Available online at http://www.journalcra.com

International Journal of Current Research
Vol. 16, Issue, 03, pp. 27593-27600, March, 2024
DOI: https://doi.org/10.24941/ijcr.46924.03.2024

INTERNATIONAL JOURNAL OF CURRENT RESEARCH

ISSN: 0975-833X

REVIEW ARTICLE

A BIBLIOMETRIC ANALYSIS FOR WETLAND IDENTIFICATION AND DISTINCTION USING REMOTE SENSING AND GIS

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ARTICLE INFO

Article History:
Received 14th December, 2023
Received in revised form
20th January, 2024
Accepted 24th February, 2024
Published online 30th March, 2024

Key words:
Wetlands, Remote Sensing, GIS, Classification, Technology, Identification.

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ABSTRACT

Wetlands are vital ecosystems bridging land and water, host diverse habitats like marshes, bogs, and floodplains. Identifying and monitoring these habitats remains challenging due to resource-intensive field surveys, limited spatial coverage, and outdated data. To overcome these obstacles, remote sensing and Geographic Information Systems (GIS) techniques are pivotal. Through bibliometric analysis, optimal tools and methods for wetland identification emerge. This analysis addresses knowledge gaps, enhancing conservation practices. Integrating remote sensing and GIS enriches data quality, coverage, and decision-making support for sustainable wetland management. Examining research globally, including cases from China, the USA, Africa, and more, the study relies on research papers. By combining manual and bibliometric analysis tools, it highlights key methods like Random Forest, Object-based Classification, Convolutional Neural Networks, HOHC and Stacking Algorithm based on Google Earth Engine (GEE) as most widely used and most accurate methods. This innovative approach, amalgamating varied techniques, advances wetland conservation and management on a comprehensive scale, offering interdisciplinary support and wide-ranging applicability.

Citation: ***Sakshi Katekhaye and Sanil Kumar.*** **2023.** "A bibliometric analysis for wetland identification and distinction using remote sensing and gis". *International Journal of Current Research*, 16, (03), 27593-27600.

INTRODUCTION

Wetlands arise from the interplay between land and water systems. As per the recent Ramsar Convention on Wetlands amendment, wetlands encompass zones like marshes, fens, peatlands, and bodies of water, whether natural or artificial, enduring or temporary (1). These areas could hold stagnant or flowing water, be it fresh, brackish, or saline, extending to seawater sections up to 6 meters during low tides (2). The intricate array and variety within wetlands empower them to offer ecological, financial, communal, and cultural roles that impact climate change, hydrology, biodiversity, and human well-being. Despite this, the global expanse of wetlands is diminishing, with the swiftest decline occurring among ecosystems owing to anthropogenic factors and climate change, among other reasons. (3). (4).

IMPORTANCE OF WETLANDS

Wetlands are ecologically and environmentally significant areas that provide a wide range of benefits to both the natural world and human society (5). Wetlands are nature's treasure chests, harbouring a plethora of diverse plant and animal species, including rare and endangered ones, essential for Earth's biodiversity (1). They serve as natural water purifiers, trapping and removing pollutants, nutrients, and sediment, thereby improving water quality in rivers, lakes, and oceans (6). Acting as nature's sponges, wetlands absorb excess rainwater and release it slowly, preventing downstream flooding and land erosion (7). Wetlands also combat climate change by sequestering carbon dioxide and cooling their surroundings through evaporation and plant respiration (8). These ecosystems play a crucial role in nutrient cycling, converting organic matter into nutrients, supporting fisheries and overall ecosystem health (9). They offer recreational opportunities like birdwatching, fishing, and hiking, driving tourism, contributing to local economies, and fostering a deeper appreciation of nature (10). Additionally, wetlands stabilize shorelines, preventing erosion and protecting coastal areas from storm impacts (1). They serve as vital habitats for migratory species during their journeys, ensuring their survival (6).

For many communities, wetlands provide traditional livelihoods through activities like fishing, agriculture, and resource gathering (11). These ecosystems also have educational and scientific value, serving as living laboratories for researchers and educators studying ecological processes and species interactions (12). Furthermore, wetlands hold cultural and spiritual significance for indigenous and local communities, often considered sacred places in various cultures worldwide (13). Finally, coastal wetlands, like mangrove forests, act as natural buffers against storm surges, protecting coastal communities during hurricanes and tropical storms (7).

POTENTIAL IMPACTS OF WETLAND DEGRADATION

Wetlands are under threat from human activities such as urbanization, agriculture, and resource extraction (14). These activities can lead to habitat loss, fragmentation, and degradation, which can have significant impacts on the biodiversity and ecological functions of wetlands. Impaired wetlands exhibit a diminished capacity to deliver critical ecosystem services, including water purification, carbon storage, and flood mitigation. This can lead to negative impacts on human communities, such as increased flooding, decreased water quality, and increased carbon emissions (7) (8) (6). Therefore, it is important to identify and protect wetlands to maintain their ecological functions and preserve biodiversity (15). With focus on documentation, the study involves collecting and analyzing various research papers and publications focused on wetland identification using GIS and Remote Sensing. The approach encompasses manual analysis and employs tools like VOSviewer for co-occurrence analysis.

ASSESSING WETLAND HEALTH AND BIODIVERSITY WITH REMOTE SENSING AND GIS

Remote sensing and Geographic Information Systems (GIS) represent formidable instruments for the evaluation and surveillance of wetland well-being and biodiversity (16). Remote sensing encompasses the utilization of satellite or aerial sensors to acquire information regarding the Earth’s surface, while GIS facilitates the visualization, examination, and explication of spatial data. A significant utilization of remote sensing and GIS in the field of wetland ecology involves the delineation and continuous monitoring of wetland dimensions and alterations over temporal scales (11). Remote sensing data serves as a resource to chart wetland flora, water levels, and modifications in land cover. Subsequently, this data can be amalgamated into GIS software to produce cartographic representations, which, in turn, are valuable for the tracking of shifts in wetland size and condition across temporal periods.

An additional application pertains to the utilization of remote sensing and GIS for the surveillance of water quality within wetland environments. Remote sensing data can be harnessed for the identification of variations in water clarity and hue, serving as indicators of shifts in water quality (7). These insights can be synthesized with GIS-derived land use and land cover data to pinpoint prospective pollution origins and to formulate strategies aimed at enhancing water quality within wetlands. Remote sensing in conjunction with GIS techniques can also serve as valuable tools for the evaluation of wetland biodiversity (11). For instance, remote sensing data can be harnessed to identify fluctuations in vegetation arrangements and the occurrence of particular plant species. This data can be fused with GIS-derived information concerning habitat attributes, such as soil composition and water depth, to pinpoint regions with the potential to sustain elevated biodiversity levels. Such methodologies are particularly advantageous for identifying critical wetland habitats for species classified as threatened or endangered. Furthermore, remote sensing and GIS offer the capacity to construct models assessing the appropriateness of wetland habitats for diverse species. Through the amalgamation of habitat feature data with information on the dispersal and prevalence of various species, it becomes feasible to forecast which segments within a wetland exhibit the greatest compatibility with distinct species. This capability proves invaluable for the identification of regions likely to foster elevated biodiversity and for the formulation of conservation strategies aimed at safeguarding these specific areas.

MAPPING WETLANDS

Remote sensing and Geographic Information Systems (GIS) have emerged as potent instruments in the realms of wetland identification, cartography, and preservation. The accessibility and calibre of data resources for these objectives are contingent on a range of factors, encompassing the wetland type, the requisite spatial precision, and the targeted temporal scope. Satellites provide a powerful tool for mapping wetlands by offering large-scale coverage, regular monitoring, data consistency, multispectral capabilities, elevation data, change detection, GIS integration, and support for international collaboration (17). These capabilities are vital for understanding, protecting, and managing the invaluable ecosystem services that wetlands provide. Table 1 shows the majorly used satellites for mapping and identification of wetlands. Satellite imagery is a crucial data source for wetland identification, mapping, and conservation (18). The availability of satellite imagery depends on the type of wetland and the spatial resolution needed. For example, high-resolution satellite imagery like World View and Geo Eye can be used for mapping small wetlands, while moderate-resolution imagery like Landsat and Sentinel can be used for mapping larger wetland. And Table 2 shows the Important data required for wetland mapping

LITERATURE REVIEW

The assessment is predicated upon a curated dataset comprising 29 scholarly research papers and publications that are focused on the implementation of GIS and Remote Sensing techniques for the purpose of wetland identification. The selection of these research papers and publications for this bibliometric analysis stems from a rigorous process involving extensive citation tracking. These citations provide a broader context, indicating that these papers have evolved from an in-depth exploration of numerous research papers, articles, and book chapters. The selection of these papers has been guided by a criterion aligned with their publication date, encompassing works released up until the year 2023. These chosen sources have been judiciously scrutinized to extract pertinent datasets as well as the methodologies harnessed in the delineation and differentiation of wetlands. Each method delineated within these sources has undergone meticulous summarization and subsequent analysis, thereby unveiling discernible trends and innovations in the realm of wetland identification techniques.

The core of this analysis lies in the comprehensive examination and synthesis of the methodologies featured in these papers. This process culminates in a consolidated overview of the current state of the art in wetland identification techniques. Such an encompassing perspective is of particular value to researchers, policymakers, and practitioners in the field who strive to remain well-informed about the most efficacious approaches. The citations not only underscore the credibility and impact of the selected papers within the academic community but also establish them as authoritative and

Table 1. Primary Satellites Employed for Wetland Mapping and Identification

Satellite name	Information
Landsat Series	Landsat satellites, such as Landsat 8 with its Operational Land Imager (OLI) and Landsat 7 featuring the Enhanced Thematic Mapper Plus (ETM+), furnish multispectral data at a moderate spatial resolution. These satellites supply valuable data for the purpose of wetland cartography, comprising spectral bands spanning the visible, near-infrared, and shortwave infrared spectrums.
Sentinel-1	It is a European satellite mission with a Synthetic Aperture Radar (SAR) sensor. It provides radar images that cut through clouds and weather conditions, making it ideal for mapping wetlands. It detects water extent, vegetation, and land changes, offering insights into wetland dynamics like water levels and floods. With frequent revisits and global coverage, Sentinel-1 aids wetland conservation, planning, and assessing vulnerability to climate change. Open-access data makes it valuable for wetland mapping worldwide.
Sentinel-2	This satellite from the European Space Agency, offers optical imaging for wetland mapping. It uses multispectral imagery to detect wetland vegetation, water quality, and land cover changes. This data tracks vegetation health, habitat types, and water extent with high resolution and frequent revisits. Combined with Sentinel-1's radar data, it provides comprehensive insights for effective wetland management and conservation.
MODIS	The Moderate Resolution Imaging Spectroradiometer (MODIS) sensors, situated aboard the Terra and Aqua satellites, provide data with an expansive coverage and moderate spatial resolution. MODIS data is commonly employed in the tracking of wetland changes and the calculation of vegetation indices across extensive geographical extents. (19).
SPOT	SPOT (Satellite Pour observation de la Terre) satellites provide high-resolution optical data, often used for wetland mapping at a local scale. SPOT imagery can capture detailed wetland features and vegetation characteristics (19).
Hyperion	The Hyperion sensor on the EO-1 (Earth Observing-1) satellite delivers hyperspectral data, featuring finely-tuned spectral bands spanning the electromagnetic spectrum. This hyperspectral information proves instrumental in the comprehensive delineation of wetlands, encompassing tasks such as species recognition and mapping in intricate detail.
WorldView series	The WorldView satellites, such as WorldView-2, WorldView-3, and WorldView-4, offer high-resolution imagery with multispectral and panchromatic bands. They are commonly used for wetland mapping requiring detailed spatial information.
RapidEye	The RapidEye constellation consists of multiple satellites providing multispectral data. RapidEye imagery is employed for wetland monitoring, vegetation analysis, and land cover classification.
IRS (Resourcesat) series	Indian Remote Sensing satellites, which encompass Resourcesat-2 and Resourcesat-2A, are equipped with instruments like the Advanced Wide Field Sensor (AWiFS) and LISS-III. These sensors furnish multispectral data at an intermediate spatial resolution and have found utility in the domains of wetland cartography and surveillance.
ALOS (Advanced Land Observing Satellite)	The Japan Aerospace Exploration Agency (JAXA) operates the ALOS satellite, which is equipped with instruments including the Advanced Visible and Near Infrared Radiometer type-2 (AVNIR-2) and the Phased Array type L-band Synthetic Aperture Radar (PALSAR). These sensors supply optical and radar data, respectively, which are applicable in the context of wetland cartography and surveillance (19).

(Source- By Author)

Table 2. Essential Data for Wetland mapping

Data	Details
Light Detection and Ranging (LiDAR)	LiDAR, a remote sensing technique, employs laser pulses to generate precise 3D representations of the Earth's terrain. This data is valuable for delineating wetland characteristics such as land elevation, vegetation arrangement, and water systems. Access to LiDAR data is attainable through governmental institutions or commercial providers.
Digital Elevation Models (DEMs)	Digital Elevation Models (DEMs) are electronic depictions of the Earth's topography, employed for the production of topographic maps. These models can be generated utilizing data originating from satellite imagery, LiDAR data, or alternative data origins.
Ground truth data	Ground truth data are acquired through on-site field surveys and offer essential insights into wetland attributes such as the variety of vegetation, water depth, and soil composition. These data serve the purpose of corroborating remote sensing information and enhancing the precision of wetland cartography.
Synthetic Aperture Radar (SAR) imagery	Synthetic Aperture Radar (SAR) is a remote sensing method that employs microwave signals to generate Earth surface images. SAR can pierce through cloud cover and dense vegetation, rendering it beneficial for wetland mapping in regions prone to frequent cloud cover or thick vegetation (Bakker et al., 2012). Nevertheless, it's worth noting that SAR imagery typically possesses a lower spatial resolution in comparison to optical imagery.
Multi-spectral and hyperspectral imagery	Multi-spectral and hyperspectral imagery have the capability to furnish data regarding the spectral attributes of wetland vegetation and water. This data can be harnessed for the purpose of delineating various wetland vegetation categories and for identifying alterations in wetland status across temporal intervals.
Topographic maps	Topographic maps serve as a means to ascertain wetland locations by assessing their altitude and hydrological characteristics. Digital topographic maps are accessible through governmental entities or commercial suppliers.
Climate and weather data	Climatic and meteorological data are valuable resources for the ongoing surveillance of wetland hydrology and the forecasting of alterations in wetland conditions. This data can be procured from governmental organizations, such as the National Oceanic and Atmospheric Administration (NOAA).
Soil data	Soil data can offer insights into the types of soil found in wetland areas, facilitating the identification of wetland regions and the evaluation of wetland well-being. Access to soil data can be obtained from governmental institutions or commercial providers.
Aerial Photography	High-resolution aerial photographs captured from airplanes or drones can provide detailed imagery of wetland areas. Aerial photography can offer finer spatial details compared to satellite imagery and can be particularly useful for local-scale mapping and classification of wetland vegetation (19).
Land Use/Land Cover Data	Preexisting land utilization and land cover data can assist in the recognition and categorization of wetland regions, relying on the encompassing land utilization trends. This aids in the identification of human-induced influences on wetlands.
Water Quality Data	Incorporating water quality indicators like turbidity, nutrient levels, and dissolved oxygen concentrations can enhance the comprehensiveness of wetland mapping endeavours, particularly in the context of evaluating the well-being of wetland ecosystems.
Historical Imagery	Historical aerial photographs and satellite images can aid in understanding wetland changes over time. Comparing historical and current imagery can reveal shifts in wetland boundaries and vegetation cover.
Cadastral Data	Cadastral maps and property boundaries are useful for understanding land ownership patterns, land use changes, and potential sources of wetland degradation.
Geological and Hydrological Data	Information about geological formations and hydrological features like rivers, streams, and groundwater can help in understanding the hydrological dynamics of wetlands.

(Source- By Author)

Table 3. Indices Utilized or Potentially Applicable for Wetland Identification, Mapping, and Distinction

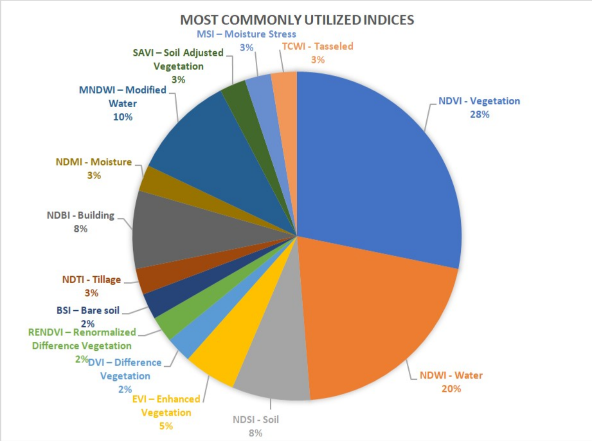
Index	Explanation
NDVI - Normalized Difference Vegetation Index	Remote sensing data can be used to compute vegetation indices like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), which offer valuable insights into the well-being and productivity of wetland vegetation (19). These indices can be used to detect changes in vegetation over time and to map wetland vegetation types.
NDWI- Normalized Difference Water Index	NDWI, or Normalized Difference Water Index, is a remote sensing index commonly used to detect and map the presence of water bodies in satellite or aerial imagery. It is a valuable tool for various applications, including wetland mapping, hydrological studies, and monitoring changes in water bodies over time.
SAVI- Soil Adjusted Vegetation Index	The Soil-Adjusted Vegetation Index (SAVI) is a vegetation index used in remote sensing and image processing to assess and analyse vegetation health and density. SAVI is an adaptation of the Normalized Difference Vegetation Index (NDVI), designed to reduce the influence of soil reflectance in satellite or aerial imagery. It takes into account the background soil brightness, making it more suitable for areas with varying soil types.
EVI- Enhanced Vegetation Index	EVI is an index that uses the blue, red, and NIR bands of remote sensing data to enhance vegetation signals and reduce atmospheric interference. EVI can be used to map wetland vegetation health and productivity.
CI- Chlorophyll Index	CI is an index that uses the red-edge and NIR bands of remote sensing data to estimate chlorophyll content in vegetation. CI can be used to map wetland vegetation health and productivity.
NDMI- Normalized Difference Moisture Index	NDMI utilizes NIR and mid-infrared (MIR) spectral bands. It helps in distinguishing moisture content in vegetation and can be useful for wetland mapping.
LSWI- Land Surface Water Index	LSWI combines NIR and shortwave infrared (SWIR) bands to detect water bodies, including wetlands.
NDBI- Normalized Difference Built-Up Index	NDBI utilizes the shortwave infrared (SWIR) and NIR spectral bands to identify built-up areas, which can be useful for distinguishing wetlands from developed or urban areas.
NDSI- Normalized Difference Salinity Index	NDSI combines the red and shortwave infrared (SWIR) spectral bands to detect areas with high salinity, which can be indicative of certain types of wetlands, such as salt marshes or coastal wetlands.
LAI- Leaf Area Index	LAI, or Leaf Area Index, serves as a quantification of the collective leaf surface area within a specified area and can be deduced from remote sensing data. This parameter is especially valuable for the assessment of wetland vegetation density and productivity.
MSI- Moisture Stress Index	MSI combines visible and NIR bands to assess the moisture stress levels of vegetation. It can provide insights into the hydrological conditions of wetland areas.
VMI- Vegetation Moisture Index	VMI combines the NIR and MIR spectral bands to estimate vegetation moisture content. It can be beneficial for identifying wetland vegetation health and waterlogged areas.
DVI -Difference Vegetation Index	DVI can be useful in wetland identification by assessing vegetation density and vigour. Wetlands typically have distinct vegetation characteristics compared to other land cover types. DVI values can help differentiate wetland vegetation from surrounding upland areas, as wetlands often exhibit denser and more vibrant vegetation.
RENDVI -Renormalized Difference Vegetation Index	RENDVI, similar to DVI, helps assess vegetation health and density. It can be used to identify and map wetland vegetation by distinguishing it from other land cover types. RENDVI's enhanced range can provide improved discrimination of wetland vegetation, which is often more abundant and lusher compared to other areas.
BSI -Bare Soil Index	BSI can aid in wetland identification by detecting areas of bare soil within wetland complexes. Wetlands may have patches of exposed or bare soil due to erosion, sedimentation, or natural processes. BSI values can help identify these bare soil areas, which are characteristic of wetland environments.
NDTI -Normalized Difference Tillage Index	While NDTI is primarily used for agricultural applications, it can be relevant in wetland identification to detect disturbed or altered areas within wetlands. Wetlands that have been subject to human activities, such as drainage or agriculture, may exhibit tillage or plowing marks. NDTI can help identify these modified areas within wetland landscapes.
MNWI- Modified Normalized Water Index	MNWI is particularly relevant for wetland identification as it assesses water content within vegetation. Wetlands are characterized by their hydrological nature, with water being a key component. MNWI can help differentiate wetland vegetation from upland vegetation by detecting higher water content in wetland plants.
TCWI -Tasselled Cap Wetness Index	TCWI focuses on the detection of wetness or water content in vegetation and soil. It can be valuable in wetland identification by highlighting areas with high moisture levels, which are indicative of wetland environments. TCWI can help delineate wetland boundaries and identify wetland areas within a landscape.

(Source- By Author)

Table 4. Frequency analysis of the methods adopted by various authors

Sr. No.	Methods for wetland identification using RS and GIS	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	Accuracy achieved	Citations received
1	Hierarchical Classification method																														>85%	14
2	Supervised Classification (Object based)																														>70%, 97-98%	35
3	Stratified random sampling technique																														92.30%	4
4	IPG-MTWM																														82.07%	2
5	GEOBIA																														91.12%	21
6	Random Forest Classification																														79-97%	171
7	HOHC- hybrid object-based and hierarchical classification approach																														90.5%, 95.1%	155
8	Stacking Algorithm based on GEE																														94.59%, 92.46%	88
9	KBRM (Knowledge-Based Rule-Based Modelling)																														95%	9
10	OTSU method																															-
11	DNN (Deep Neural Network) Algorithm																														93.33%	25
12	SESS (Simple and effective spatial-spectral)																														96.92%, 94.84%	21
13	CNN (Convolutional Neural Network)																														96-98%	9
14	Vision Transformer classifier for large-scale wetland mapping																														71-75%	5

(Source- By Author)



(Source- By Author)

Figure 1. Pie chart representing the different indices used for wetland identification through remote sensing and GIS.

influential sources in the domain of wetland identification using GIS and Remote Sensing techniques. Moreover, the insights garnered from this extensive analysis will form the bedrock for crafting recommendations pertaining to optimal strategies for wetland identification. These recommendations carry added weight as they derive from a meticulous assessment of extensively cited papers, underscoring a profound grasp of established best practices and emerging trends within the field. The culmination of this comprehensive analysis serves as a cornerstone in the formulation of recommendations concerning the optimal, efficacious, and widely endorsed approach for the identification of wetlands.

FREQUENCY ANALYSIS FOR METHODS USED

The study collectively employed a diverse range of methodological approaches, reflecting the dynamic nature of contemporary research in this domain. Among the notable methodologies identified, the following 14 methods emerged as prominent tools in these endeavors: Hierarchical Classification .(21), Supervised Classification (Object-based)(22)(21)(23), Stratified random sampling technique(24), IPG-MTWM(25), GEOBIA (26), Random Forest Classification(27) (28)(29)(30) (31) (32) (33), HOHC (hybrid object-based and hierarchical classification approach)(34)(35), Stacking Algorithm based on GEE(36) (37), KBRM (Knowledge-Based Rule-Based Modelling) (17), OTSU method(28), DNN (Deep Neural Network) Algorithm(38), SESS (Simple and effective spatial-spectral)(39), CNN (Convolutional Neural Network) (40) (41)(38), and Vision Transformer classifier for large-scale wetland mapping(42). These methods, utilized in diverse combinations, represent the multifaceted strategies employed by researchers to address the challenges of wetland identification and distinction using state-of-the-art technology and methodologies in the realm of remote sensing and GIS. Table 4 presents a comprehensive compilation of various methodologies employed in the research corpus, delineating their respective frequencies of utilization by distinct authors, the associated accuracy levels achieved, and the corresponding citation counts garnered. This comprehensive tabulation serves as the foundation for the discernment of prominent methods in the context of wetland identification and distinction. The bibliometric analysis has yielded discerning insights into the prevailing landscape of wetland identification methodologies.

Among the array of techniques investigated, several prominent approaches have emerged as recurrent and robust choices within the scholarly discourse. Collectively, these methodologies—Random Forest Classification, Supervised Classification (Object-Based), CNN, HOHC (Hybrid Object-Based and Hierarchical Classification), and Stacking Algorithm based on GEE—have consistently emerged as preeminent choices within the scholarly discourse, owing to their demonstrated accuracy and widespread adoption.

Random Forest Classification: The application of Random Forest Classification has garnered significant attention within the realm of wetland identification. Its adaptive nature, coupled with its capability to accommodate complex data relationships, positions it as a dependable and widely utilized method.

Supervised Classification (Object-Based): The implementation of supervised classification, particularly when integrated with object-based methodologies, has demonstrated noteworthy effectiveness in distinguishing wetlands.
This approach harnesses comprehensive training data to inform the classification process, enhancing the accuracy of wetland identification outcomes.

Convolutional Neural Network (CNN): Convolutional Neural Networks, a subset of deep learning techniques, have emerged as a compelling contender in the arena of wetland identification. The ability of CNNs to automatically extract intricate spatial features from imagery contributes to their recognition as a potent method for this purpose.

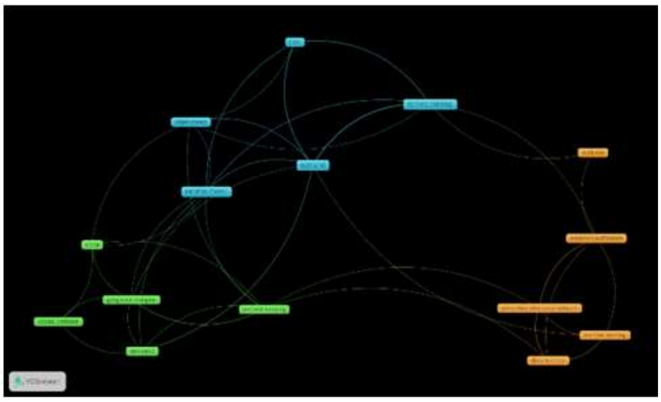
HOHC (Hybrid Object-Based and Hierarchical Classification): The hybrid approach that combines object-based and hierarchical classification techniques exhibits pronounced utility in wetland identification. This amalgamation leverages the strengths of both methodologies, resulting in a comprehensive and refined identification process.

Stacking Algorithm based on Google Earth Engine (GEE): The utilization of Stacking Algorithms in conjunction with the Google Earth Engine platform has garnered substantial traction due to its capacity to amalgamate diverse data sources. This synergy enhances the precision of wetland identification by synthesizing complementary information

Figure 1 represents dataset encompassing various remote sensing indices tailored to discern distinct land cover attributes. NDVI and NDWI shine as dominant indices, with NDVI (Vegetation) and NDWI (Water) appearing multiple times. Their prevalence reflects their importance in vegetation and water identification. Other indices like NDBI (Building), NDSI (Soil) and MNDWI (Modified Water) make notable appearances, underlining their roles in urban and water assessments. The dataset's diversity underscores its potential to holistically analyze ecosystems, aiding in applications ranging from environmental monitoring to urban planning.

CO-OCCURRENCE OF KEY WORDS ANALYSIS

The authors performed a co-occurrence analysis to identify the keywords associated with wetland identification. The co-occurrence analysis was conducted to uncover and identify the keywords that are frequently mentioned together or associated with wetland identification.



(Source- By Author)

Figure 2. Diagram representing co-occurrence analysis of Keywords

VOSviewer is selected over other software options due to its user-friendly interface, robust visualization capabilities, efficient clustering and mapping features, direct integration with bibliographic databases, customization options, cost-effectiveness as a free and open-source tool, and the availability of a supportive user community.

The co-occurrence analysis network visualization represented in figure 2 made in VOS viewer offers a comprehensive view of the prominent terminologies driving the discourse in wetland identification via Remote Sensing and GIS. The interplay of terms like "Random Forest," "Object-Based," "Google Earth Engine," "Machine Learning," "Deep Learning," and "Generative Adversarial Networks" collectively paints a vivid picture of a dynamic and multidisciplinary field that integrates traditional techniques with contemporary advancements, aiming for accuracy, efficiency, and innovation. The results of the co-occurrence analysis, as visualized through network visualization in VOS viewer, shed light on the intricate web of connections and prevalent themes within the realm of wetland identification using Remote Sensing and GIS.

The analysis unearthed several pivotal terms that stand as keystones in the discourse, collectively painting a comprehensive picture of the field's intellectual landscape. At the forefront of these interconnected terms, the prominence of "Random Forest" signifies the substantial utilization and significance of this classification algorithm in the identification and distinction of wetlands. The term "Object-Based" emerges prominently, highlighting the synergy between Geographic Information Systems (GIS) and Remote Sensing in the context of wetland identification. The inclusion of "Google Earth Engine" underscores the growing importance of cloud-based geospatial data analysis platforms. Its integration reflects a contemporary trend, harnessing the power of large-scale data processing for advanced wetland identification methodologies. Furthermore, the appearance of "Machine Learning" and "Deep Learning" resonates with the application of artificial intelligence in the field. These terms underscore the paradigm shift towards automated and data-driven techniques, demonstrating a push for enhanced accuracy and efficiency. Notably, the presence of "Generative Adversarial Networks" speaks to the cutting-edge nature of research within wetland identification. These advanced networks, rooted in deep learning, showcase the field's inclination towards innovative and sophisticated methodologies that offer potential for novel breakthroughs.

CONCLUSION

Through a comprehensive bibliometric analysis, this chapter uncovers insights into current research trends, knowledge gaps, and potential areas for improvement in wetland identification. This analysis bridges gaps in knowledge and enhances wetland conservation and management practices. The chapter's dataset includes research conducted across diverse countries and continents, highlighting the global applicability of remote sensing and GIS techniques. Case studies from various regions, including Canada, China, India, Egypt, USA, Africa, France, and more, underscore the wide-ranging relevance of these methodologies. The analysis identifies widely used methods, such as Random Forest, Object-based Classification, Convolutional Neural Networks (CNN), HOHC, and Stacking Algorithm based on Google Earth Engine (GEE). The co-occurrence analysis visualized through VOS viewer demonstrates the interplay of terms that are pivotal in wetland identification discussions. "Random Forest," "Object-Based," "Google Earth Engine," "Machine Learning," "Deep Learning," and "Generative Adversarial Networks" collectively depict the multidisciplinary nature of the field, blending traditional techniques with contemporary innovations. The integration of bibliometric analysis ensures the incorporation of the latest research advancements into wetland identification practices. This comprehensive approach enhances accuracy, precision, and knowledge currency, thereby amplifying wetland conservation and management efforts.

The proposed solution encompasses both manual analysis and bibliometric analysis tools and software. Its practical implications are far-reaching, applicable to diverse geographical locations and environmental contexts. The solution supports interdisciplinary collaboration, accommodating various scales from local to global, and promoting effective wetland management and conservation endeavors. Through this innovative approach, the chapter provides a robust foundation for advancing wetland identification processes in alignment with sustainable development goals.

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