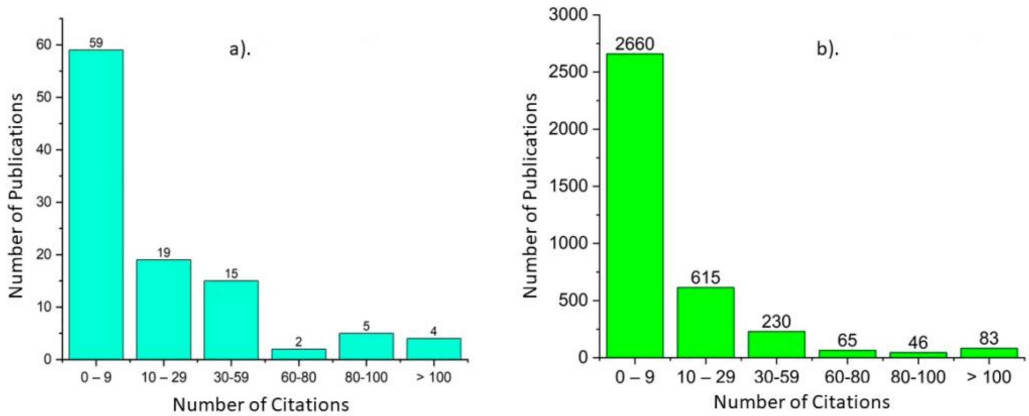

Figure 7. Citation comparison: (**a**) VMD publications, (**b**) global publications.

Rice mapping research in the Vietnamese Mekong Delta (VMD) has resulted in highly cited papers, with four prominent ones garnering over 100 citations. However, there are also 34 articles without any citations, mostly from conference proceedings. Globally, rice mapping research has produced top-cited papers from various research areas, with "Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s" being the highest cited paper. Several highly cited articles have been identified, such as "Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s" [60] and "Mapping paddy rice agriculture in southern China using multi-temporal MODIS images" [63]. The top-cited articles specific to the VMD area include works by Sakamoto et al. (2006) [65], Kuenzer and Knauer (2013) [57], Kontgis et al. (2015) [58], and Nguyen et al. (2012) [59]. The journals "Remote Sensing of Environment" and the "International Journal of Remote Sensing" have the highest citations in this research field. The co-occurrence analysis of keywords revealed eight, four, and two clusters for the top three, five, and ten co-occurrences, respectively, indicating the critical research fronts in rice mapping using EO data. Over time, the number of publications on the VMD has increased, with the highest number observed in 2020 and 2021. Similarly, the uppermost number of journal publications specific to the VMD was recorded in 2018 and 2020, spanning from 1997 to 2022.

While some articles have received high citation scores, a significant number have not received any citations, showcasing the diverse nature of research in this field.

3.5. Co-Occurrence and Connectivity Analysis

Using the full counting approach, 837 unique keywords were used for the co-occurrence analysis. The keywords were divided into clusters based on the colour scheme, ranging from dark blue to yellow.

A bibliometric network was constructed by adopting the full counting technique, where each link that results from an interaction has a total weight of 1, suggesting that the total weight of a choice is equivalent to the number of linkages emanating from it [66]. In cases where full counting is used, the occurrences variable reflects the aggregate number of times an expression appears across all the research articles. The interconnected web and the circles describe the periodic arrangements of research publications. The dark blue colour symbolizes papers before 2010, and the yellow colour variation represents the publications of recent years. The clusters were formed based on the co-occurrence of keywords for the year-wise publication on rice mapping using EO data. The connectivity network of all keywords examined using the VOSviewer (version 1.6.19) is displayed in the figure (Figure 8). The analysis and connectivity diagrams were made using default parameters. A co-occurrence of only 18, 53, and 117 of the comprehensive 837 keywords was found at least ten, five, and three times, respectively.

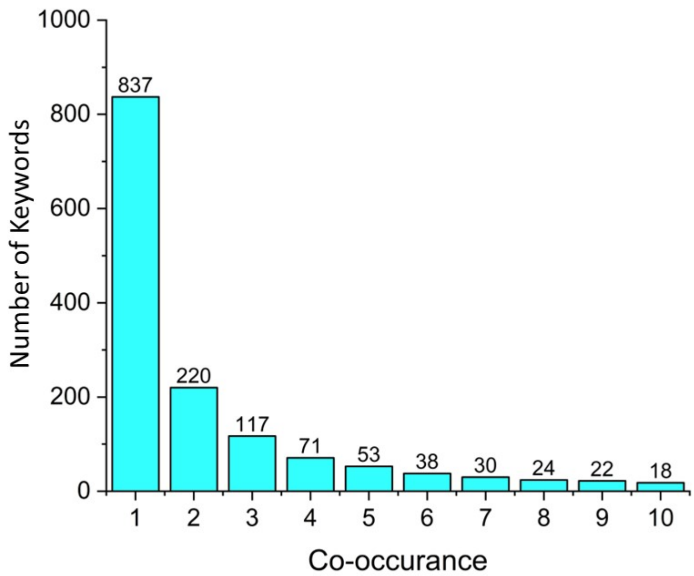

Figure 8. Number of co-occurring keywords.

The interconnections between the clusters include the keywords based on the number of co-occurrences, and the radius of the circles symbolizes the number of publications in which each term appears. In general, a keyword repeats relatively frequently in circles of larger sizes. Consequently, if two words co-occurred more commonly in the analysed list of publications, they appeared closer to one another. The word “remote sensing”, located in the focal point of the image in a large font, is related to several other items, suggesting that it is a significant subject or area of research in the dataset under analysis. Several colour-coded term clusters surround it, indicating that the terms are interconnected with other terms within the framework of the literature or data under analysis. With each colour denoting a thematic group, the clusters appear to be arranged around remote sensing-related subjects. Terms such as “paddy field”, “agriculture”, and “food supply”, for instance, may be included in a cluster pertaining to the use of remote sensing in agricultural settings. The lines indicate the correlations or co-occurrences between the terms. With the aid of this visualization, authors can rapidly comprehend the main areas of study within a field, their connections, and potentially even the topics' historical development. The thickness of the connecting lines indicates the degree of link between phrases; larger lines denote stronger connections. These visual clusters make understanding the conceptual relationships between concepts and the degree of their interdependence easier. A timeline with a gradient from 2010 to 2022 is also included at the bottom of the image. This timeline is used to illustrate how the words or focal areas in remote sensing have changed over time. This temporal feature enables viewers to follow the evolution of the field's focus over time. Similarly, the citation clusters help the reader quickly comprehend the citation and how it relates to the literature's keywords. The visualizations show that links turn from blue to yellow in hue as the number of citations grows.

There are seven significant clusters, which stand for seven different subfields of rice study. Other colours are associated with various groups of keywords, indicating the yearly significance of keywords, such as the gradient from blue to yellow, which denotes the associated publication year. The yellow colour suggests connectivity of significant keywords in recent years; the dark blue link indicates keywords used in the older literature. The network visualization shown in the figure below has four clusters, which are colour-coded using red, blue, green, and yellow. The red network denotes cluster 1 comprising 18 keywords like aquaculture, Asia, drought, Eurasia, farming system, flood, GIS, irrigation, Landsat, Lulc, MODIS, paddy field, rivers, satellite data, Southeast Asia, Thailand, time series, and Vietnam. The second cluster is coded in green with 16 keywords, which are backscattering, biology, classification, Decision Tree, forestry, image classification, mapping, NDVI, polarization, radar remote sensing, SAR, Sentinel-1, space optics, space-based radar, vegetation, and vegetation index. Climate change, crops, Enhanced Vegetation Index, food supply, mean square error, Mekong Delta, Mekong River, remote sensing, rice, rice monitoring, rice production, rice systems, and rice yield are the 14 keywords that come under the third cluster that is coded using blue. Lastly, agricultural production, agricultural robots, agriculture, cultivation, and image processing are categorized in cluster 4, demarcated using yellow (Figures 9–11).

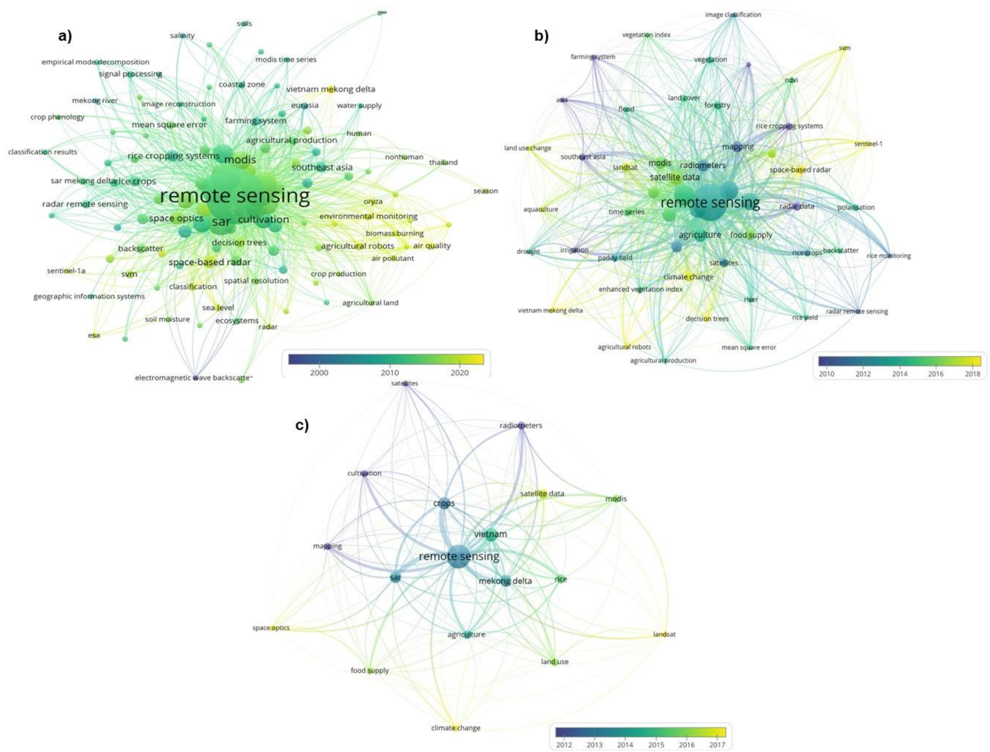

Figure 9. Publication year: (**a**) 3 co-occurrences, (**b**) 5 co-occurrences, and (**c**) 10 co-occurrences.

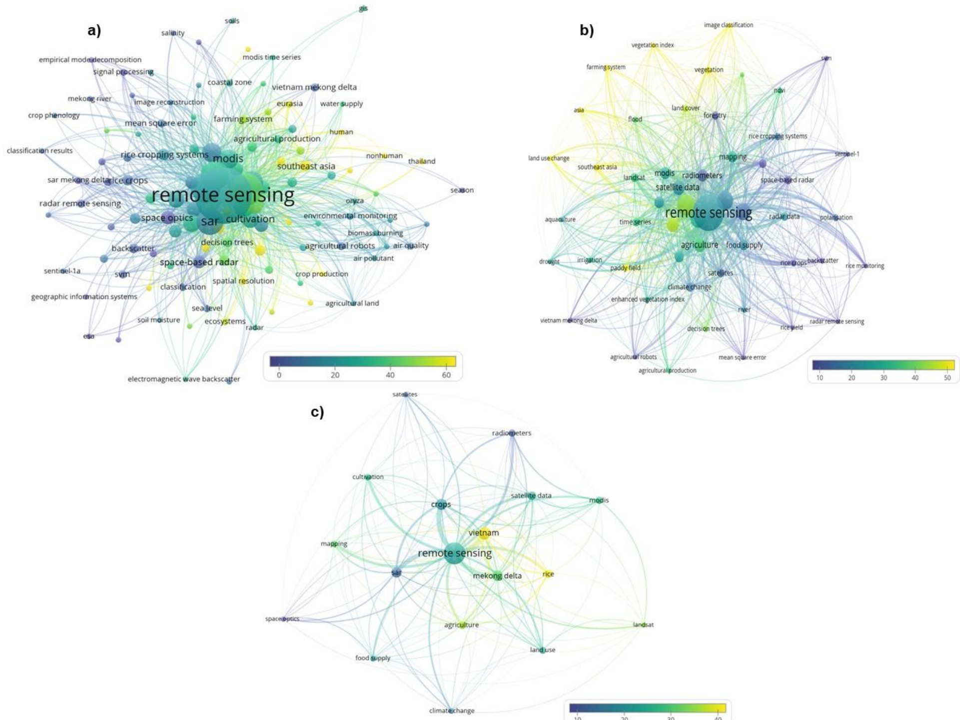

Figure 10. Citations: (**a**) 3 co-occurrences, (**b**) 5 co-occurrences, and (**c**) 10 co-occurrences.

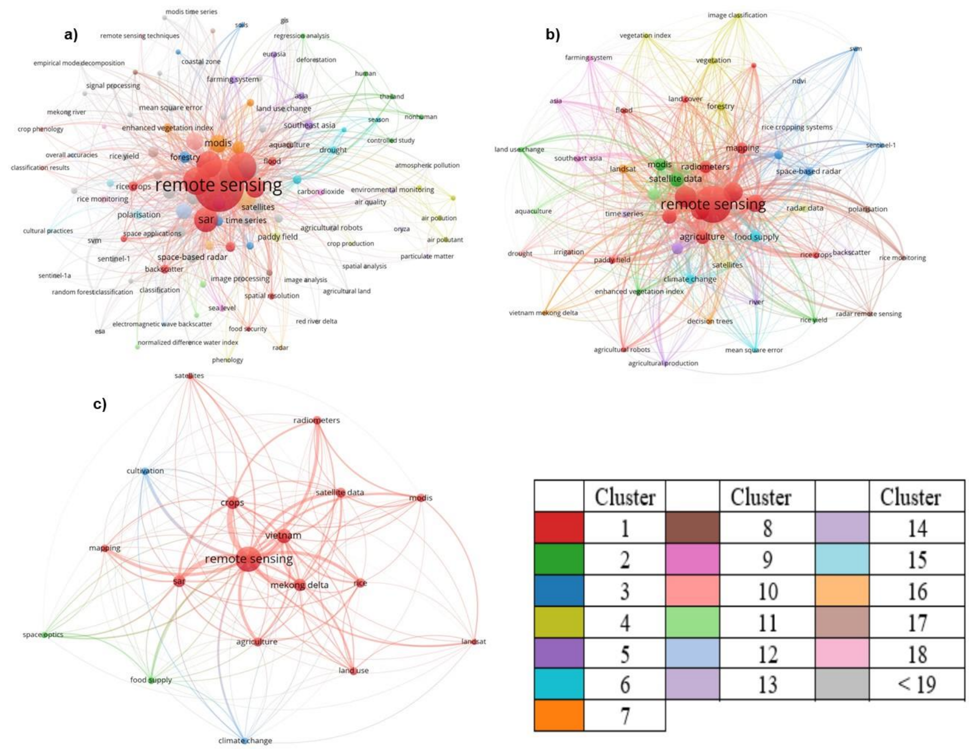

Figure 11. Clustering: (**a**) 3 co-occurrences, (**b**) 5 co-occurrences, and (**c**) 10 co-occurrences.

The analysis revealed a notable increase in publications on EO-based rice mapping in the VMD and the global context over recent decades. However, it became evident that the VMD is an area of particular interest, accounting for a significant portion of the research output. This emphasis can be attributed to the region's importance in rice production and the increasing demand for sustainable agricultural practices. The citation analysis highlighted seminal studies that have significantly influenced the field and served as a foundation for subsequent research. Thematic analysis of the selected publications revealed common research themes, including mapping rice cropping patterns, monitoring yield variability, assessing water management practices, and studying the impacts of climate change on rice production. These studies have contributed to a better understanding of the dynamics of rice cultivation in the VMD and provided valuable insights into improving sustainability and food security. The research output in this region reflects the pressing need for accurate and up-to-date information to support effective land management decisions, water resource allocation, and climate change adaptation strategies [67] (Figure 11).

4. EO-Based Rice Mapping and Its Linkages with SDGs and Food Security

EO-based rice mapping studies directly align with SDG 2 (Zero Hunger) by providing accurate information on rice cropping patterns, yield variability, and water management practices. These studies support efforts to enhance food security and promote sustainable agricultural practices in the VMD. The insights gained from such studies can inform decision-making processes related to crop management, resource allocation, and adaptation strategies, ultimately contributing to the goal of ending hunger and achieving food security. Secondly, EO-based rice mapping studies contribute to SDG 15 (Life on Land) by monitoring and assessing the impacts of climate change on rice production. These studies provide valuable information for land management and conservation efforts. Understanding the dynamics of rice cultivation and its relationship with land use can support sustainable land management practices and help protect ecosystems in the VMD, contributing to preserving biodiversity and promoting sustainable land use.

Furthermore, EO-based rice mapping studies indirectly contribute to other SDGs, such as SDG 13 (Climate Action), by providing insights into the vulnerability of rice production to climate change and facilitating the development of climate-resilient agricultural practices. Additionally, these studies can contribute to SDG 6 (Clean Water and Sanitation) by assessing water management practices in the context of rice cultivation and supporting the sustainable use of water resources in the region. Thus, EO-based rice mapping studies provide valuable insights and information that can support sustainable agricultural practices, enhance food security [68], promote climate resilience, and contribute to conserving ecosystems in the VMD. By addressing these sustainability challenges, EO-based rice mapping studies play a crucial role in advancing progress towards the broader agenda of the UN SDGs.

5. Conclusions

The bibliometric analysis carried out in the present study provides a quantitative and comprehensive overview of rice mapping using EO data. Compared to global studies, the bibliometric analysis presented here provides valuable insights into the role of EO-based rice mapping studies in the VMD. These studies have significantly contributed to understanding rice cultivation dynamics, monitoring agricultural practices, and improving sustainability and food security in the region. The findings highlight the importance of continued research efforts and collaboration to address the evolving challenges faced by the VMD and similar agricultural regions worldwide.

Evidence of AI/ML techniques integrated with EO data for rice mapping in the VMD is limited. It is expected that these kinds of studies may gain momentum in the near future. However, using bibliometric analysis may also give further scope for studies on the application of rice mapping using EO datasets, such as the amount of methane emission and its impact on climate change. EO-based rice mapping has scope for aiding in coping with natural calamities like floods and drought, where rice mapping can provide information on crop growth/yield estimation and thus provide a rapid assessment for estimating food production, a path towards food security and crop insurance.

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