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AQUACULTURE MAPPING: A LITERATURE REVIEW ON CLASSICAL METHODS AND MACHINE LEARNING APPROACHES

MAPEAMENTO DA AQUICULTURA: UMA REVISÃO DE LITERATURA SOBRE MÉTODOS CLÁSSICOS E ABORDAGENS DE APRENDIZADO DE MÁQUINA

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Abstract
The aquaculture sector has been expanding rapidly due to the growing demand for animal-based food and the pressure on natural fisheries resources. This expansion is driven by advances in farming technologies and more sustainable practices. In this context, geotechnologies have proven essential for monitoring and mapping aquaculture areas. This article presents a literature review integrating bibliometric and systematic approaches to mapping aquaculture areas using remote sensing, Geographic Information Systems, and machine learning techniques. Based on 355 publications between 2007 and 2025, the bibliometric analysis revealed a significant increase in scientific output, particularly after 2018, with notable contributions from Asian institutions. From a systematic perspective, 35 studies were analyzed, identifying the frequent use of satellite images from LANDSAT 8, Sentinel-2, and ZY1-02D, combined with indices such as NDVI, NDWI, and SAVI. Classical methods such as threshold segmentation, edge detection, and Tasseled Cap are still employed. Still, there is a growing adoption of machine learning algorithms, including Random Forest, SVM, LVQ, and neural networks. Despite advancements, challenges remain in result validation, and research in tropical regions is scarce. The article concludes that combining traditional and modern methods can enhance the accuracy and applicability of mapping efforts, contributing to the sustainable management of aquaculture on a global scale.

Keywords: Aquaculture; Remote sensing; Geographic information system; Machine learning; Systematic review..

Resumo

O setor aquícola vem se expandindo rapidamente devido ao crescente aumento na demanda por alimentos de origem animal e à pressão sobre os recursos pesqueiros naturais. Essa expansão é impulsionada pelos avanços nas tecnologias de cultivo e pela adoção de práticas mais sustentáveis. Nesse contexto, as geotecnologias têm se mostrado essenciais para o monitoramento e o mapeamento de áreas aquícolas. Este artigo apresenta uma revisão de literatura que integra abordagens bibliométrica e sistemática sobre o mapeamento de áreas aquícolas com o uso de sensoriamento remoto, Sistemas de Informações Geográficas e técnicas de aprendizado de máquina. Com base em 355 publicações entre 2007 e 2025, a análise bibliométrica revelou um aumento significativo na produção científica, especialmente após 2018, com destaque para as contribuições de instituições asiáticas. Sob a perspectiva sistemática, foram analisados 35 estudos, que identificaram o uso frequente de imagens de satélite provenientes dos sensores LANDSAT 8, Sentinel-2 e ZY1-02D, combinadas a índices como NDVI, NDWI e SAVI. Métodos clássicos, como segmentação por limiar, detecção de bordas e Tasseled Cap, ainda são empregados; contudo, observa-se uma crescente adoção de algoritmos de aprendizado de máquina, incluindo Random Forest, SVM, LVQ e redes neurais. Apesar dos avanços, ainda persistem desafios quanto à validação dos resultados, e há escassez de pesquisas em regiões tropicais. O artigo conclui que a combinação entre métodos tradicionais e modernos pode aprimorar a precisão e a aplicabilidade dos esforços de mapeamento, contribuindo para a gestão sustentável da aquicultura em escala global.

Palavras-chaves: Aquicultura; Sensoriamento remoto; Sistema de Informações Geográficas; Aprendizado de máquina; Revisão sistemática.

Introdution

Food production has diversified worldwide, driven by increasing demand, advances in nutrition research, and the pursuit of food security. In this context, the production of aquatic organisms stands out, contributing significantly to the supply of high-quality proteins and essential nutrients, such as omega-3 fatty acids, vitamins, and minerals (Henchion et al., 2017; Hua et al., 2019; Boyd et al., 2022). Aquaculture is the science that studies and develops techniques for cultivating and reproducing aquatic organisms, both animals and plants, whose life cycle occurs entirely or partially in aquatic environments (Lacerda et al., 2025). Moreover, aquaculture involves ownership of the cultivated stock, making it comparable to agricultural activity (Verdegem et al., 2023).

Aquaculture production should be understood as a broad process involving interconnected elements forming a complex network—the production chain (Toufique and Belton, 2014). It has emerged as the fastest-growing food production sector in the world in recent decades as a competitive and sustainable activity for food production (FAO, 2022). Consequently, this economic activity contributes to job creation, income generation, and the reduction of poverty and hunger in various parts of the world (Belton, Bush and Little, 2018; Bush et al., 2019; Naylor et al., 2021; Silva et al., 2024).

The productive sector reached 130.9 million tons worldwide in 2022, highlighting the significant increase and demand for cultivated species (FAO, 2024). Furthermore, according to FAO (2024), aquaculture-derived fish production surpassed, for the first time, the volume of capture fisheries, accounting for 51% of the global fish supply for human consumption.

Aquaculture has rapidly expanded within the food industry in recent years (Xu et al., 2021). Its global growth potential is considerable, as the technology is easily assimilated, with most production units requiring low implementation costs. Additionally, the activity can be conducted in the oceans, which, despite covering approximately 70% of the Earth's surface, currently provide only 2% of human food.

The importance of this economic activity stems from the fact that, according to the FAO (2024), by 2050 the world will need to produce more food to support a population of approximately 10 billion people. However, the need to restructure projects and ensure environmental sustainability certification as a prerequisite for participation in the aquaculture sector is becoming increasingly evident.

The sector's shift toward production that responsibly utilizes and maintains natural resources presents an effective alternative for producing healthy food on a global scale (Noor and Harun, 2022). Additionally, aquaculture must be oriented toward competitive and sustainable practices to address current challenges, such as the impacts of climate change in general and on agriculture specifically (Noor & Harun, 2022). Consequently, encouraging production system development, enhancing production techniques, and the relationship between aquaculture, climate change, and greenhouse gas emissions actively demand more sustainable production systems and actions (Häder et al., 2020).

In this context, recognizing the infrastructure that supports aquaculture activities is essential and widely explored through indirect methods, among which geotechnologies stand out (Gentry et al., 2017; Duan et al., 2020; Ottinger et al., 2021; Clawson et al., 2022; Zhang et al., 2023). Research on extracting fishing areas from facilities based on remote sensing technology is crucial for efficiently understanding coastal aquaculture patterns and establishing scientifically robust plans for managing and administering these areas (Chen et al., 2024).

For example, in remote sensing, satellite images can indicate where unproductive lands exist and assist in integrating aquaculture planning within coastal zone management (Jayanthi et al., 2020). Thus, remote sensing-based mapping can generate high-quality datasets on the spatial distribution of aquaculture tanks and help map their global distribution (Duan et al., 2020).

Another example is the use of Geographic Information Systems (GIS). Jayanthi et al. (2022) state that GIS is ideal for incorporating spatial aspects into aquaculture planning. This is because GIS can integrate various factors related to geographic location, aiding development and administrative decision-making. These tools facilitate decision-making for the sustainable development of aquaculture areas and ecological protection at both national and global scales (Xu et al., 2021) and have recurring applications (Anand et al., 2021; Ottinger et al., 2021; Zhang et al., 2023).

Despite its potential, Zou et al. (2022) argue that aquaculture system mapping can be affected by the quality of remote sensing images and the spectral confusion of targets. These challenges impact the ability to define boundaries and extract coastal aquaculture tanks accurately. Image processing techniques based on machine learning can overcome such difficulties.

Applying machine learning techniques for land-use mapping has become increasingly common, including in the aquaculture area mapping (Zhang et al., 2023; Silva et al., 2024; Xie et al., 2024). Therefore, recognizing the state of the art in aquaculture mapping is essential for identifying indirect methods that advance aquaculture science, particularly regarding its geographic characterization. This is even more relevant given the need to prevent losses caused by the environmental impact of extreme climate events (Silva et al., 2024), making it urgent to precisely monitor and evaluate aquaculture distribution and development (Rajandran et al., 2022). Accurate information on the spatial distribution of aquaculture is crucial for scientific aquaculture management, post-disaster assessment, and the protection of aquatic environments (Zhang et al., 2022).

Thus, aquaculture mapping is an essential process that involves collecting, analyzing, and representing geospatial data related to the cultivation of aquatic organisms. However, the number of studies evaluating aquaculture area mapping, remote sensing, Geographic Information Systems, and machine learning techniques remains limited. Given this, this research aims to conduct a literature review on global aquaculture mapping using bibliometric and systematic perspectives.

Materials and Methods

The analysis integrates bibliometric and systematic approaches to provide a broad and detailed overview of the state of the art, encompassing quantification and qualification by exploring methodological and systematic aspects of aquaculture mapping studies.

This study describes artificial intelligence (AI) techniques from a bibliometric perspective and establishes criteria for article selection in the systematic analysis, following Feitosa Junior et al. (2024). Researchers conducted the search for scientific publications through the Journal Portal of the Coordination for the Improvement of Higher Education Personnel (CAPES), accessed via the Federated Academic Community (CAFe), using the search strings "Aquaculture" AND "Geographic Information System" AND "mapping" AND "machine learning" applied to the Scopus (Sco) and Web of Science (WoS) platforms. They selected these databases because Web of Science and Scopus are central bibliographic sources (Costa et al.,2023), offering various resources and tools that facilitate bibliographic reviews on specific topics (Costa et al., 2023).

Next, they processed the obtained data using R software and analyzed it in Biblioshiny, as presented in Feitosa Junior et al. (2024). To check for duplicate documents, they employed the function remove.duplicated = TRUE, which identified one repetition in R. They used the bibliometrix (Aria and Cuccurullo, 2022) and rio packages to read tabular file formats. Then, they examined the generated file in Biblioshiny, an open-source tool that enables various analyses, including sources, authors, documents, clustering by coupling, and conceptual, intellectual, and social structures (Aria & Cuccurullo, 2017). Researchers used Biblioshiny to classify the most cited authors and conduct bibliometric analysis, verifying bibliographic metadata completeness across 16 types classified as 'Excellent,' 'Acceptable,' and 'Poor and/or absent' (Aria & Cuccurullo, 2017).

This review, using Bibliometrix, applies bibliometric indicators adapted from Feitosa Junior et al. (2024), including the evolution of published articles, total citations per article, top 10 keywords, top 10 publishing institutions, top 10 journals with the highest H-index, top 10 authors, and leading publishing countries (Figueredo et al., 2020).

The study followed the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), ensuring that systematic reviews are conducted transparently, replicable, and of high quality. This framework establishes rigorous guidelines for transparency, standardization, and reproducibility throughout all process stages, from initial identification to final inclusion of studies.

Following PRISMA guidelines (2020), researchers eliminated duplicate documents. They identified the ten most cited authors, promoting a structured and reliable systematic review on the state of the art in aquaculture mapping using remote sensing and geotechnologies. They pre-screened the studies using Rayyan, a collaborative tool to facilitate systematic review selection (Santos et al., 2024). This tool allows blind screening, inclusion and exclusion criteria marking, and conflict resolution among reviewers (Santos et al., 2024).

Thus, Feitosa Junior et al. (2024) determined that eligible studies addressed remote sensing technologies and digital image processing techniques applied to aquaculture mapping.

To understand the current aquaculture mapping landscape, the systematic analysis seeks to answer the following research questions: Which methods and techniques do scientists use to map aquaculture areas in studies worldwide? What are the main challenges in using remote sensing images for aquaculture tank mapping? How do machine learning techniques enhance the detection and classification of aquaculture areas? What trends and gaps exist in the scientific literature regarding geospatial aquaculture mapping?. A figure 1 illustrates the complete methodological workflow used in this study, encompassing the bibliometric and systematic review stages, tools, and screening process.

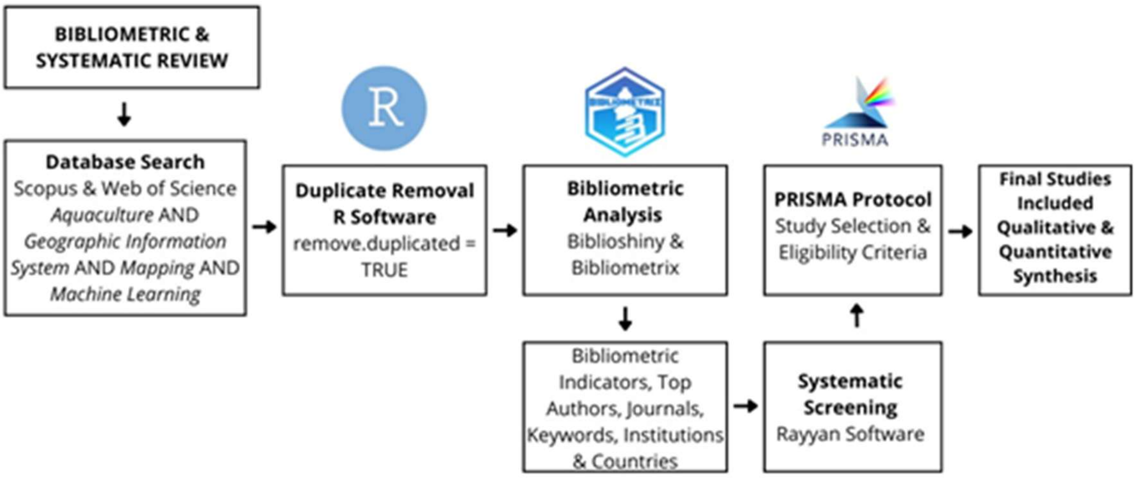

Figure 1. Flowchart of the bibliometric and systematic review workflow.

Results

The primary data, obtained using the Bx tool, indicated 355 published articles between 2007 and 2025, with one indexed in Web of Science (WoS) and 354 in Scopus. Although the Bx tool was used to select the article, this research advanced into a systematic approach, presented in the second part of the results.

Bibliometric Perspective

The results showed that the annual growth rate of scientific production was 12.25%, and the average age of the analyzed documents was approximately 2.91 years. Each document received an average of 18.04 citations. Regarding document content, 2,815 Keywords Plus (ID) and 1,296 author-assigned keywords (Author's Keywords – DE) were identified, indicating significant thematic diversity.

The author's analysis revealed participation from 1,577 professionals, 15 of whom published single-author articles. Scientific collaboration averaged 5.13 co-authors per document. Regarding document types, most publications were scientific articles (252), followed by reviews (55), book chapters (17), and complete books (19). Additionally, conference papers (8), data papers (1), and a small number of duplicate documents classified as "article article" (3) were identified.

Regarding bibliographic metadata completeness, of the total generated by Biblioshiny, seven parameters were classified as excellent, four as good, one as acceptable, one as poor, and two were completely absent. The most affected metadata were Keywords Plus, classified as poor due to their absence in 31.27% of documents, and cited references and scientific categories, which were entirely missing.

The analysis of annual scientific production reveals significant growth over the period studied (2007-2025) (figure 2). In the early years, between 2007 and 2014, the number of publications remained low and relatively stable, ranging from 1 to 3 articles per year

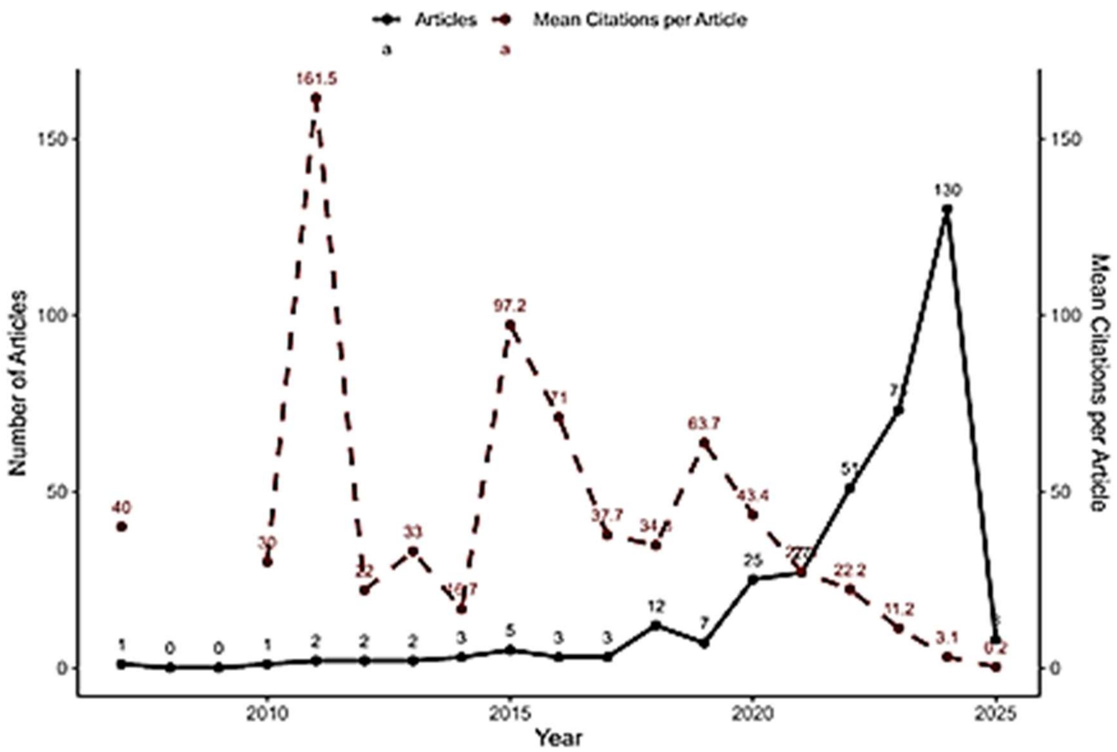

Figure 2. Scientific production and annual citations over the period analyzed (2007-2025).

Starting in 2015, a gradual increase in publications became evident, with a more pronounced surge beginning in 2018. This growth intensified in subsequent years, reaching 25 publications in 2020 and 51 in 2022. The peak of scientific output was recorded in 2024, with 130 articles published. The average number of citations per article over the years (figure 3) shows significant variation, reflecting the impact of publications and the time required for citation consolidation. In the early years, citation counts exhibited sharp peaks followed by declines.

The analysis of scientific production by institutions (figure 3) highlights Mississippi State University and Wuhan University as the leading contributors in recent years. Mississippi State University demonstrated steady growth in 2022, with four publications that increased to 28 annual publications by 2024 and 2025.

Meanwhile, despite its initial contribution in 2020, Wuhan University experienced a notable increase, growing from nine articles in 2022 to 26 in 2024 and 2025.

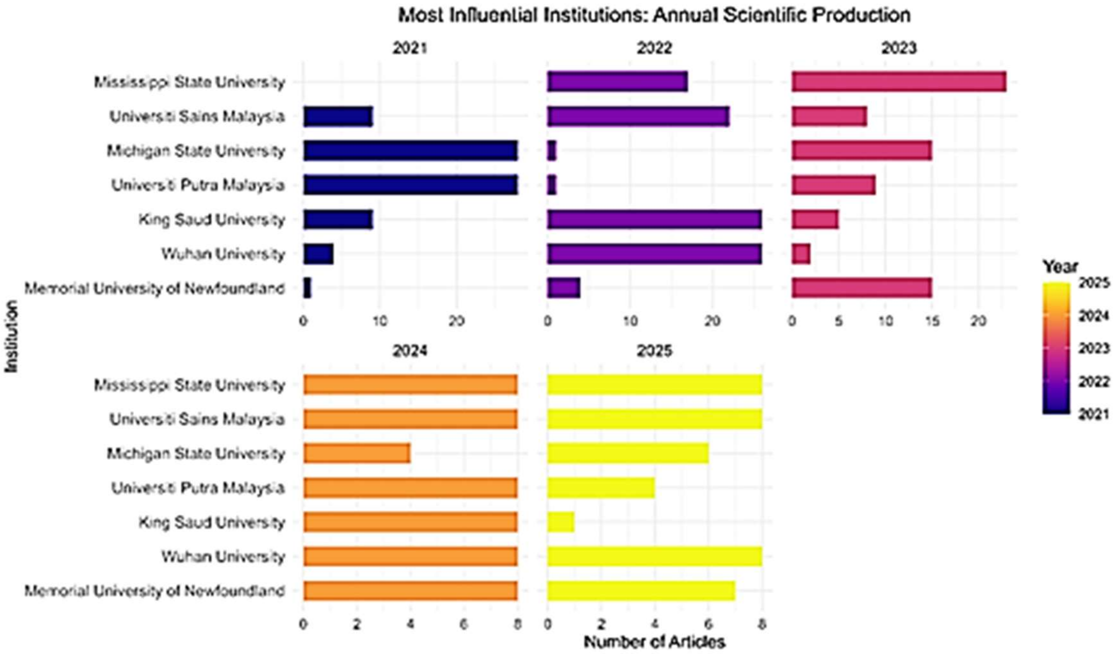

Figure 3. Analysis of the institutions' scientific output.

Other institutions, such as King Saud University, Universiti Putra Malaysia, and Michigan State University, also experienced growth, although with a lower number of publications. King Saud University increased from one annual publication in 2022 to 22 in 2024, while Universiti Putra Malaysia expanded from two articles in 2018 to 15 in 2024 and 2025. Michigan State University has maintained a stable output of eight articles per year since 2021.

Figure 4 illustrates the frequency of terms associated with research topics, highlighting the growing importance of various fields over the years. The term "remote sensing" is the most influential, appearing 124 times, indicating a significant rise in relevance from 2022 to 2024. Other terms, such as "climate change" (68), "GIS" (67), and "machine learning" (60), also show upward trends, reflecting increased research activity in these areas. Additionally, terms like "satellite data" (20) and "satellite imagery" (32) demonstrate the increasing importance of satellite-based data utilization starting in 2020, with peaks in popularity in 2023 and 2024.

Figure 4. Top 10 keywords.

Additionally, topics such as environmental monitoring (56), water quality (54), and land use (49) highlight concerns about natural resource management. Finally, sustainable development (43) and risk assessment (37) reinforce the focus of studies on strategies aimed at environmental preservation and impact mitigation.

The results of the bibliometric analysis (figure 5) indicate that Tariq A is the most productive author, with 26 articles and a fractional contribution of 3.83, demonstrating his significant influence in the field. Soufan W ranks second, with 11 articles and a fractional contribution of 1.31, followed by Chen C, Nguyen H, and Zhang Y, each with six articles but varying fractional contributions, suggesting differences in co-authorship and individual impact. Other notable authors include Islam F and Qin S, with five articles, Ali S, Al-Mutairi K, and Aslam R, who each contributed four articles. The analysis suggests a diverse distribution of scientific output, with some authors playing central roles in research on this topic.

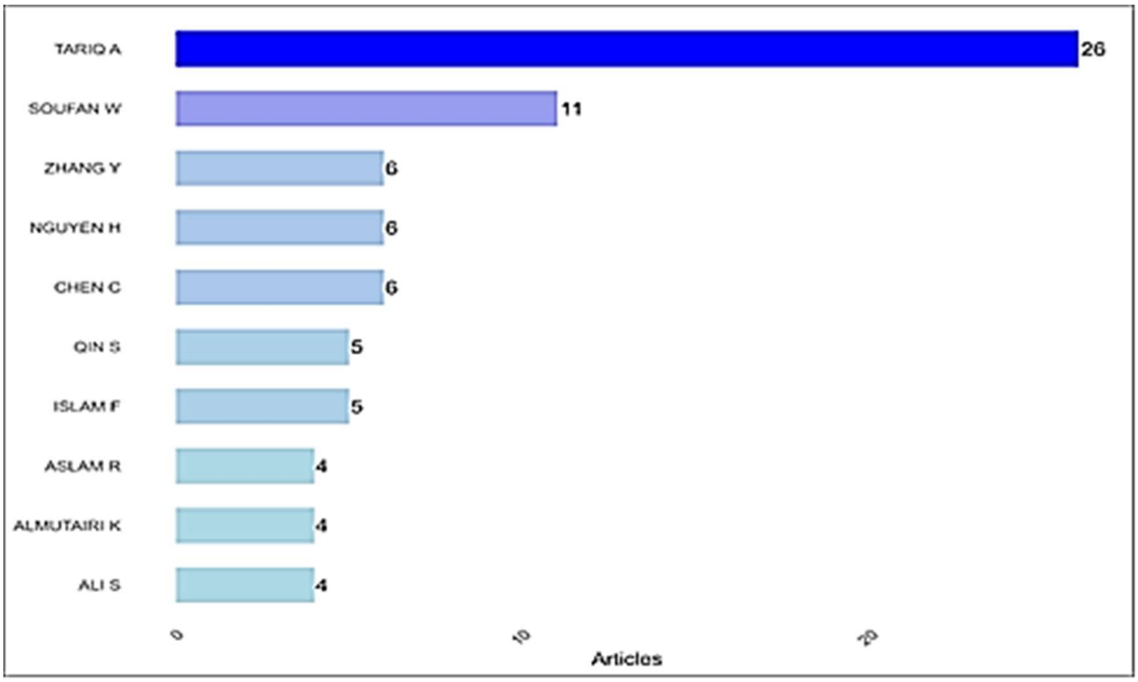

Figure 5. Top 10 authors.

Aqil Tariq has demonstrated superior recent performance, with high average citation rates per year (figure 6). Other authors, such as Qin S and Soufan W, also show strong citation metrics, but none match the combination of quantity and growing impact exhibited by Tariq A. He stands out as the most influential author, with a strong and increasing impact in the aquaculture area, mapping through geotechnologies.

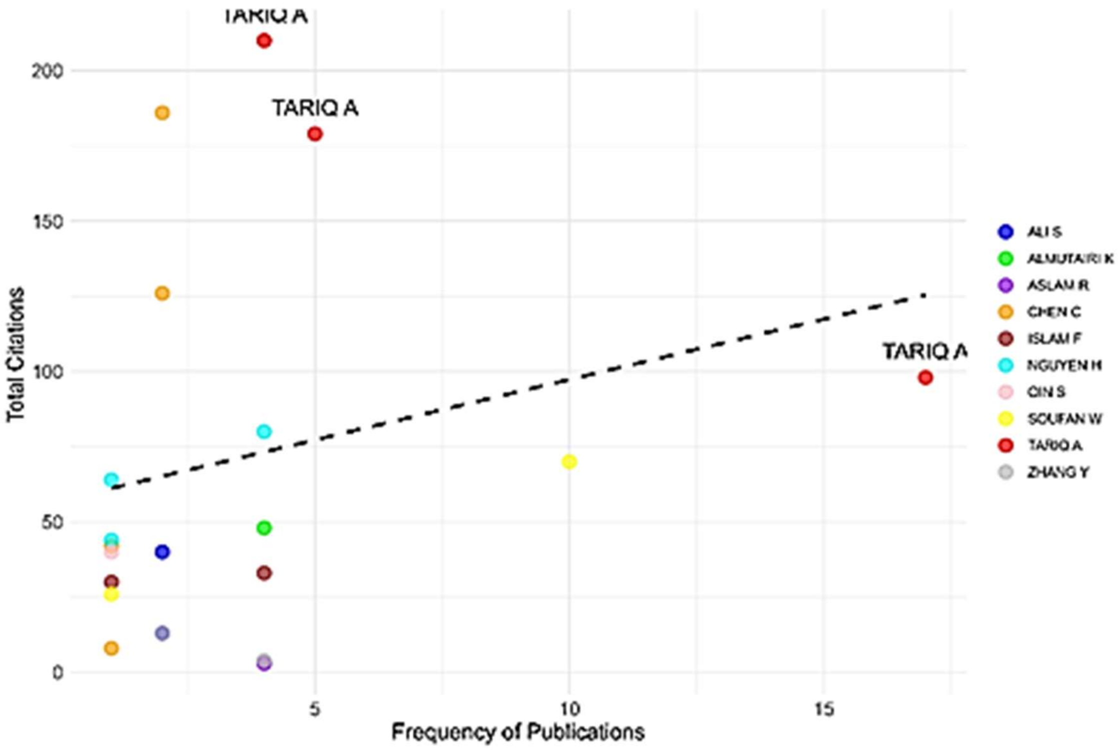

Figure 6. Total Citations (TC) vs Publication Frequency.

The results indicate a significant concentration of publications on the topic in certain countries (figure 7), with India leading with 53 articles, China with 48 articles, and the United States with 32 articles. The United Kingdom (16), Saudi Arabia (13), and Canada (11) also appear on the list, reflecting the relevance of the topic in their respective regions. Geographic diversity is evident, with substantial contributions from Germany, Malaysia, Spain, and Italy.

The distribution of articles suggests that the topic is of greater interest in Asian, North American, and European countries. Nonetheless, many countries still have limited or emerging contributions in the field.

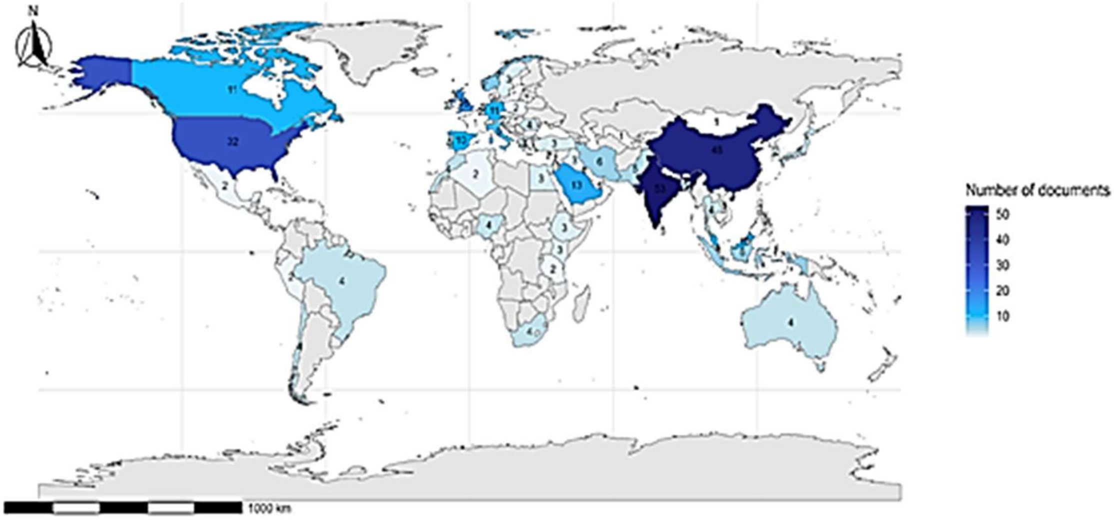

Figure 7. Distribution of Articles by country.

The evaluation of article sources (figure 8) indicates that the journal Remote Sensing is the leading reference in the field, hosting 21 related documents. Following this, Water (Switzerland) presents 12 articles, while Environmental Monitoring and Assessment, Science of the Total Environment, and Sustainability (Switzerland) each contribute 10 publications.

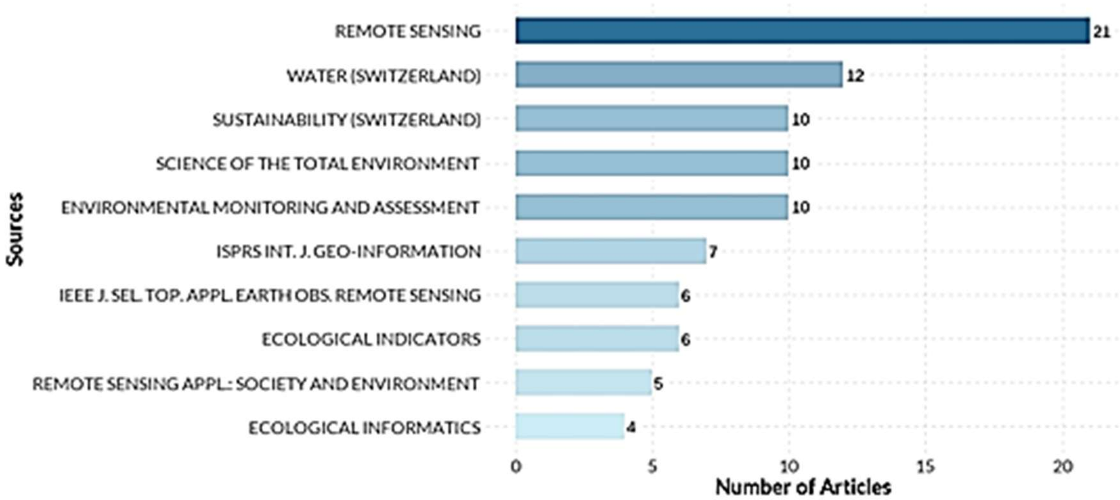

Figure 8. Top 10 journals.

Other relevant journals include the ISPRS International Journal of Geo-Information (7 articles), Ecological Indicators and IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (6 articles each), as well as Remote Sensing Applications: Society and Environment (5 articles) and Ecological Informatics (4 articles). This scenario highlights the predominance of publications focused on remote sensing, environmental monitoring, and sustainability in the examined scientific output.

Systematic Perspective

The 10 most relevant authors identified through the Bx search were associated with 77 documents. However, 36 of these documents were duplicates, as they were linked to multiple authors on the Bx list. Additionally, two articles were excluded because they were literature reviews, and four were removed due to restricted access. As a result, the final number of articles analyzed in the systematic review was 35, representing 9.8% of the total identified, figure 9. These selected documents cover the period from 2015 to 2024.

Through the systematic review, supported by objective questions presented in the methodology, it was possible to analyze remote sensing products. Furthermore, digital image processing techniques applied to aquaculture area analysis were mapped, involving a combination of automated techniques that use algorithms to extract information.

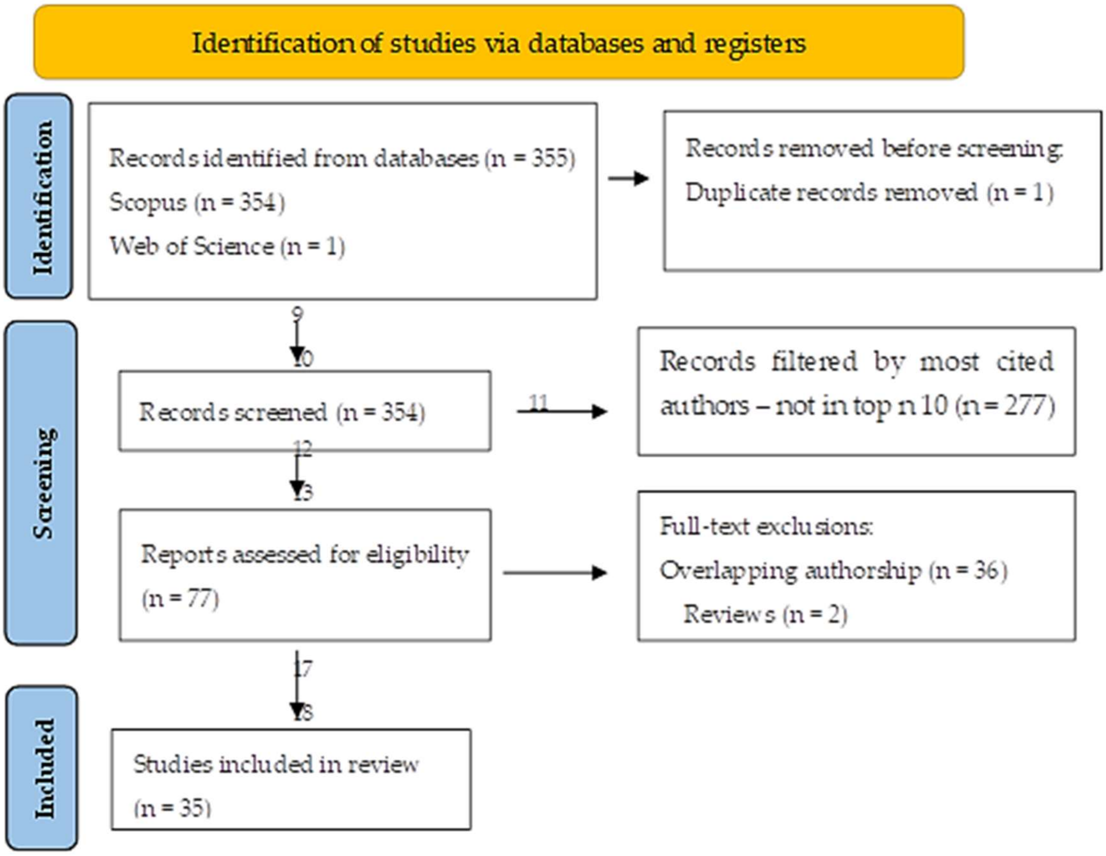

Figure 9. Flowchart of study selection process following PRISMA (2023) methodology.

Most Common Methods and Techniques Used for Aquaculture Mapping

The most frequently used classical techniques involve image classification through various methods, with the most common being Maximum Likelihood Classification (MaxVer), pixel-based classification, and Object-Oriented Classification (OOA/OBIA). Spectral indices such as the Normalised Difference Water Index, Modified Normalised Difference Water Index, and Hyperspectral Index for Floating Raft Aquaculture are widely applied. The Tasseled Cap transformation has proven efficient in satellite image segmentation, as it eliminates spectral band correlation, facilitating the extraction of key features. Among machine learning techniques, Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and Deep Learning methods, based on deep neural networks, including CNN, 3D-2D CNN, FCNN, and SSAE, stand out.

From a methodological perspective, atmospheric and radiometric correction techniques are applied to remote sensing images. Moreover, aquaculture mapping studies frequently employ image fusion techniques and principal component analysis.

The most commonly used remote sensing products are Land Satellite (LANDSAT) (Chen et al., 2022), Sentinel-1 (Synthetic Aperture Radar—SAR), Sentinel-2 (Optical/Multispectral), PlanetScope, hyperspectral data, and satellites such as ZY1-02D AHSI. Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) datasets were also mentioned.

Challenges in Using Satellite Images for Aquaculture Mapping

Challenges include spectral pixel mixing through classical methods. A primary challenge is the difficulty in accurately distinguishing aquaculture features (such as floating rafts or shallow ponds) from surrounding water bodies, particularly in complex marine environments.

Furthermore, environmental factors significantly impact data quality and interpretation. High concentrations of suspended sediments in coastal water or aquaculture tanks can alter spectral characteristics, making traditional water-land separation methods less effective (Wu et al., 2020). In coastal or estuarine aquaculture, tidal variations may introduce temporal inconsistencies in information extraction, affecting mapping accuracy.

Despite the advantages of remote analysis, field evaluations remain essential for validating remote sensing and GIS data while mitigating potential land-use conflicts. Generally, conducting geophysical field surveys for precise assessments is valuable, albeit costly and time-consuming (Du et al., 2024).

Application of Machine Learning Techniques for Enhancing Aquaculture Area Detection and Classification

Machine learning (ML) techniques are used in classification tasks to distinguish aquaculture areas in cage farming systems from other features such as seawater, vegetation, or terrestrial objects. ML techniques, especially advanced ones like Deep Learning, are employed due to their ability to achieve high accuracy. The Support Vector Machine (SVM) technique, frequently used, demonstrates strong performance in supervised classification of remote sensing images. In the study by Hou et al. (2022), which focused on floating fish farms (cage aquaculture), the SVM method was used for classification and comparison, showing better performance than the object-oriented method, although inferior to the proposed method that combined a spectral index with Random Forest. In the study by Xu et al. (2021), the classification process based on Random Forest was used in conjunction with a new hyperspectral spectral index (HSI-FRA) to extract information about offshore floating aquaculture.

Trends and Gaps in Aquaculture Area Mapping

There is growing recognition of the accessibility and high performance of remote sensing (RS) technologies in facilitating aquaculture management and sustainable development. Integrated geospatial analysis with GIS is considered an excellent and innovative approach for conducting comprehensive and precise investigations at regional scales.

ML techniques, including Deep Learning, are increasingly applied to extract information and perform accurate classifications in remote sensing, as evidenced by numerous references to SVM, ANN, RF, and DL in various sources for mapping and classification tasks. This reflects persistent technical challenges in target discrimination within complex environments, data requirements for advanced models, and the generalization of methodologies.

Efforts continue to develop optimized spectral indices for specific targets, such as the HSI-FRA (Hyperspectral Index for Floating Raft Aquaculture), which improves floating aquaculture detection.

A key geographic gap identified is the lack of relevant studies in the Southern Hemisphere. This gap may be attributed to research published in local journals or non-English languages (such as Spanish or Japanese) that may not be included in major databases like Web of Science.

Discussion

Bibliometric Perspective

The analysis of scientific production benefited from the quality of metadata. In general, this may have occurred because the harmonization process resulted in a clear set of definitions for metadata processing, focusing on data integration (Ulrich et al., 2022). Data losses may be related to academic search mechanisms on various platforms collecting less information and exhibiting a low degree of completeness due to data being derived from integrating different sources (Delgado-Quirós and Ortega, 2024).

The results revealed a growing and dynamic trend in the field, with a clear predominance of recent publications and a significant impact within the scientific community. This growth may reflect innovations that have enhanced production process control and competitiveness in the aquaculture sector (Afewerki et al., 2023). Additionally, it may be associated with continuous innovation and the dynamics of discoveries in indirect mapping methods. The low average age of documents suggests that the field is constantly evolving, with new approaches and methodologies frequently being incorporated (Ercan et al., 2025).

As the aquaculture sector expands, alongside the global fish consumption rate, which has doubled over the last century (Naylor et al., 2023), research on aquaculture areas continues to gain importance, especially in environmental contexts. Geospatial research applied to aquaculture has recently gained prominence, particularly regarding monitoring and mapping aquaculture area distribution in coastal regions (Xu et al., 2021; Silva et al., 2024).

Furthermore, aquaculture has increasingly adopted more sustainable practices, incorporating technologies such as remote sensing, artificial intelligence, and biotechnology. These innovations are essential for monitoring and optimizing natural resource use, minimizing environmental impacts, and ensuring animal welfare. The growing interest, along with aquaculture's financial and social potential, has driven further studies aiming to better understand sector dynamics and their implications for the sustainable future of aquaculture (Yen and Chen, 2021).

Scientific collaboration is another important point to discuss. Although the average number of co-authors per publication is reasonable, the international collaboration rate remains very low. This could reflect preferences for more localized research networks or external barriers such as financial constraints or language difficulties. This aspect leads us to consider how global limitations may impact the creation of more integrated research networks, potentially enhancing the impact of scientific discoveries (Waltman, 2016).

Moreover, the growth of scientific production is also closely linked to the evolution of specific institutions that have stood out in the academic landscape. Universities' leading recent publications are becoming strategic research centers, contributing to advancing knowledge in their respective fields. This phenomenon reflects the growing importance of universities in global scientific development and the need to consolidate these institutions as innovation hubs (Xinxin et al., 2022).

The prominence of Mississippi State University is linked to the work of researchers from this institution conducting studies in other countries (Tariq and Qin, 2023; Abdulrahaman et al., 2024; Zhran et al., 2024) and the contributions of Professor/Researcher Aqil Tariq (Tariq & Qin, 2023; Islam et al., 2023; Medina-Medina et al., 2024).

Another crucial point is the role of keywords and how they reflect shifts in the scientific community's interests. The rise of terms such as "remote sensing," "climate change," and "machine learning" indicates a convergence of various disciplines addressing environmental and social issues like climate change. This convergence is also related to technological advancements, including remote sensing and artificial intelligence, which have provided new ways to analyze and predict natural phenomena. Analyzing large volumes of data precisely and predictively is a significant advantage for environmental research and reflects a transformation in approaches to global challenges (Li et al., 2023).

The prominence of emerging authors, such as Tariq A, is significant and exemplifies a growing trend of valuing new researchers who, through recent contributions, have demonstrated a notable impact in the field. This phenomenon is not solely related to the quantity of publications but, more importantly, to the quality and relevance of the contributions made. The success of these emerging authors also highlights how environmental research is expanding and adapting, with an increasing emphasis on innovative methodologies shaping the frontiers of knowledge (Berrang et al., 2015).

Professor/researcher Aqil Tariq has published studies in co-authorship with researchers from various countries (Tariq and Qin, 2023; Islam et al., 2023; Medina-Medina et al., 2024), as previously mentioned. Aqil conducts research in various fields, including vegetation dynamics analysis, agricultural expansion, 3D geoinformation, urban analysis, spatial analysis for land use and coverage assessment, and geospatial data science, among others. His prominence is also associated with using machine learning tools for diverse mapping applications (Tariq et al., 2023a; Tariq et al., 2023b; Hao et al., 2024).

The current scientific production landscape has shown higher numbers in East and South Asia. According to Naylor et al. (2023), Asia accounted for 92% of the global live fish production in 2020. China alone contributed 57% of the total aquaculture volume and 59% of the global value (FAO, 2022). Despite this, most of the aquaculture policy literature, particularly related to the economics of aquaculture regulation, originates from industrialized countries in Europe and North America rather than Asia (Naylor et al., 2023). According to Chan et al. (2024), Asia and Europe have consistently displayed greater species diversity, whereas the Americas and Oceania have exhibited less diversity within the same species group.

This reflects a rapidly expanding field, with an increasing emphasis on new methodological approaches, local and international collaborations, and a growing focus on global challenges, such as environmental issues. The continuous advancement of technologies and the emergence of new voices suggest that the field will continue evolving, with new solutions being constantly explored to address global challenges (Molinaro and Leal, 2018).

Finally, the prominence of the scientific journal Remote Sensing reflects its role as a multidisciplinary publication specializing in remote sensing technologies, including satellite imagery, digital image processing, and applications in environmental, agricultural, and aquatic sciences. The journal is indexed in major databases such as Scopus, Web of Science, Ei Compendex, PubAg, GeoRef, the Astrophysics Data System, Inspec, dblp, and others.

Systematic Perspective

The selection of documents for systematic analysis followed widely used criteria (Feitosa Junior et al., 2024; Silva et al., 2025), and the number of selected articles was comparable to other analyses (Abu Samah et al., 2021; Georgopoulos et al., 2023). The fact that document selection on aquaculture area mapping covers the period from 2015 to 2024 is positive for several important reasons.

First, the analysis reveals updated techniques, new data platforms, and advances in temporal and spatial image resolution, among other aspects. Additionally, a ten-year timeframe is broad enough to identify patterns, seasonality, and spatial transformations while still being recent enough to maintain scientific relevance and practical applicability.

Classification is undoubtedly the most widely used satellite image analysis method worldwide (Martins et al., 2024). Its application aligns with the fundamental purpose of remote sensing, which is to assign semantic labels to captured images, thereby organizing them in a meaningful order (Mehmood et al., 2022).

Martins et al. (2024) showed that the Maximum Likelihood classifier was more frequently used for traditional methods, while Random Forest was the preferred choice for machine learning applications. Tran et al. (2022) also identified the spectral indices most frequently appearing in this research, particularly the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI).

A spectral index is an equation combining pixel values from two or more spectral bands in a multispectral image using various algorithms, primarily focused on band relationships or resource scaling (e.g., normalized or standardized algorithms) (Xue et al., 2017).

These methods have proven effective in distinguishing between water bodies and land areas, making them essential for data extraction in aquaculture regions. This technique applies mathematical transformations to multispectral satellite images, generating new components (or bands) with physical meanings that are easier to interpret than the original bands (Liu et al., 2020).

For classification model training, researchers used visible bands from the Land Satellite (LANDSAT) alongside the Normalized Difference Vegetation Index (NDVI), which aids in identifying water areas and different vegetation types. The development of vegetation indices is historically linked to the LANDSAT mission in 1972 (Tran et al., 2022).

The Tasseled Cap transformation also stood out in this review, demonstrating efficiency in reducing spectral band correlation and consequently facilitating the extraction of key features for image classification (Pardo-Pascual et al., 2012; Wang et al., 2017a; Alqadhi et al., 2021).

The trends in machine learning applications for the aquaculture area mapping, as observed by Mehmood et al. (2022), align with broader advancements in remote sensing image analysis. According to the authors, recent trends indicate a shift toward deep learning models in remote sensing image processing. This transition has occurred due to recent advances in remote sensing and machine learning (ML) techniques, which have significantly improved land-use and land-cover classification and monitoring accuracy and efficiency.

Sheykhmousa et al. (2020) noted that several machine learning algorithms have been proposed for remote sensing image classification over the past two decades. In this context, the authors emphasized that Random Forest (RF) and Support Vector Machines (SVM) have attracted significant attention in various remote sensing applications (Sheykhmousa et al., 2020; Yen and Chen, 2021; Nguyen and Nguyen, 2021; Nguyen et al., 2021; Hou et al., 2022; Tariq and Qin, 2023; Zhang et al., 2024). In a study by Han et al. (2018), Random Forest outperformed comparative classifiers regarding recognition accuracy, stability, and robustness, particularly when working with a small training dataset.

These models have proven highly effective in area classification, with some achieving greater precision in specific applications. However, result validation remains challenging, mainly due to spectral variations in similar objects and climate-related interference in satellite images, complicating problem resolution in marine regions. Despite these difficulties, these methods have been essential for accurately distinguishing water bodies from land areas, a crucial step in the aquaculture area image analysis (Hou et al., 2022).

Atmospheric and radiometric correction techniques are commonly applied to remote sensing images. Generally, these techniques are used because aerosols, characterized by spatial-temporal heterogeneity, can result in blurring effects in remote sensing imagery (Li et al., 2024).

Nevertheless, result validation continues to be a significant challenge, particularly due to spectral variations in similar objects and climate interference in satellite images, which can complicate problem resolution, especially in marine environments (Zhang et al., 2024; Khalil et al., 2022; Tariq and Qin, 2023; Jalayer et al., 2022).

Regarding the most widely used remote sensing products, the longstanding history of LANDSAT imagery contributes to its continued use. Sentinel imagery is favored due to its availability and resolution. According to Wulder et al. (2022), since 1972, the LANDSAT program has continuously monitored Earth, providing 50 years of digital, multispectral, and medium spatial resolution observations.

Using satellite images, particularly LANDSAT 8 and Sentinel-2, offers a significant advantage by overcoming the limitations of field surveys, covering vast areas with high precision and providing multiple spectral bands. This enables a detailed and accurate analysis of aquaculture areas, especially distinguishing between cultivation zones and other land uses. LANDSAT, Sentinel-2, and China's ZY1-02D have provided high- and moderate-resolution images for aquaculture mapping. LANDSAT and Sentinel-2 satellites can achieve a minimum spatial pixel size of 15 and 10 meters, respectively (Chen et al., 2024). According to the authors, this resolution level is sufficient to provide comprehensive information and facilitate precise classification and quantitative analysis of fishery areas in measurement facilities (Chen et al., 2024).

Mapping aquaculture areas using satellite imagery, while offering great potential, still faces practical challenges. Environmental institutions and agencies often encounter limitations such as inadequate technological infrastructure, high operational costs, restricted access to specific regions, and a shortage of specialized personnel. These barriers make fieldwork costly and, in some cases, unfeasible. In this context, integrating machine learning techniques emerges as a promising alternative. Although it requires computers with robust configurations, it enables the optimization of image classification and reduces reliance on extensive field campaigns.

The adoption of different sensors has further strengthened this advancement. Optical data from satellites such as Landsat and Sentinel-2, combined with synthetic aperture radar (SAR) from Sentinel-1, have been widely documented (Ottinger, Clauss & Kuenzer, 2017; Duan et al., 2020; Sun et al., 2020; Wang et al., 2022; Xu et al., 2021; Tian et al., 2022; Peng et al., 2022). This combination offers important complementarity: while optical sensors allow the exploration of spectral indices and reflectance patterns of water and vegetation, SAR stands out for its ability to penetrate cloud cover and capture structural surface information an essential aspect in tropical regions where cloud coverage is frequent.

Cloud-based platforms such as Google Earth Engine (GEE) play a central role by enabling the processing of large volumes of data and the construction of automated workflows (Duan et al., 2020; Sun et al., 2020; Wang et al., 2022; Xu et al., 2021; Tian et al., 2022; Peng et al., 2022; Liu et al., 2024). In addition to democratizing access to data and algorithms, GEE expands the scale of analysis and facilitates scientific reproducibility, making multitemporal studies feasible, essential for understanding the spatial dynamics of aquaculture areas.

In the field of automated classification, algorithms such as decision trees, Random Forest, and object-based image analysis (OBIA) techniques have become recurrent tools (Ottinger, Clauss & Kuenzer, 2017; Duan et al., 2020; Sun et al., 2020; Xu et al., 2021; Wang et al., 2022; Tian et al., 2022; Han et al., 2023). These approaches perform well in heterogeneous scenarios and reduce sensitivity to noise. Segmentation based on geometric features is particularly relevant when the morphology of ponds or cages is a key criterion for identification. Nevertheless, the efficiency of these methods may be limited in transitional areas or environments with high spectral complexity, requiring fine-tuning and prior knowledge of the cultivation system.

Image classification presents significant challenges when dealing with small structures, primarily due to spectral confusion. Aquaculture tanks may exhibit different signatures depending on their condition: when filled with eutrophic water, they may resemble vegetated areas; when dry, they may appear similar to exposed land. Moreover, spectral and geometric similarity with other water bodies, such as lakes, rivers, salt pans, and reservoirs, adds to the uncertainty and reinforces the need for field validation until more effective methods are consolidated (Fu et al., 2020; Peng et al., 2022; Lekunberri et al., 2024).

Another limiting factor is the spatial resolution of the imagery. Small tanks are difficult to detect using medium-resolution sensors, which may lead to under- or overestimating aquaculture areas (Fu et al., 2020; Peng et al., 2022). Additionally, temporal and seasonal variation in farming practices and the diversity of species and structures hinder consistent detection over time (Ottinger et al., 2021; Nujaira et al., 2022). Finally, classification models trained in one region tend to show limited performance when applied to other contexts, revealing generalization challenges (Lekunberri et al., 2024).

The results highlighted a substantial concentration of studies on aquaculture mapping in Northern Hemisphere countries, particularly in regions such as the northeastern United States, the North Atlantic and Indian Oceans, and France, Spain, and Portugal maritime areas. In general, the collection of satellite image data, mapping technologies, and Geographic Information Systems (GIS) plays a crucial role in storing, analyzing, and visualizing data (Zhang et al., 2024), including aquaculture areas.

The analysis of research hotspots reveals a growing trend of studies in the Northern Hemisphere, particularly in regions like the northeastern United States and the North Atlantic and Indian Oceans. However, there is a considerable research gap in remote sensing applications for aquaculture in the Southern Hemisphere, especially in tropical and subtropical regions. This suggests a need for more studies in these areas, which could expand knowledge on aquaculture area mapping in tropical ecosystems and contribute to advancing aquaculture mapping science (Yen & Chen, 2021).

This geographical predominance can be interpreted through the lens of the coloniality of knowledge, which manifests in the centralization of scientific production in Global North countries, often at the expense of local, traditional, or peripheral knowledge systems (Quijano, 2005). The coloniality of knowledge involves epistemic structures and methodologies that naturalize colonial hierarchies (Hoagland, 2010). However, as Feitosa Junior et al. (2024) point out, understanding this phenomenon helps reveal the mechanisms behind the global evaluation of research and the role of English as the dominant academic language, which privileges scholars from English-speaking countries.

In summary, the systematic review highlights significant advances in methodologies applied to aquaculture mapping, particularly the use of remote sensing technologies and advanced machine learning techniques. However, persistent challenges remain, including precise result validation and the need for further studies in tropical regions, identifying key opportunities for future research.

Conclusions

The literature review identified the most common digital image processing methods applied to the analysis of the aquaculture area. The use of remote sensors, such as satellite images, is a well-established practice essential for capturing data on the Earth's surface and monitoring specific areas. These data enable the identification, segmentation, and quantification of aquaculture cultivation zones, widely applied in various fields, including environmental monitoring and natural resource management. Spectral indices such as NDVI, NDWI, and SAVI have proven particularly useful for analyzing vegetation and water conditions in aquaculture areas.

Classical methods, such as image segmentation and classification, remain popular. However, machine learning techniques like Random Forest and SVM are emerging as standout approaches. They offer efficient solutions and can handle large volumes of data but require labeled datasets for training. Validating results remains a challenge, as satellite data often do not perfectly match field observations, highlighting the importance of using local data and adapting methods to each region's environmental conditions.

The integration of classical and modern methods, such as combining machine learning techniques with traditional segmentation and classification algorithms, is emerging as a promising trend to enhance the accuracy of aquaculture mapping. Exploring specific spectral band combinations for different types of cultivation and developing validation standards are crucial steps to improving the precision and applicability of aquaculture mapping methods, contributing to more effective management of these natural resources.

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