remote sensing

Review

Remote Sensing and Machine Learning Tools to Support Wetland Monitoring: A Meta-Analysis of Three Decades of Research

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Abstract: Despite their importance to ecosystem services, wetlands are threatened by pollution and development. Over the last few decades, a growing number of wetland studies employed remote sensing (RS) to scientifically monitor the status of wetlands and support their sustainability. Considering the rapid evolution of wetland studies and significant progress that has been made in the field, this paper constitutes an overview of studies utilizing RS methods in wetland monitoring. It investigates publications from 1990 up to the middle of 2022, providing a systematic survey on RS data type, machine learning (ML) tools, publication details (e.g., authors, affiliations, citations, and publications date), case studies, accuracy metrics, and other parameters of interest for RS-based wetland studies by covering 344 papers. The RS data and ML combination is deemed helpful for wetland monitoring and multi-proxy studies, and it may open up new perspectives for research studies. In a rapidly changing wetlands landscape, integrating multiple RS data types and ML algorithms is an opportunity to advance science support for management decisions. This paper provides insight into the selection of suitable ML and RS data types for the detailed monitoring of wetland-associated systems. The synthesized findings of this paper are essential to determining best practices for environmental management, restoration, and conservation of wetlands. This meta-analysis establishes avenues for future research and outlines a baseline framework to facilitate further scientific research using the latest state-of-art ML tools for processing RS data. Overall, the present work recommends that wetland sustainability requires a special land-use policy and relevant protocols, regulation, and/or legislation.

Keywords: wetlands; remote sensing; machine learning; meta-analysis; systematic review

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1. Introduction

Wetlands are the most valuable dynamic biophysical resources [1] existing at the terrestrial-aquatic interface [2] and the hub of a great variety of flora and fauna species [3]. Wetlands, which are landscape features that exist all over the world, in every kind of climate zones from the tropics to the tundra [4], provide an appropriate living environment for aquatic vegetation and various biological activities and play an irreplaceable role in improving the environment and mediating the ecological balance [5].

They serve multiple ecological functions and values [6,7]. Erosion prevention, flood control, pollution alleviation, climate regulation, sewage purification, biodiversity maintenance, water storage and groundwater recharge, and wildlife support are just a few of the functions that wetlands perform [7–10]. Wetlands also contribute to tourism facilities, bio-energy production, and social benefits [8]. As such, understanding the distribution of wetland types and sites is crucial to ensure sustainable management and assessment of resource use [3]. As such, wetlands have been referred to as the "kidneys" of nature [11] because of the many environmental services and ecological benefits they provide.

In terms of levels and purposes, more than 50 definitions of wetlands throughout the world have been presented [12,13]. The varying definitions come from the characteristics of the wetlands and how they are managed in different countries. However, in most definitions, wetlands are regarded as a unique ecosystem formed by interactions between the local area's geomorphology, hydrology, soil, and ecology. As defined explicitly in the Ramsar Convention, wetlands are distinct ecosystems that can be detected and monitored on a variety of scales using satellite remote sensing (RS) imagery and machine learning (ML) algorithms [14]. The combination of RS and ML can greatly relieve the heavy burden of manual work for wetland-related studies and offer huge potential and a wide scope of application space in these areas.

Even though there is a lack of reliable data, it is a concern to stakeholders that wetlands continue to be lost and degraded, as no science-based protocols are available in the most wetland regions to guide the monitoring of wetlands [6,7]. Under the joint influence of natural accumulation, artificial reclamation, and urbanization, wetlands are constantly changing over time. Moreover, several factors influence wetland changes, including the local terrain, hydrology, soil, economy, population, and policy. As such, wetland sustainability requires special land-use policy and relevant regulation and/or legislation to monitor and assess the status of these crucial habitats locally, regionally, and globally. Furthermore, the rapid expansion of agricultural areas and urbanization are important factors in wetland areas having decreased significantly over the past three decades. Wetland resources can be effectively preserved by having up-to-date information on the status and extent of land cover within the ecosystem [15].

Monitoring and assessing wetlands by RS is an advanced analytical approach [16,17] that allows for faster, less destructive, and more geographically expansive observation of the spatiotemporal changes in wetlands, as well as changes in the surrounding land use and land cover (LULC). Currently, Satellite RS technology is acknowledged as the most powerful source of data for wetland identification by the U.S. Army Corps of Engineers (USACE) [18], and it has been extensively and successfully employed to monitor, assess, and preserve wetland areas in the past 50 years [12,18]. As a complement to conventional approaches in wetland monitoring, RS has the potential to deepen our understanding of both local and global patterns of landscape and biodiversity. Through the development of satellite and sensor technology as well as ML algorithms, human involvement in wetland delineation has gradually decreased, leading to progress in techniques and algorithms for mapping these natural resources with RS tools [19,20]. Using various satellite datasets (e.g., Landsat, Sentinel, MODIS, . . .), researchers have produced land cover maps that include wetlands at national, provincial, regional, and local scales.

With the increased development of optical and radar sensor platforms, space-borne sensors are becoming more accurate and useful in characterizing wetland extent and discriminating LULC types [21]. A broad range of users, organizations, and researchers can now benefit from technological advances in open-access satellite data streams, cloud computing, and data science to perform fast, accurate, large-scale, and high-resolution land cover classifications [22–24]. Recently, the advent of the Google Earth Engine (GEE, https://earthengine.google.com (accessed on 20 August 2022)) has provided a professional platform to assist geoscientists interested in geo-big data analysis [7,25]. This cloud-based platform has revolutionized the processing and analysis of open-source earth observation data, introduced automatic training sample migration possibilities, and supports some ML methods [7,26]. The most impressive feature of GEE is its ability for large spatial and temporal scale environmental (e.g., wetland) monitoring through parallel computation service.

Meanwhile, the development of data science algorithms and the open-source Python language environment and its packages (such as TensorFlow and Keras) have resulted in detailed modeling and analysis of a wide variety of open-source satellite data sets. Therefore, coupling easy access RS satellite data with data analysis, visualization, geo-computation, modeling, and ML tools/packages has dramatically enabled scientists to map and monitor landcover within larger regions more accurately and in an automated and repeatable way. Currently, the combined use of GEE with state-of-the-art deep learning (DL) models in wetland studies is absent from the literature and has not yet been well documented.

As listed in Table 1, several review papers have summarized the studies conducted on wetlands from different perspectives. Given its importance, a meta-analysis of studies on the capabilities of RS sensors, features, and ML models for monitoring and characterizing worldwide wetlands is overdue. Thus, we reviewed the literature related to RS data and the methods of producing spatial information on wetlands.

Table 1. List and a brief summary of previous reviews related to the topic. The list was sorted by publication date (the number of citations is reported by 30 June 2022 on the WoS database).

#	Reference	First Author	Year	#Citation	Publication Journal	Review Type		Reviewing Period
						DR *	QR *	
1	[This Paper]	Jafarzadeh, H.	2022	0	Remote Sensing	✔	✔	1990–2022
2	[27]	Czapiewski, S.	2021	0	Land	✔	✔	2010–2021
3	[28]	Mirmazloumi, S.M.	2021	0	Remote Sensing	✘	✔	1976–2020
4	[29]	Montgomery, J.	2021	1	Remote Sensing	✔	✘	N/A
5	[30]	Gxokwe, S.	2020	9	Remote Sensing	✔	✘	2000–2020
6	[31]	Adeli, S.	2020	31	Remote Sensing	✘	✔	1991–2019
7	[13]	Mahdianpari, M.	2020	21	Remote Sensing	✘	✔	1980–2019
8	[32]	Chasmer, L.	2020	14	Remote Sensing	✔	✘	1973–2018
9	[33]	Chasmer, L.	2020	6	Remote Sensing	✔	✘	1973–2018
10	[34]	Minasny, B.	2019	34	Earth-Science Reviews	✔	✔	N/A
11	[11]	Mahdavi, S.	2018	79	GIScience & Remote Sensing	✔	✘	N/A
12	[12]	Guo, M.	2017	154	Sensors	✔	✘	1964–2015

Note: * DR and QR stand for descriptive review and quantitative review, respectively.

The findings of the available review studies indicate that a further review paper should be carried out to compare the different techniques and concepts. Moreover, to the best of our knowledge, a comprehensive review of recent achievements regarding ML and DL for global wetland studies using RS data is still lacking. In order to reach this objective, the following lead questions are considered, and the current meta-analysis sought to address them:

- Which ML method is best suited to monitor wetlands surface cover and adjacent areas and provide the best result from RS imagery? To what extent are the commonly applied ML approaches valid?
- How have the ML models varied over the last decades?
- What are the key factors in ML model selection for wetland studies? Are there any specific problems that are being solved preferentially by a specific algorithm?
- How important is optical imagery compared to SAR (synthetic aperture radar) data? What is the contribution of clear-sky observations from SAR imagery relative to optical imagery?
- Is multi-sensor (multi-source dataset) integration more accurate for wetland area delineation than a single sensor?
- What are the individual and combined contributions of SAR and optical data to wetland monitoring?
- What are the common satellite sensor types utilized for wetland studies?

- What are the common RS image features utilized for wetland studies?
- What are recommended steps for future wetland studies and management?

Toward responding to these important questions and describing future needs, empirical evidence is needed for protecting natural resources, resolving conflicts, and appropriately managing common pool resources of wetland areas among stakeholders. As a step in reacting to these calls, this paper's main objective is to help find the best combination of data sources and methods to successfully follow the needs of wetland studies, as pictured in Figure 1.

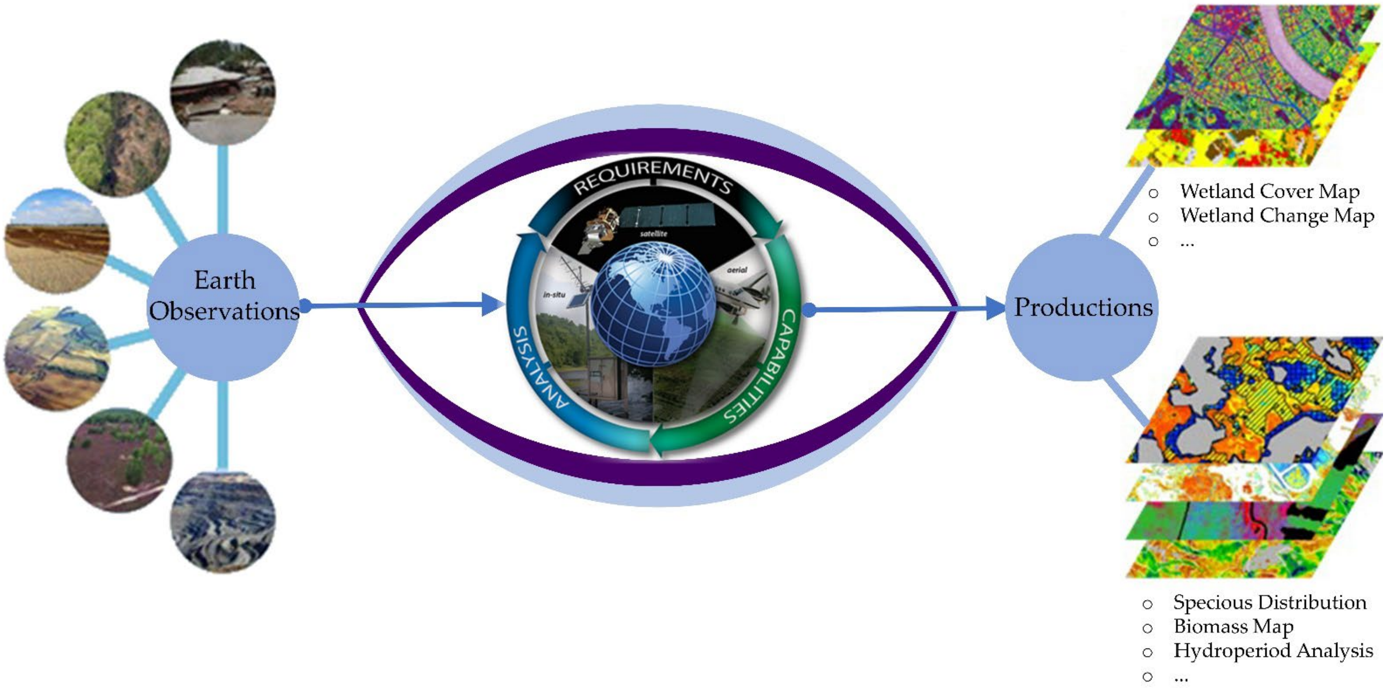


Figure 1. A conceptual overview of the use of ML and RS tools to derive productions.

The paper is structured as follows. A searching procedure will be defined as the first step in finding and evaluating the candidate studies in consideration of this paper's objectives. Our next step is presenting a typology of the main wetland-based practices with their definitions. We identified the following main categories of practices: classification, change detection (CD), vegetation mapping, biomass estimation, wetland area delineation, hydrological characterization, soil, and carbon estimation. We reviewed RS-based studies used to address each practice. In turn, the most critical features of the studies are highlighted and discussed, as are the research requirements for producing accurate and robust information on the wetlands. Finally, we present recommendations for future research in this field. In the conclusion section, the findings of this meta-analysis are summarized regarding the questions mentioned earlier.

2. Methods

2.1. Bibliographic Base and Search Query Definition

In preparation for this meta-analysis and systematic review, the Science Citation Index (Web of Science (WoS) Core Collection) bibliographic database was used on and up to 30 June 2022 to retrieve scientific documents, including papers published in journals and conference proceedings constrained to the time span from 1990 to 2022. For this purpose, three sets of keywords were systematically defined, providing a logical literature search query to locate highly relevant references in the database (see Figure 2). To retrieve papers that incorporated RS data and ML tools to address a wetland application, the search was conducted in the topic field (i.e., title/abstract/keyword) using the keywords listed in the second and third columns. However, to narrow down the search results and make them more specific, the first column keywords were only searched in the title field. Consequently, the predefined search query retrieved 528 journal and conference papers in the primary search in the WoS database. Afterward, the PRISMA checklist, known as the methodology of Preferred Reporting Items for Systematic Reviews and Meta-Analyses, was followed [35,36] to delineate the papers that fit within the scope of the topic and are eligible to be included in this meta-analysis. An overview of the paper selection methodology as per the PRISMA statement and review process is outlined in Figure 3.

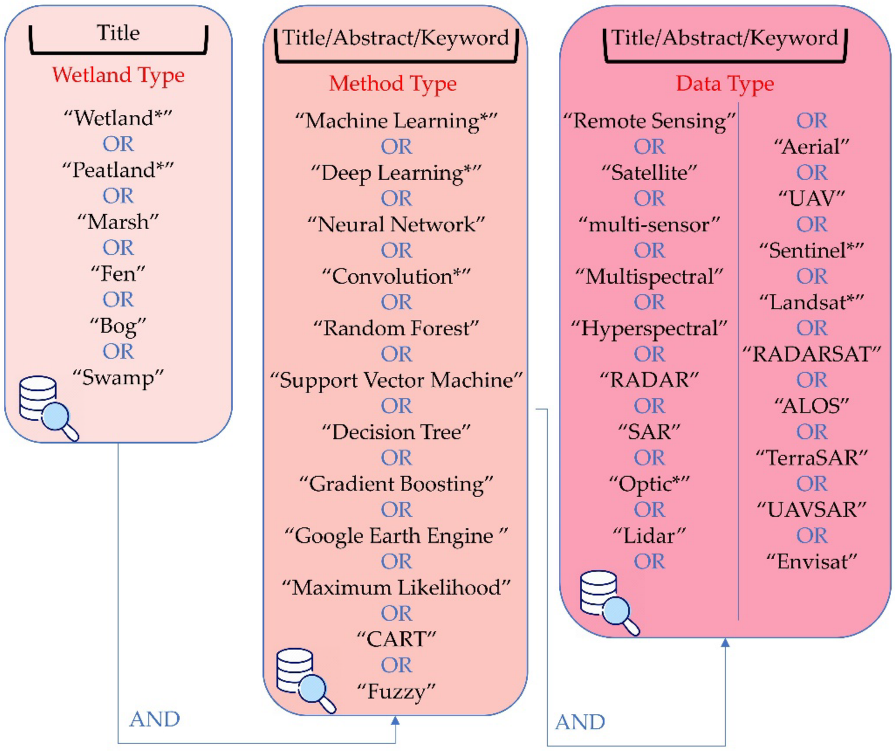


Figure 2. The predefined search query and list of keywords to prepare the procurements of this meta-analysis.

The screening of the resulted 528 potential papers was then started to filter them by title and abstract, providing 404 candidates. The meta-analysis did not consider documents categorized as review studies, book chapters, reports, and non-English papers. In the next stage, by assessing the full texts of those candidates, only publications utilizing RS and ML techniques in wetland monitoring were selected as the final items for review to comply with the predefined inclusion criteria and maintain a controllable workload while focusing on the lead questions and objectives of the current study. Finally, a total of 344 papers were included in our meta-analysis procedure (see Figure 3).

2.2. Extracted Attributes from the Screened Records

The review process was conducted based on the 344 selected papers by full-text reads while looking for and focusing on a set of primary attributes. Looking at the previous review papers in the field of wetland studies, several study characteristics (presented in Table 2) were identified for the analysis of the final set of included papers in the context of our systematic review using a custom-made data extraction worksheet. In the current meta-analysis, these attributes are summarized to attain an overview of how RS imagery and ML techniques have been used to support wetland studies.

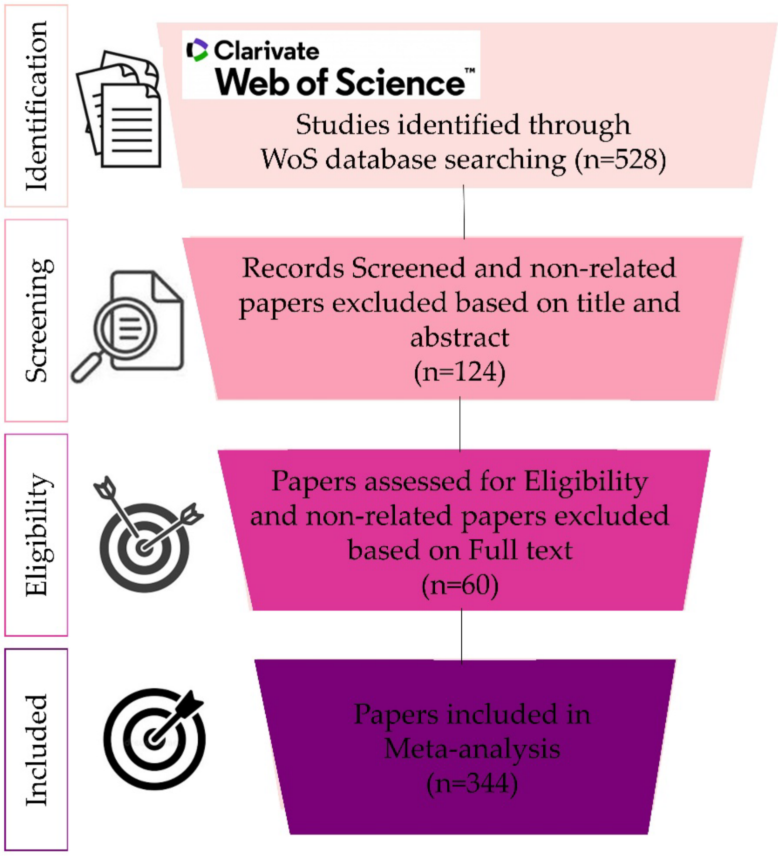


Figure 3. Paper selection and the review process flow diagram. A total of 528 papers were found in our primary search in the WoS database.

Table 2. A listing of extracted sub-fields/attributes considered for the content analysis of included papers.

#	Attribute	Type	Categories
1	Publication Title	Free-text	-
2	Keywords	Free-text	-
3	Authors	Free-text	First Author Name
4	First Author Affiliation	Free-text	University/Organization Country
5	Publication Year	Free-text	Published Year
6	Document Type	Classes	Journal; Conference
7	Source	Free-text	Published Journal or Conference
8	Publisher	Classes	MDPI, IEEE, Elsevier, etc.
9	Citation	Numeric	-
10	Study Focus/Objective	Classes	classification, change detection, vegetation mapping, etc.
11	Study Area Country	Free-text	Countries all around the world
12	Study Area Extent	Classes	Very small, Local, Regional, Provincial, National
13	Data Type	Classes	Multispectral, Hyperspectral, SAR, etc.
14	Sensor type	Classes	Landsat, Sentinel, RADARSAT, etc.
15	Feature Type	Classes	Imagery Features, Spectral Indices, Textural metrics, etc.
16	Methodology	Classes	ensemble learning, decision tree, DL-based, etc.
17	Accuracy Assessment	Numeric	Overall Accuracies analysis based on seven factors
18	Processing Tools	Classes	ArcGIS, ENVI, Python, SNAP, etc.

3. Results and Discussion

A detailed report of the systematic review will be provided in this section. We will begin by giving an overview of the general characteristics of wetland publications, including the author affiliations, journals, and the number of publications per year/journal/publisher.

Afterward, study objectives and applications, study regions, data and sensor type, and ML algorithms utilized in the literature will be discussed.

3.1. General Characteristics of Wetland Publications

3.1.1. Scientific Productions Trend

Figure 4 reflects the temporal distribution of the total number of reviewed papers along with the publication trends from three top publishing countries among 344 papers reviewed using PRISMA from 1997 to 2022. As shown, there is an increasing trend of scientific publications highlighting the importance of wetlands to the scientific community. The apparently drastic reduction from 2021 to 2022 can be attributed to the fact that the query results are until the middle of 2022. Considering the growing number of RS sensors and their promising performances in environmental monitoring tasks, about 67% (n = 232 out of 344) of the papers were published in the last five years (2018–2022).

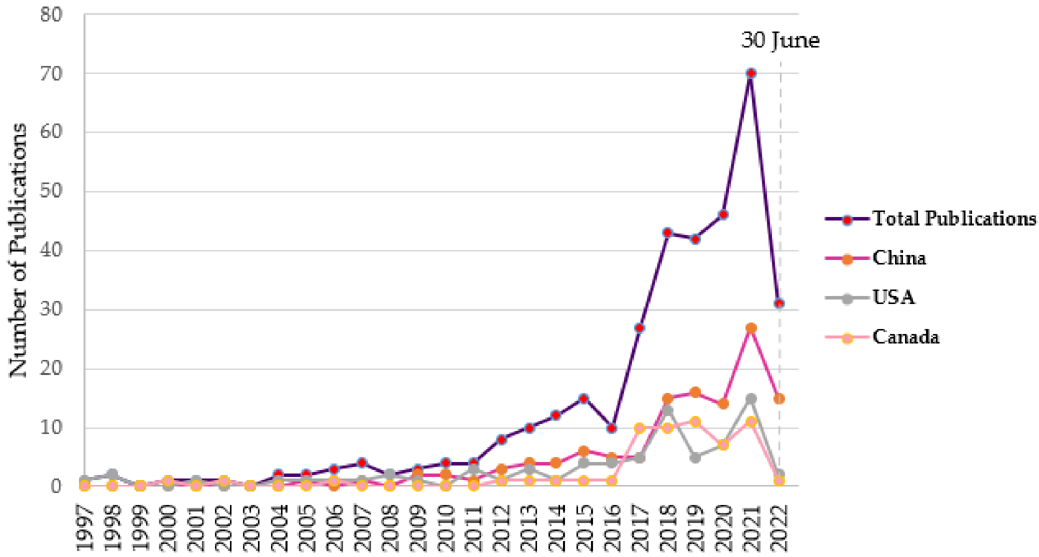


Figure 4. Temporal distribution and the total number of reviewed papers per year, and publication trends from three top publishing countries.

3.1.2. Keyword Frequency Analysis

A word cloud based on keyword frequencies is shown in Figure 5. Keyword size is calculated by the frequency of occurrence of each keyword in all included papers. The size of each particular keyword corresponds to how frequently it appears throughout all papers in the review. Considering the combination for the literature search, "Wetland" and "Remote Sensing" were the most frequently mentioned keywords in the reviewed literature. Note that there was a lack of consistency in the keywords because the reviewed papers came from a wide variety of journals in different formats. Therefore, some simplifications were made before feeding the keywords into the word-cloud generator. Our approach was to convert plural keywords into singular forms, capitalize all the keywords, and exclude those rarely appearing in the reviewed papers.

Figure 5. Word cloud shows the most frequent terms in wetland studies. The larger the text, the more frequently the word appeared in considered papers.

3.1.3. Journal and Conference Analysis

The eligible publications in our systematic review appeared in 88 different journals and conferences, illustrating the diversity of disciplines interested in wetland studies. Among the selected papers, 307 and 37 were journal and conference papers, respectively (see Figure 6).

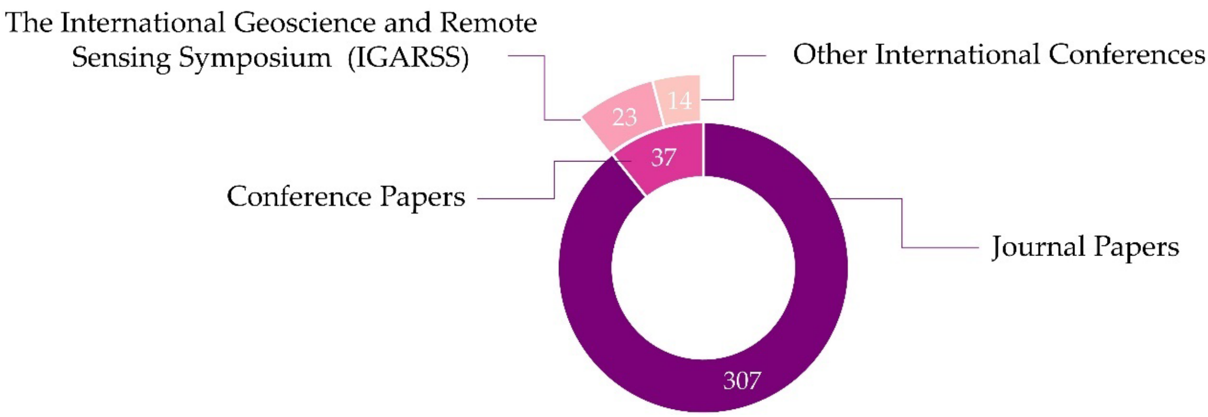
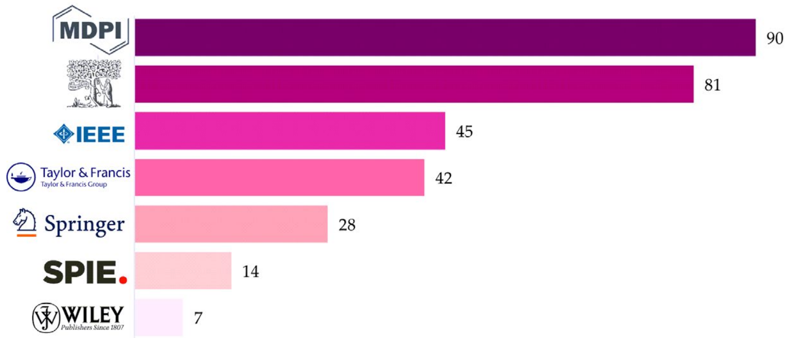


Figure 6. The number of journal and conference publications included in the meta-analysis.

Among peer-reviewed publishing journals, 51 have published one or two papers on the topic. The majority of reviewed sources come from 8 peer-reviewed journals (with a share of 52%); see Figure 7a. Only journals with at least three publications are included in this figure. As shown, the highest number (top five) of publications associated with wetland studies occurs in the *Remote Sensing (MDPI)*, *Remote Sensing of Environment (RSE)*, *International Journal of Applied Earth Observation and Geoinformation*, *IEEE Journal Selected Topics in Applied Earth Observation and Remote Sensing (IEEE-JSTARS)*, and *Canadian Journal of Remote Sensing (CJRS)* journals.

(**a**)



(**b**)

Figure 7. An overview of (**a**) the journals included in this meta-analysis and the number of papers per journal. (**b**) A listing of the leading publishers and the number of papers per publisher.

As shown in Figure 7b, the order of the publisher centers, whose journals account for the majority of the published papers is as follows: *MDPI*, followed by *Elsevier*, and *IEEE* (with an overall share of 70%). Moreover, 14% of the journal papers were published by *Taylor & Francis*, 9% by *Springer*, 5% by *SPIE*, and only 2% by *WILEY*. Among the conference proceedings, the *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, with 63% of papers (n = 23 out of 37), is the first ranked conference for publishing papers with the focus on wetland studies.

3.1.4. First Author Affiliation Analysis

The spatial distribution of the first author's affiliations illustrated in Figure 8 clearly indicates the dominant share has Asian affiliations (with 42%), with 35% having Chinese affiliations alone. Furthermore, North American affiliations (with 40%) ranked second in this review, with 21% coming from the USA and 17% from Canada. Around 13% of publications are attributed to European affiliations. The high percentage of publications from Chinese, USA, and Canadian affiliations can be associated with the extensive wetland coverage in these countries, which need to be studied, as well as a significant contribution of papers with strong methodological backgrounds. Researchers conducted such studies to develop ML algorithms and evaluate RS datasets considering field data collection for wetland studies.

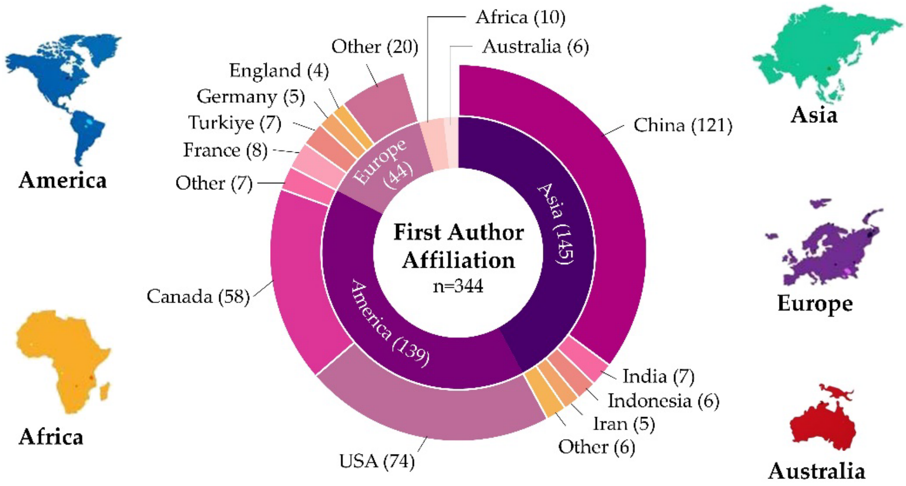


Figure 8. Country and continent-based overview of first author affiliations. Among the continents, Asia (with 42%), America (with 40%), and Europe (with 13%) hold the largest shares, and among countries, China (with 35%), the USA (with 21%), and Canada (with 17%) hold the largest shares.

3.1.5. Citation Analysis

Analysis of citations provides a way to identify papers that have a significant impact on the field. Citation analysis also indicates the quality and objectivity of a paper by demonstrating the number of researchers or scholars who are attracted to cite that paper. As a result, the citation numbers of all considered papers until 30 June 2022 were extracted from the WoS database in order to identify those that contributed the most. In Table 3, papers were ranked based on the number of citations; however, we also calculated the average citation per year to lessen the effect of elapsed time since the publication of the cited documents.

Table 3. List of highly cited papers in the database, ranked by the total number of citations (as of 30 June 2022).

Rank	Ref.	First Author	Total Citations	Average Citation	Publication Year
1	[37]	Millard, K	260	37.14	2015
2	[38]	Dronova, I	176	16	2011
3	[39]	Bwangoy, JRB	169	14.08	2010
4	[40]	Baker, C	168	10.5	2006
5	[41]	Mandianpari, M	155	31	2017
6	[42]	Han, XX	147	21	2015
7	[43]	van Beijma, S	142	17.75	2014
8	[44]	Liu, T	138	34.5	2018
9	[45]	Corcoran, JM	130	14.44	2013
10	[46]	Mahdianpari, M	114	38	2019

3.2. Study Focus and Applications

Knowledge of the status and extent of wetlands is essential to a series of research questions and applications. Thus far, many studies have characterized wetlands and monitored, mapped, and assessed them over time using a variety of satellite datasets with different spatial and temporal resolutions [47,48]. Satellite imagery, such as the Landsat series, Sentinel, SPOT, and MODIS, provide long-term spatial data archives to assess, monitor, and manage ecological environments. These data collections have been widely utilized in environmental studies, for instance, in LULC change analysis, wetland status monitoring and extent mapping, biomass estimation, soil moisture retrieval, inundation mapping, and water level monitoring [7,49–52], amongst others.

As depicted in Figure 9, satellite imagery is mainly applied in seven major application domains for wetland studies: (1) the generation of landscape-type thematic maps for wetland types; (2) the dynamic change analysis of wetlands; (3) wetland vegetation mapping; (4) the survey and recognition of wetland extent; (5) the evaluation and estimation of biomass in wetland areas; (6) wetland hydrological characterization and surface water hydroperiod; and (7) soil and carbon estimation. The share of each of these applications within the reviewed literature is also presented in Figure 9. Of all reviewed publications, 51% investigate wetlands from the perspective of the classification of wetland classes. Following the classification, 14% of the publications analyzed wetlands' changes. Wetland vegetation mapping and wetland extent recognition are in third and fourth places, with a share of 12% and 7% among all reviewed papers. Since the classification and CD frameworks have the most significant shares, a brief discussion of these applications is presented below.

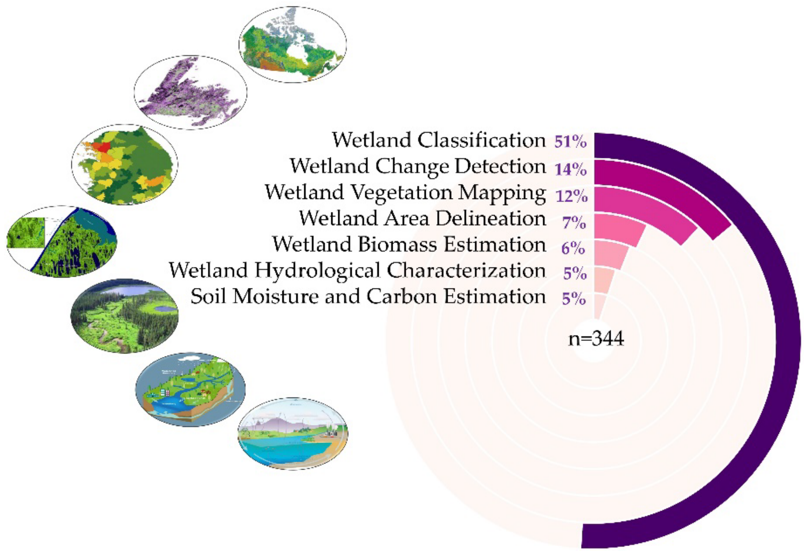


Figure 9. Overview of the diversity of application domains of RS Earth observations in wetland areas.

3.2.1. Classification

Wetland cover classification arises from the monitoring and management needs to categorize wetland ecosystems into several types displaying different landscapes within wetlands. Traditional in situ surveys are too costly and slow to meet the demand for extensive and fast monitoring of wetland habitats [11]. The RS technology, in contrast, offers labor- and cost-effective advantages for mapping and assessing wetlands due to its intuitive observations of the ground in the broad coverage area, along with timely, regular, and rapid monitoring capabilities [53–55].

With the current advancement in Earth observation instruments (e.g., multi/hyperspectral, SAR, etc.), there are ever more types of airborne or space-borne images with different resolutions available (i.e., spatial/spectral/temporal resolution). This leads to significant demand for intelligent Earth observation based on RS imagery, enabling the smart identification and classification of wetland areas from airborne and space platforms. The problem of scene classification has emerged as an active research area in RS data analysis and has drawn remarkable attention in recent years, as it is essential for effectively interpreting remotely sensed images. It attempts to label given scene images correctly based on their contents with predefined semantic land cover categories [56]. Currently, satellite image data for Earth observation are being made continuously available to the public. Governmental programs, including the ESA's Copernicus and NASA, are putting considerable effort into making such data freely available for universities and institutions, researchers, scientists, and technology experts to use in order to inspire innovation and entrepreneurship.

3.2.2. Change Detection

As one of the leading research topics in earth systems, land cover CD in terrestrial surfaces has profound implications for human society and ecosystems (especially in wetland ecosystem functioning) [57]. Due to their vulnerability and sensitivity to variations in the environment, wetlands have become key regions for monitoring land cover changes over time. Wetland ecosystems interact with the physical environment, including hydrology, meteorology, and topography, in a variety of ways. Land cover CD in wetland sites provides an understanding of the patterns of the spatial distribution of wetland surface cover and the complexity of its spatiotemporal variations [38].

As the most comprehensive and longest time-series RS image available, Landsat imagery is one of the most suitable data sources that provide suitable spatial and spectral resolutions as well as free-of-charge imagery. Moreover, in many developing countries, the limited data resources make Landsat imagery an important data source for filling the knowledge gaps in investigating local small-scale wetland dynamics.

Using satellite imagery for wetland CD involves a variety of methods, which can broadly be divided into two categories: (1) change enhancement approaches, including direct comparison, vegetation indices differentiating, spectral mixture analysis, and fuzzy CD, and (2) 'from-to' change information extraction approaches [58–60]. The former methods (e.g., image differencing) do not indicate what types of land cover have been changed; they only provide information on whether there has been a change or not, and in some cases, measure the relative magnitude of that change. By contrast, the latter methods, such as the post-classification comparison approaches, are the most commonly used and effective CD techniques [61]. Post-classification comparison methods use separate classifications for images acquired at different times to produce different maps from which 'from-to' land-cover change trajectories can be detected [62]. In addition, 'from-to' quantitative information about the type of LULC changes can be gained from a cross-tabulated change matrix [63].

Among all wetland CD methods in our meta-analysis, the post-classification approach is the most-employed technique, with a share of $n = 46$ out of 49. Taking a time interval perspective, CD studies can be categorized into two categories: (1) long-term CD and (2) short-term CD. As depicted in Figure 10, short-term CD (i.e., CD studies within a period of (1) 1–5 years and (2) 5–10 years) has a share of 20%, and long-term CD (i.e., CD studies within a period of (1) 10–20 years, (2) 20–30 years, and (3) 30–40 years) has a share of 80% among all post-classification change analysis papers. Long-term CD provides a better understanding of wetland trends and sudden changes; therefore, it is helpful to protect and analyze the dynamics of wetlands.

3.3. Case Study Analysis

The worldwide distribution of study regions grouped by countries of case studies is shown in Table 4. As shown, most studies were conducted in study areas in China (35%), the USA (19%), and Canada (18%). Additionally, the literature review found the following study areas were studied at least four times: South Africa ($n = 12$), India ($n = 9$), Australia ($n = 9$), France ($n = 6$), Indonesia ($n = 6$), Iran ($n = 5$), Brazil ($n = 4$), Turkiye ($n = 4$), and Sweden ($n = 4$).

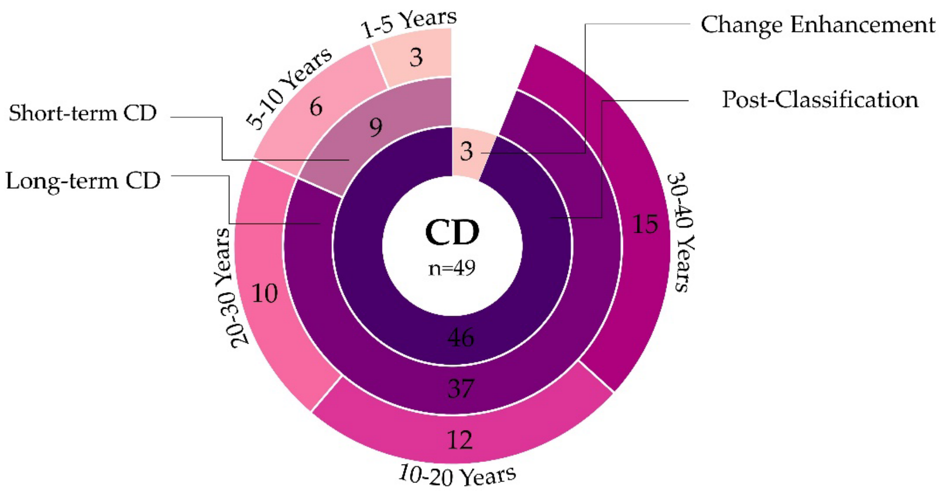


Figure 10. Frequency of short-term and long-term CD.

Table 4. Overview of study site locations grouped by countries coupled with various scales of the study site's extent. Sites with four or more studies were included.

#	Study Area (Country)	#Studies	VS	L	R	P	N	#	Study Area (Country)	#Studies	VS	L	R	P	N
1		(120)	39	50	27	3	1	7		(6)	5	1	0	0	0
2		(66)	34	21	8	2	1	8		(6)	4	2	0	0	0
3		(62)	9	36	6	6	5	9		(5)	1	2	2	0	0
4		(12)	5	3	4	0	0	10		(4)	3	1	0	0	0
5		(9)	3	3	3	0	0	11		(4)	3	1	0	0	0
6		(9)	4	3	2	0	0	12		(4)	2	1	1	0	0

Note: very small (VS), large (L), regional (R), provincial (P), national (N).

Based on the extent of the study sites, the publications were categorized into five groups (see Table 4). To have consistency with [28], these divisions are considered in terms of the following five groups: (1) very small (less than 100 km^2), (2) local (between 100 km^2 and 3000 km^2), (3) regional (more than 3000 km^2 and less than a provincial scale), (4) provincial, and (5) national (country-wide) scales. This investigation shows that most wetland RS studies call attention to very small, local, and regional scales and that very few consider provincial or country-wide scales.

3.4. RS Data Used in Wetland Studies

3.4.1. Data Type

The use of satellite RS in environmental research studies has been widely adopted as a rapid scientific tool for monitoring and investigative purposes [7,21,64,65], as shown in Figure 11. It offers a powerful alternative over-ground survey, providing a synoptic view, multispectral data, multitemporal coverage, and cost-effectiveness [36,66]. With these improvements and advances in quality, volume, and diversity, spectral imagery is being used to study wetlands more effectively and with a wider variety of applications. These advances support increases in the quality, volume, and diversity of applications of spectral imagery in the study of wetlands, in particular, accurate assessment of their status and measuring the pattern of the changes, as well as the success of restoration efforts. Meanwhile, wetland studies conducted by optical and SAR imagery have by far the largest shares.

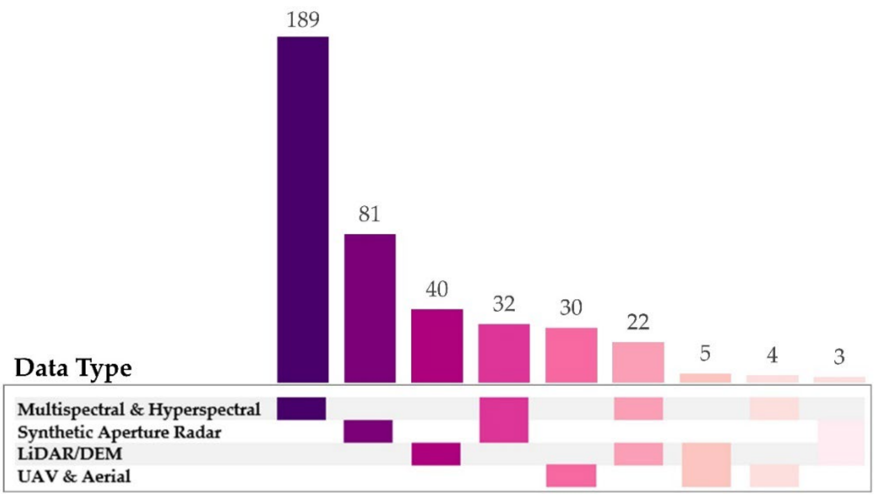


Figure 11. Distribution of employed data types and their combinations with the largest shares for multispectral and hyperspectral (46%), SAR (20%), and LiDAR/DEM (10%) data types.

A variety of applications have been proposed and studied for RS optical sensors, from small target evaluation to global issue resolution. In the wetland field of studies, in addition to providing information on vegetation cover and community type, optical sensors are capable of identifying and differentiating wetlands and vegetation zones, as well as mapping wetlands on a large scale, among other applications [67]. Over the last two decades, improvement of satellite spatial resolution and reduced costs of multi- and hyperspectral sensors have increased the scope for applying spectral imaging to advance wetland study. Multispectral satellite imagery can be acquired at resolutions < 5 m, enabling examination of wetland systems at much finer scales and supporting longitudinal analyses of change over extended periods. However, due to their inability to penetrate clouds and atmospheric haze or a dense vegetated canopy, optical sensors are limited to daytime clear-sky image acquisition [24]. Even though optical satellite imagery successfully detects and monitors wetlands, the presence of cloud cover limits their usefulness, especially in coastal areas [14,68,69].

Unlike optical sensors, as an active RS system, SAR is not affected by atmospheric conditions, can detect sub-canopy soil and vegetation structural features, and does not rely on external sources of radiation (i.e., sunlight) for its operation. It has the ability to overcome the above limitations (unaffected by weather conditions) and can operate in all-weather and daylight-independent conditions [36,70,71], so it is well suited for wetland monitoring. SAR has proven to be a preferred alternative or supplemental source to optical images for wetland mapping, especially in coastal wetlands and intertidal zones [69,72,73]. However, several factors affect SAR data and its components, such as the effects of surface moisture content and roughness and instrument viewing direction, and incidence angle [74]. As a result, the collected backscattering SAR signals influenced by vegetation and soil properties carry information related to wetlands and soil's geometric structure and dielectric properties [73]. This makes SAR data essential to distinguish certain land cover classes such as "built-up" and "bare soil", or classes with different levels of moisture and inundation such as "heterogeneous wetland sites" and "intermittent water bodies".

Considering the advantages of optical and SAR data, the combination of optical and SAR imagery can offer the greatest potential for supporting wetland mapping and monitoring tasks, as described in [21]. It is critical, therefore, to explore the extent to which optical and SAR RS data may supplement the LULC studies, particularly in wetland regions. Our findings showed that multispectral and hyperspectral optical imagery and SAR data present the greatest portion of wetland studies. Regarding the data type usage, as shown in Figure 11, 247 studies employed multispectral and hyperspectral optical images, followed by SAR images (n = 116), LiDAR/DEM data (n = 65), and UAV/Aerial imagery (n = 39). Moreover, the integration of optical and SAR imagery includes 32 studies, followed by the integration of optical and LiDAR/DEM with 22 studies.

3.4.2. Single-Source Versus Multi-Source Data

Although individual RS data have proven successful in monitoring wetland areas, data fusion techniques employing multi-source satellite data sets can improve the determination of wetland hydrological, vegetation, and topographic characteristics, which are important indicators of wetland characteristics and offer the potential for improved wetland classification accuracy [21,75–77]. For example, optical images can reflect the rich spectral information of objects, and SAR is capable of providing valuable geophysical parameters. The combination of polarimetric and optical data to classify wetlands fully exploits the spectral and backscattering characteristics of the habitat. In addition, it reduces radar speckle noise and enhances the separation between wetland objects, making it a helpful monitoring strategy. Many experts and geoscientists have recently utilized multi-source RS imagery to monitor wetlands with varying results [11]. Many works have attempted to employ multi-source imagery to monitor wetlands considering data fusion and feature fusion techniques to use the complementary merit of different types of RS data. For instance, in a newly published paper, Jafarzadeh et al. [21] established a two-stream DL framework based on a graph convolutional network and convolutional neural network for wetland classification using Sentinel-1 and Sentinel-2 images. Based on their ablation analysis, the accuracy of classification reached its highest when two kinds of data sets were combined. By combining LiDAR and SAR data, Millard et al. [78] observed improved wetland extent mapping and classification accuracy of wetland types compared to individual data source analysis. The significant advancements and improvements in spaceborne RS in parallel with the rise of the trend toward open-source data sharing have led to opportunities for combining multiple data types in monitoring and fully understanding the unique characteristics of wetland environments.

Using multi-source satellite images helps in understanding, modeling, and projecting land change effectively by providing timely and spatially distributed information. In particular, moderate-resolution multispectral sensors (e.g., Landsat, SPOT, and ASTER) have been successfully used to study flooding and affected land cover, detect wetlands in heterogeneous landscapes, and monitor invasive plants. More recent studies reported high accuracies in obtaining wetland characteristics when fusing the datasets from Sentinel-1 and Sentinel-2 sensors [21,50,73,77]. This meta-analysis reveals that about 55% of studies benefited from multi-source or multi-sensor RS data combination, while the remaining utilized only a single-source or single sensor imagery (see Figure 12).

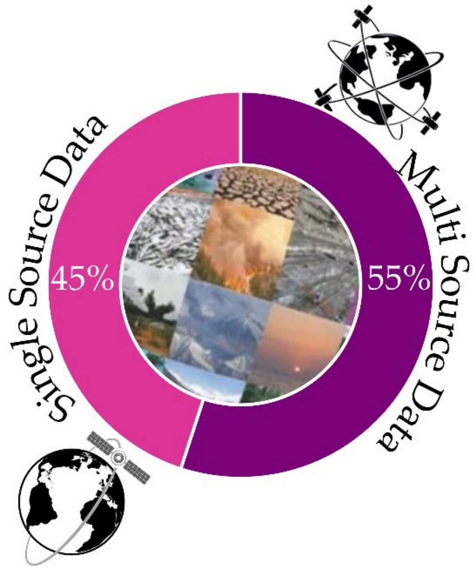


Figure 12. Frequency of single- and multi-source RS data usage in wetland studies.

3.4.3. Sensor Type

Based on our search query in WoS, we can indicate an increase in the use of RS methods in wetland research during the last decade, which is likely a result of the greater availability of new RS data sets (e.g., Sentinel 1 and 2; Landsat 8) paired with the rapid development of ML approaches. As shown earlier, a variety of RS data have been applied to evaluate wetlands, including very high-resolution (VHR) satellite imagery, Landsat, and SAR.

The most broadly used wetland RS data source is Landsat multispectral imagery that, as of Landsat 8, is 30 m in spatial resolution for most spectral channels, with a repeat cycle of 16 days, including 11 bands, which is publicly accessible at no cost [12]. Scholars in a wide range of studies have achieved accurate wetland identification results through the incorporation of the Landsat dataset, specifically from the Landsat 8 Operational Land Imagery (OLI) satellite (e.g., [79,80]). The limitations of approaches using data at this spatial resolution, such as the inability to exactly identify wetland locations, are in turn balanced by the possibility of such data to rule out large-scale regions as not being likely to include wetlands. Landsat-5, which holds the Guinness World Record for the longest on-orbit time (from 1984 to 2012), was also widely applied to historical wetland mapping [7,10,45,81,82]. Because they provide more spatial and structural characteristics than spectral information, the high-resolution images obtained from the RapidEye, Quickbird, WorldView-2, and SPOT 5 satellites also have become one of the main sources for resources and environmental management and application [20,83–87]. The utilization of optical and SAR data for wetland studies is growing. As shown in Tables 5 and 6, various satellite data with different resolutions are used in different studies. Among optical sensors, the Landsat Archive (including Landsat 4, 5, 7, and 8) has the greatest share by far (with n = 201 studies), followed by Sentinel-2 and RapidEye with a share of n = 54 and n = 14 studies, respectively. In SAR equipped satellites, Sentinel-1 (n = 45), RADARSAT-2 (n = 31), and ALOS PALSAR (n = 25) are the mostly used SAR data sets.

Table 5. List of the commonly used optical satellites in wetland studies ranked by the number of times they have been utilized in the papers.

Satellite	Life Span	#Channels	Range	Image Type			Spatial Resolution	Repeat Cycle (Days)	#Studies	Ref.
				Pan	MSI	HSI				
Landsat-8	2013–now	12	B1–9 (0.43–1.38) B10–11 (10.6–12.51)	☑	☑	☒	15, 30, 100 m	16	74	[7,10,42,81,88–91]
Landsat-5	1984–2013	8	B1–5 (0.45–1.75) B6 (10.40–12.50) B7 (2.08–2.35)	☒	☑	☒	30, 120 m	16	62	[7,10,42,45,81,82,92,93]
Sentinel-2	2015–now	12	0.443–2.190	☒	☑	☒	10, 20, 60 m	5	54	[21,55,89,91,94–99]
Landsat-7	1999–now	8	B1–5 (0.45–1.75) B6 (10.40–12.50) B7 (2.08–2.35)	☑	☑	☒	15, 30, 60 m	16	50	[7,10,42,81,100]
1-11 Landsat-4	1982–2001	7	B1–5 (0.45–1.75) B6 (10.40–12.50) B7 (2.08–2.35)	☒	☑	☒	30, 120 m	16	15	[10,42,101–103]
1-11 RapidEye	2008–now	4	0.44–0.85	☑	☑	☒	5 m	1–5.5	14	[104–106]
MODIS	1999/2002–now	36	B1–19 (0.405–2.155) B 20–36 (3.66–14.28)	☒	☑	☒	250,500, 1000 m	1–2	12	[107–111]
WorldView-2	2009–now	8	0.45–0.80	☑	☑	☒	0.52, 2.4 m	1.1	12	[2,86,112]
Quickbird	2001–now	5	0.45–0.9	☑	☑	☒	0.61, 2.4 m	1–3.5	8	[83–85,113,114]
Gaofen-1	2013–now	5	0.45–0.89	☑	☑	☒	2, 8 m	4	8	[115–117]
ASTER	1999–now	14	B1–3B (0.52–0.86) B4–B9 (1.6–2.43) B10–B14 (8.12–11.65)	☒	☑	☒	15, 30, 90 m	4–16	7	[91,118,119]
SPOT-5	2002	4	0.5–1.75	☑	☑	☒	2.5, 5, 10 m	2–3	5	[83,87]
Gaofen-5	2018–now	330	0.39–2.51	☒	☒	☑	30 m	2	5	[95,120]
Pléiade	2011	4	0.43–0.95	☑	☑	☒	0.5, 2 m	26	3	[121]
Gaofen-2	2014–now	5	0.45–0.89	☑	☑	☒	0.8, 3.2 m	4	3	[5]

Table 6. List of the commonly used SAR satellites wetland studies, ranked by the number of times they have been utilized in the papers.

Satellite	Life Span	Polarization	Wavelength (cm)/Band	Repeat Cycle (Days)	#Studies	Ref.
Sentinel-1A, Sentinel-1B	2014–Present 2016–Present	Single/Dual	5.54/C-band	6	45	[21,82,89,96,97,115,122]
RADARSAT-2	2007–Present	Single/Dual/Quad	5.55/C-band	24	31	[41,45,78,82,106,123,124]
ALOS PALSAR	2006–2011	Quad	23.6/L-band	46	25	[110,124–129]
TerraSAR-X	2007–Present	Quad	3.11/X-band	11	9	[41,124,130]
ENVISAT ASAR	2002–2012	Dual	5.63/C-band	35	6	[110,131]
Gaofen-3	2016–Present	Single/Dual/Quad	5.4/C-band	29	3	[69]
Huan Jing-1C	2012–Present	Single-VV	3.13/S-band	31	2	[132]
ERS-1	1991–2000	Single-VV	5.66/C-band	35, 3, 168	2	[126]
ERS-2	1995–2011	Single-VV	5.66/C-band	35	2	[126]

Along with varieties of RS data that have been engaged in wetland studies, employing the new generation of RS data provides promise for resolving the remaining challenges in this field. Meanwhile, it is recommended to utilize the RADARSAT Constellation Mission (RCM) and the upcoming NASA-ISRO SAR Mission (NISAR) in future wetland studies by establishing new methodologies.

3.4.4. Data Type Resolution

The RS data types employed in wetland studies can be classified into three categories based on their spatial resolution: high-resolution (5 m), medium-resolution (5 to 30 m), and coarse-resolution (>30 m). Figure 13 illustrates how frequently each of these data types is used in review papers. Medium-resolution images hold the largest share (with 66%) by far out of all data types. This is followed by high-resolution images, which take up 30% of the share, and coarse-resolution images, which take up 4%.

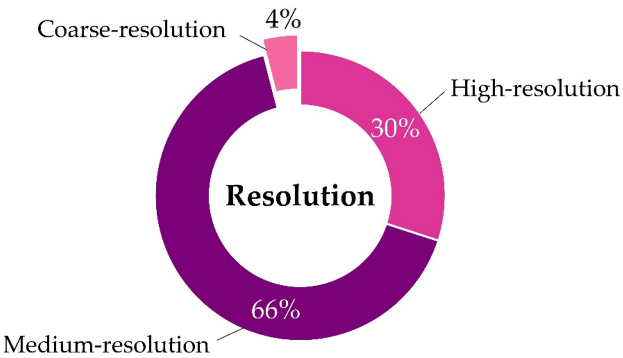


Figure 13. Frequency of high-resolution, medium-resolution, and coarse-resolution images used in wetland studies.

3.4.5. Single Date Versus Multi-Date

Multi-date and time series RS data has been widely conducted with many sensors to monitor the status of wetlands and detect land cover changes globally [6,7,109,133]. There are a number of satellite missions, both optical and SAR systems, which provide long time-series and ongoing multi-temporal imageries with global coverage for LULC mapping, wetland monitoring, and CD efforts [7,40]. Our systematic review provides insights into the available data types for investigating wetland covers in a multi-date manner. For example, of the optical sensors, Landsat archive, MODIS, and Sentinel-2, and among SAR missions, Sentinel-1 and RADARSAT-2 are suitable for large spatial and long time-series wetland studies. In some cases, such as the MODIS sensor, which provides a historical observation of the earth's surface, the coarse resolution of such imagery cannot precisely identify the details of the wetlands and smaller wetland sites. Looking at Figure 14, about two-thirds of the studies have applied multi-date RS data for wetland studies.

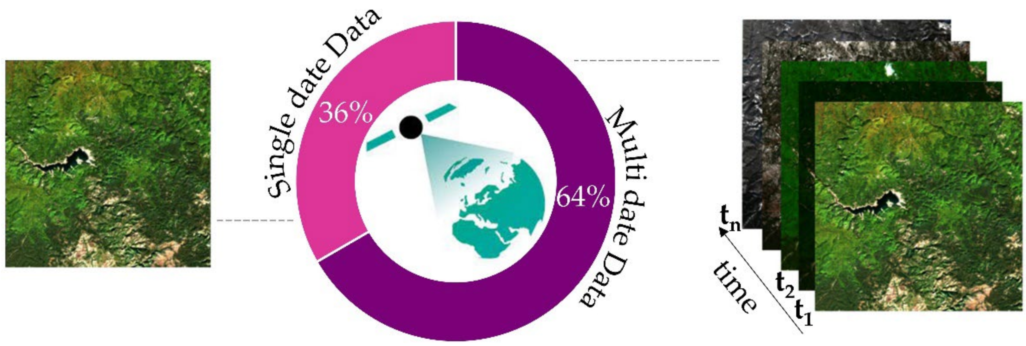


Figure 14. Frequency of single- and multi-date RS data usage in wetland studies.

3.5. Methodology Analysis

3.5.1. ML Classifier Categories

In the aftermath of its introduction, land cover mapping algorithms have been refined and upgraded many times [134]. For instance, when it comes to water extraction, the procedure can be done considering three stages: visual interpretation, semi-automatic interpretation, and automatic interpretation [135]. In recent years, ML has emerged as the most common wetland extraction method for automatic interpretation, and supervised and unsupervised ML techniques for RS image classification have progressed greatly. The challenges and difficulty of discrimination among classes, however, continue to affect the accuracy of surface mapping and data extraction. Therefore, classification is still a difficult task due to confusion with different cover classes.

Various classification techniques have been used to deal with land cover classification and improve classification accuracy. At present, the use of shallow ML algorithms, such as support vector machine (SVM), backpropagation (BP) neural networks, decision tree (DT), random forest (RF), extreme gradient boosting (XGBoost), and K-Nearest Neighbors (KNN), have been widely applied to RS data in extracting wetland information and improving the accuracy of wetland classification and CD. These approaches are able to handle complex nonlinear relationships without taking into account the statistical assumptions. However, as a diverse type of land cover, wetlands involve a variety of spatial, temporal, and spectral characteristics, and no single algorithm has proven to meet all the needs of wetland monitoring and be optimal across all use cases [76]. The shallow ML algorithms work well in extracting information from wetland areas; however, they require a lot of prior knowledge to be trained and high learning costs to migrate models.

Since its inception, DL, a subfield of ML, is emerging as a powerful tool to address problems by learning from data. DL is a milestone data representation learning technology that has taken the world by storm due to its success. As a way to automate predictive analytics, DL allows trainable models composed of sequence of processing layers and nonlinear mappings to learn representations of data with multiple levels of abstraction [136]. A DL network has a strong function expression ability, can learn more complex training samples, and has good robustness for the classification of complex features such as wetland landscapes in RS images [21,77,137]. CNN is a breakthrough technique in DL, and it is a kind of feed-forward neural network, which has good performance in image processing and data mining. The artificial neurons in CNN models can respond to a part of the surrounding units in the coverage area. By the inclusion of several building blocks, such as convolutional layers and pooling layers in its structure, a CNN framework is capable of better extracting medium and high-level abstractions from the original images. Some scholars have applied it in wetland classification studies and have reported higher overall accuracy values than those obtained using shallow ML [21,77,96,138].

ML algorithms' robustness and generalization capability have made them the major classification methods. Various ML and classification techniques have been used successfully and widely in wetland studies. Considering the structure of different methodologies employed during the last three decades, the classification algorithms were grouped into eight major categories in this paper: (1) ensemble learning; (2) decision tree; (3) Kernel-based; (4) distance-based; (5) DL-based; (6) ANN; (7) instance-based; (8) Bayesian (see Figures 15a and 16). While there is an overlap between the ANN and DL categories, the former includes shallow, two- or three-layer networks, whereas the latter includes more complex and deeper networks. As illustrated in Figure 15b, the most common form of ML, deep or not, is supervised learning.

According to Figure 16, among these algorithms, CNN as a DL model, and RF as a ML model have drawn attention to wetland mapping. As far as the accuracy of algorithms is concerned, DL models are usually the best to use. However, recent studies on challenging classification tasks using multi-source and multi-temporal RS data have pointed to the superiority of the RF approach. RF, as a tree-based ensemble method, has shown superior performance among other ML techniques and has become an often-used method in wetland identification and mapping. RF has several advantages, such as the ability to handle high-dimensional data while being less affected by noise, incorporating continuous and categorical data, and measuring descriptive variable importance [139]. Although many studies indicate that RF produces higher classification accuracy than traditional techniques, it is not usually the most accurate ML method (the reader is referred to [21] and Section 3.7. in this paper). The ensemble methods combine several base estimators' predictions, improving a single estimator's performance and accuracy [139]. In a recent study, a new ensemble-based model, called the multi-grained cascade forest (gcForest), was proposed by Zhou [140]. In this approach, several base estimators are stacked to form a layer-by-layer model. As the name implies, a multi-grained scanning technique is used to construct this estimator, and a cascade forest is included to enhance the depth and diversity of the traditional forest model. Shallow structure models combine spectral, structural, and semantic features for the classification of remotely sensed imagery [141]. However, the hetero-spectrum phenomenon in high-resolution RS image classification is very obvious. Therefore, in complex structures, such as heterogeneous wetlands, shallow structure models may be negatively affected by computing power and unable to learn the sample information adequately.

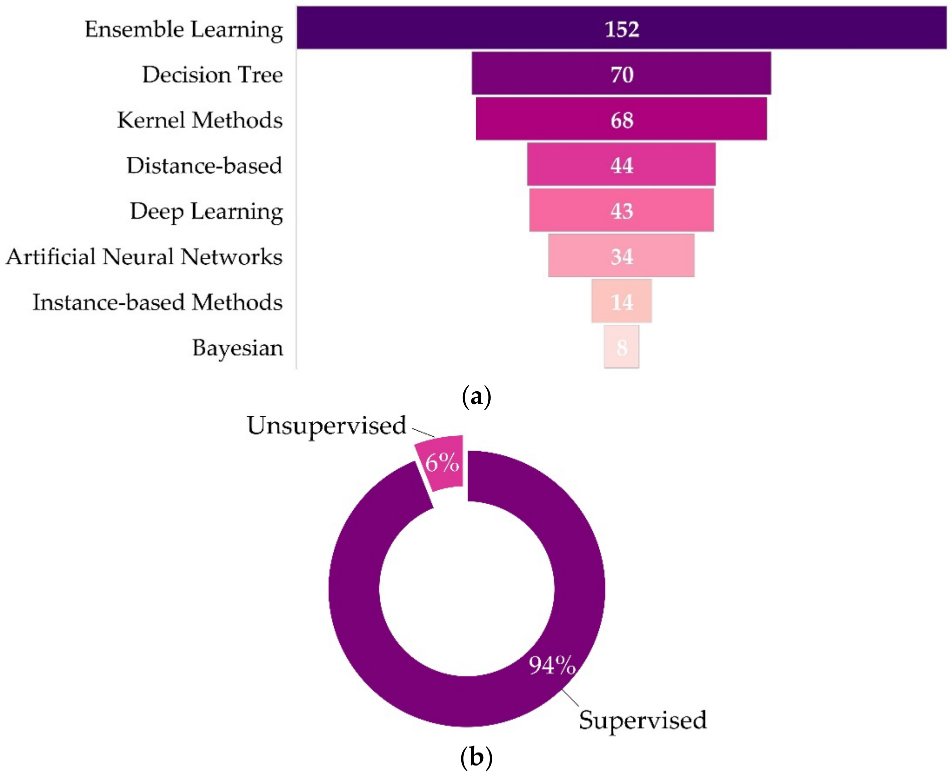


Figure 15. (**a**) Frequency of ML algorithms in wetland studies with (**b**) percentage of supervised and unsupervised approaches.

The selection of ML algorithms in RS applications such as wetland studies is subjected to several influential factors, such as sensor type and its spatial and spectral resolution, training sample size, and the complexity of the classification problem, etc. For instance, the RF model could be considered to be the most efficient if useful features can be derived from the RS imagery and fed to it. In the case that extracted features are not beneficial in classification, DL models could be the best selection as they have the ability to retrieve complex patterns and informative features from the satellite image data. For example, CNN has shown performance improvements over SVM and RF [21,142]. However, the main problem with DL approaches is the lack of interpretability due to their hidden layers, "black box" nature [143]. Additionally, the efficiency of DL models strongly depends on the availability of a high number of training samples, i.e., ground truth data [21]. Moreover, DL models require specialized knowledge, are expensive to implement computationally, and require dedicated hardware to operate.

Overall, the direct comparisons of different kinds of methodologies might not be fair since the experiment settings, and the hyperparameter tuning process for different ML and DL models are not the same (e.g., the input features used for RF and other DL methods are different). With the advent of big data and the continuous addition of satellite-based data, we cannot rely on only one specific methodology for all RS applications. There is a need to develop ensemble and hybrid approaches to tackle this voluminous data coming from a variety of sources. As such, giving merit to a single approach is difficult, as past comparison-based studies and some review papers provide readers with often contradictory conclusions based on processing workload, input datasets, and the evaluated performance metrics, which is somewhat confusing.

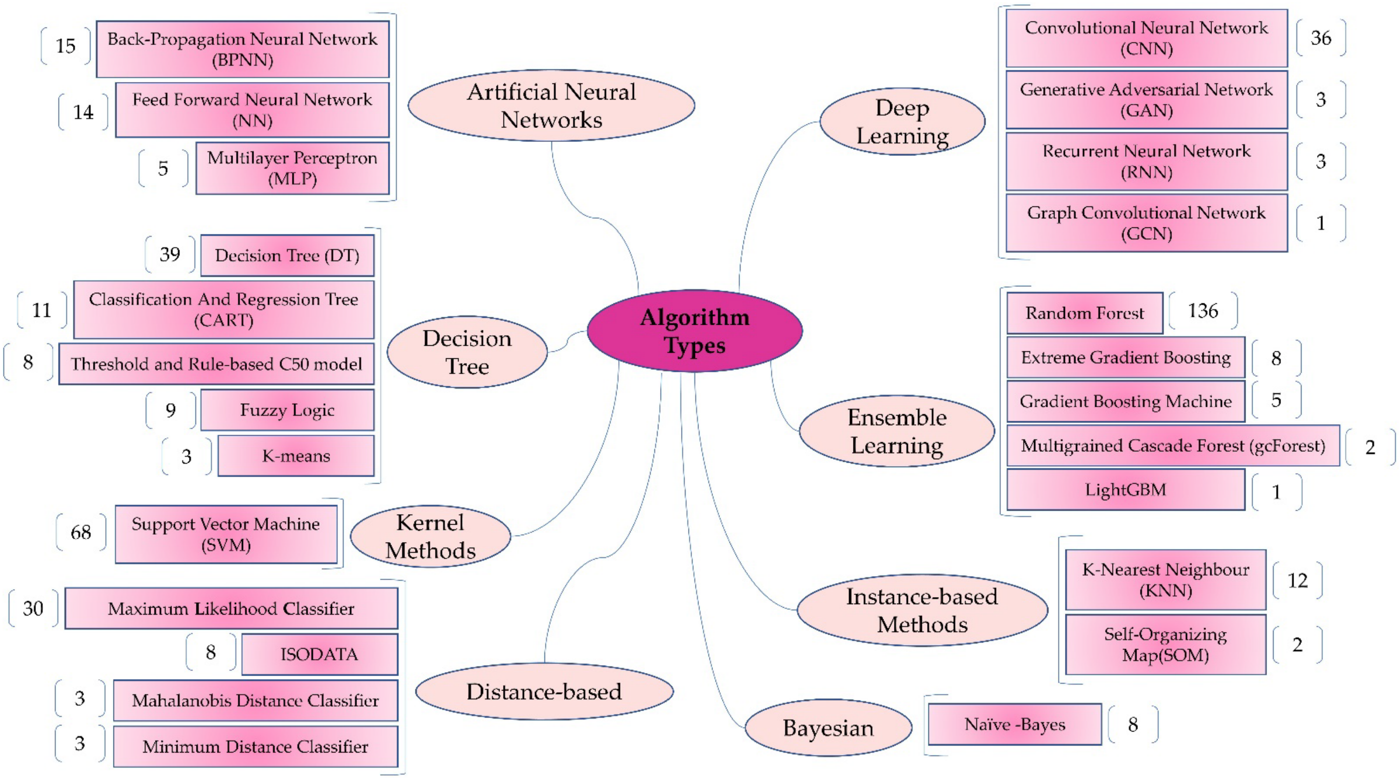


Figure 16. Number of studies employed different ML models in wetland studies.

3.5.2. Google Earth Engine (GEE)

For the mapping and monitoring of wetlands over broad spatial scales and for long periods of time, long-term earth observation data archives, such as those provided by the optical Landsat repository (1984 onwards), are crucial resources. Mapping wetlands on a long-time scale along with high spatial resolution requires collecting and storing large datasets and often involves complicated processing and manipulation. It is infeasible or time-consuming to use conventional image processing software, such as ENVI and ERDAS; thus, an effective platform is required. For such a system to be established, strong computing power and high capacity of data storage is needed, and these can be limiting factors for many decisionmakers around the world, especially in resource-poor regions. With GEE, users can freely access cloud-based computing resources and parallel processing for analysis on a global scale [7]. To provide benefits to the broader community, GEE offers an online integrated development environment using Earth Engine JavaScript, designed to ease geospatial data analysis and preparation complexities, without the need of heavy data downloading and data-intensive processing. It hosts petabyte-scale RS data, including the NASA's Landsat and ESA's Sentinel archives, crucially corrected to surface reflectance, providing a unique opportunity for developing and disseminating worldwide environmental monitoring systems. In addition to the data provision, GEE is equipped with many ML tools, such as RF Classification. Studies using GEE as an RS data provider with ML techniques have become more numerous since its advent in 2015. Such studies account for 11% of included studies (n = 40 of 344) in the current systematic review. More details of these publications have been presented in Figure 17 and Table 7.

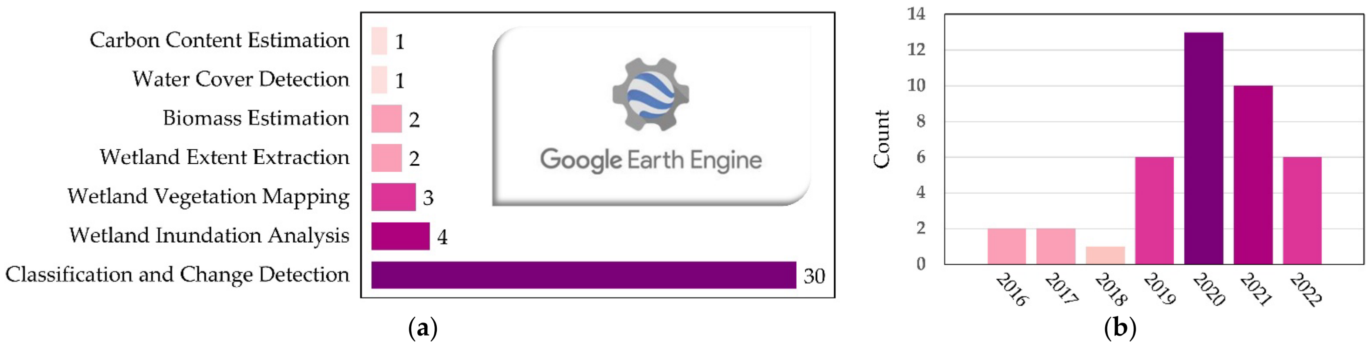


Figure 17. (**a**) Frequency of each type of wetland study using GEE. (**b**) Frequency of GEE-based wetland studies per year.+.

Table 7. List of included papers in the meta-analysis that applied GEE in wetland studies sorted by publication date.

#	Ref.	Application Type	Publication Date	#	Ref.	Application Type	Publication Date
1	[144]	Change Detection	May, 2016	21	[145]	Classification	Aug, 2020
2	[146]	Wetland Inundation Analysis	Dec, 2016	22	[147]	Classification	Sep, 2020
3	[148]	Classification	Dec, 2017	23	[7]	Change Detection	Nov, 2020
4	[22]	Classification	Dec, 2017	24	[149]	Wetland Extent Extraction	Dec, 2020
5	[150]	Carbon Content and Biomass	May, 2018	25	[151]	Wetland Vegetation Mapping	Feb, 2021
6	[46]	Classification	Jan, 2019	26	[152]	Classification	Jun, 2021
7	[153]	Classification	Apr, 2019	27	[154]	Change Detection	Jun, 2021
8	[24]	Classification	Jun, 2019	28	[127]	Classification	Aug, 2021
9	[19]	Wetland Inundation Analysis	Jul, 2019	29	[155]	Change Detection	Sep, 2021
10	[156]	Classification	Oct, 2019	30	[157]	Classification and Change Detection	Oct, 2021
11	[158]	Change Detection	Oct, 2019	31	[159]	Wetland Vegetation Mapping	Oct, 2021
12	[160]	Classification	Jan, 2020	32	[161]	Change Detection	Nov, 2021

Table 7. *Cont.*

#	Ref.	Application Type	Publication Date	#	Ref.	Application Type	Publication Date
13	[96]	Classification	Jan, 2020	33	[162]	Classification	Nov, 2021
14	[163]	Inundation analysis and Biomass	Feb, 2020	34	[134]	Classification	Dec, 2021
15	[164]	Classification	Mar, 2020	35	[97]	Wetland Extent Extraction	Jan, 2022
16	[51]	Wetland vegetation mapping	Apr, 2020	36	[94]	Classification	Jan, 2022
17	[165]	Classification	Apr, 2020	37	[166]	Classification	Feb, 2022
18	[99]	Classification	May, 2020	38	[167]	Wetland Inundation Analysis	May, 2022
19	[168]	Water Cover Detection	May, 2020	39	[169]	Classification	May, 2022
20	[170]	Classification	May, 2020	40	[171]	Change Detection	Jun, 2022

3.6. Feature Selection and Derivation

The features used in wetlands research from optical data are mostly spectral reflectance characteristics, such as the normal difference vegetation index (NDVI), normal difference water index (NDWI), and soil-adjusted vegetation index (SAVI), etc. These feature indices have been widely used in monitoring and mapping wetlands [7,46,76,99]. When identifying wetlands, relations to neighbor objects may be useful features because of the spatial relationship of objects in distribution. These features aid the identification of wetlands and improve the accuracy of classification. For instance, texture consists of visual patterns or spatial patterns of pixels that may have statistical properties, structural properties, or both [172]. The texture of imagery has been extensively investigated and studied as a supplement to spectral data for the analysis of wetland zones, and has proven effective [172,173]. There are many ways to describe texture. The gray-level covariance co-occurrence matrix (GLCM) has proven effective for the identification of wetlands [174].

In the current meta-analysis, different feature sets employed in wetland studies are grouped as follows: (1) original spectral bands or backscattering coefficients; (2) spectral indices; (3) image texture components derived from the GLCM; (4) SAR polarimetric features (5) geometric features; and (6) topographic variables derived from digital terrain models (see Figure 18 and Table 8).

Rather than relying solely on a single feature category, the majority of wetland studies combine several features from multiple categories. Spectral indices and SAR polarimetric decompositions, followed by textural, topographical, and geometric features, are frequently used to determine the contribution of each feature category. According to several studies involving the feature selection process, the spectral and polarimetric features that are simple and easy to extract have been shown to be more powerful than other types of features in wetland studies and in discriminating class types.

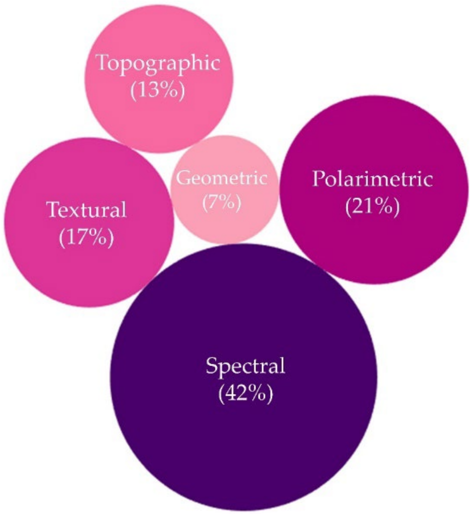


Figure 18. Percentage of studies that use each type of feature category. Note that as almost all studies have used either optical or SAR imagery features, the category of imagery features was excluded here.

3.7. Accuracy Assessment

Here, the reported overall accuracies were assessed and compared to comprehensively investigate the RS-based wetland studies. Figure 19a shows the histogram of the overall accuracies reported in wetland classification studies. Note that the papers (*n* = 67 out of 344) that did not report the overall accuracy of their classification methods have not been counted in this chart. According to Figure 19b, about 69% of the studies have an overall accuracy of greater than 85%. Additionally, studies of very small-scale areas yielded the highest overall accuracy, followed by investigations involving local and provincial study areas. The studies on a national scale, however, were found to have the lowest median overall accuracy. In Figure 19c, the overall accuracies based on the input data have been presented. Accordingly, the integration of optical and SAR datasets presents high classification accuracies in the case of wetland studies. Figure 19d depicts the reported overall accuracies from the methodological viewpoint. As can be seen, DL, ANN, and ensemble learning algorithms yielded the best classification results in the reviewed literature. Supervised and object-based methodologies reported high median overall accuracies compared to unsupervised and pixel-based techniques, respectively (see Figure 19e,f). Finally, Figure 19g represents the median overall accuracy reported in reviewed papers using high, medium, and coarse spatial resolution imagery. A median overall accuracy of more than 84% was achieved for all spatial resolution imagery. Studies using medium-resolution datasets achieved the highest median overall accuracies in wetland mapping, followed closely by those using high-resolution data.

3.8. Preprocessing and Processing Tools

Dealing with various RS datasets requires sufficient toolboxes and software. Several commercial and free open-source tools exist for RS image preprocessing and processing. Although great advances have been reached regarding toolbox development, a public release of processing software can further facilitate and promote experimentations. Figure 20 represents the most frequently employed tools and software for data preprocessing and processing in wetland studies (according to the reviewed literature). As shown, ArcGIS, ENVI, and Python programming packages (such as Scikit-learn, Keras, Tensorflow, PyTorch, Matplotlib, and Numpy) are the most popular and widely used tools for RS data processing when it comes to the study of wetland areas.

Table 8. Common features extracted from Optical and SAR imagery in wetland studies.

Category	Imagery	Indicator/Band	Ref.
Imagery Features	Optical	blue band, red band, green band, the red-edge band, near-infrared, shortwave-infrared	-
	SAR	Backscatter Coefficient (HH, HV, VH, VV)	-
Spectral Indices (vegetation/water/soil indices)	Optical	Normalized Difference Vegetation Index (NDVI)	[155,156,169,175–180]
	Optical	Normalized Difference Water Index (NDWI)	[155,156,169,175–177,180,181]
	Optical	Enhanced Vegetation Index (EVI)	[169,175]
	Optical	Simple Ratio (SR)	[169]
	Optical	Modified Normalized Difference Water Index (MNDWI)	[177]
	Optical	Soil-Adjusted Vegetation Index (SAVI)	[175,176,181]
	Optical	Modified Soil-Adjusted Vegetation Index-2 (MSAVI2)	[175]
	Optical	Modified Normalized Difference Water Index (MNDWI)	[175]
	Optical	Tasseled-Cap Transformation Brightness (TCB)	[175,182]
	Optical	TC-Greenness (TCG)	[175,182]
	Optical	TC-Wetness (TCW)	[175,182]
	Optical	Green Chlorophyll Index (Clgreen)	[177]
Textural Metrics (GLCM)	Optical and SAR	Mean	[169,176,178]
	Optical and SAR	Variance	[169,176]
	Optical and SAR	Homogeneity	[169,176–178,181,183]
	Optical and SAR	Contrast	[169,176,178,181,183]
	Optical and SAR	Entropy	[169,176,178,181,183]
	Optical and SAR	Angular Second Moment	[169,176,183]
	Optical and SAR	Correlation	[177,178,181,183]

Table 8. *Cont.*

Category	Imagery	Indicator/Band	Ref.
	Optical and SAR	Standard Deviation	[177,178]
	Optical and SAR	Dissimilarity	[177,183]
SAR Polarimetric Features	SAR	Pauli	[125,184,185]
	SAR	Cloude–Pottier	[3,41,45,69,73,125,184,185]
	SAR	Freeman–Durden	[3,41,45,72,185,186]
	SAR	Yamaguchi	[69,125,184–186]
	SAR	Neumann	[69,125,185]
	SAR	Touzi	[41,125,185,186]
	SAR	H/A/Alpha	[125,184,185]
	SAR	Single-Bounce Eigenvalue Relative Difference	[69,185]
	SAR	Double-Bounce Eigenvalue Relative Difference	[69,185]
	SAR	Shannon Entropy	[69,73,130,187]
	SAR	The Total Power (Span)	[21,69,99,160]
	SAR	Ratio	[21,99,130,160]
	SAR	Radar Vegetation Index	[69]
Geometric/Contextual Features	Optical and SAR	Area	[176,178]
	Optical and SAR	Shape Index	[176,183]
	Optical and SAR	Border Index	[176,183]
	Optical and SAR	Number of Pixels	[176]
	Optical and SAR	Perimeter	[176,183]
Topographic Features	LiDAR/DEM	Elevation data	[175]
	LiDAR/DEM	SLOP	[175]
	LiDAR/DEM	Topographic Wetness Index	[175]
	LiDAR/DEM	Terrain Surface Texture	[175]

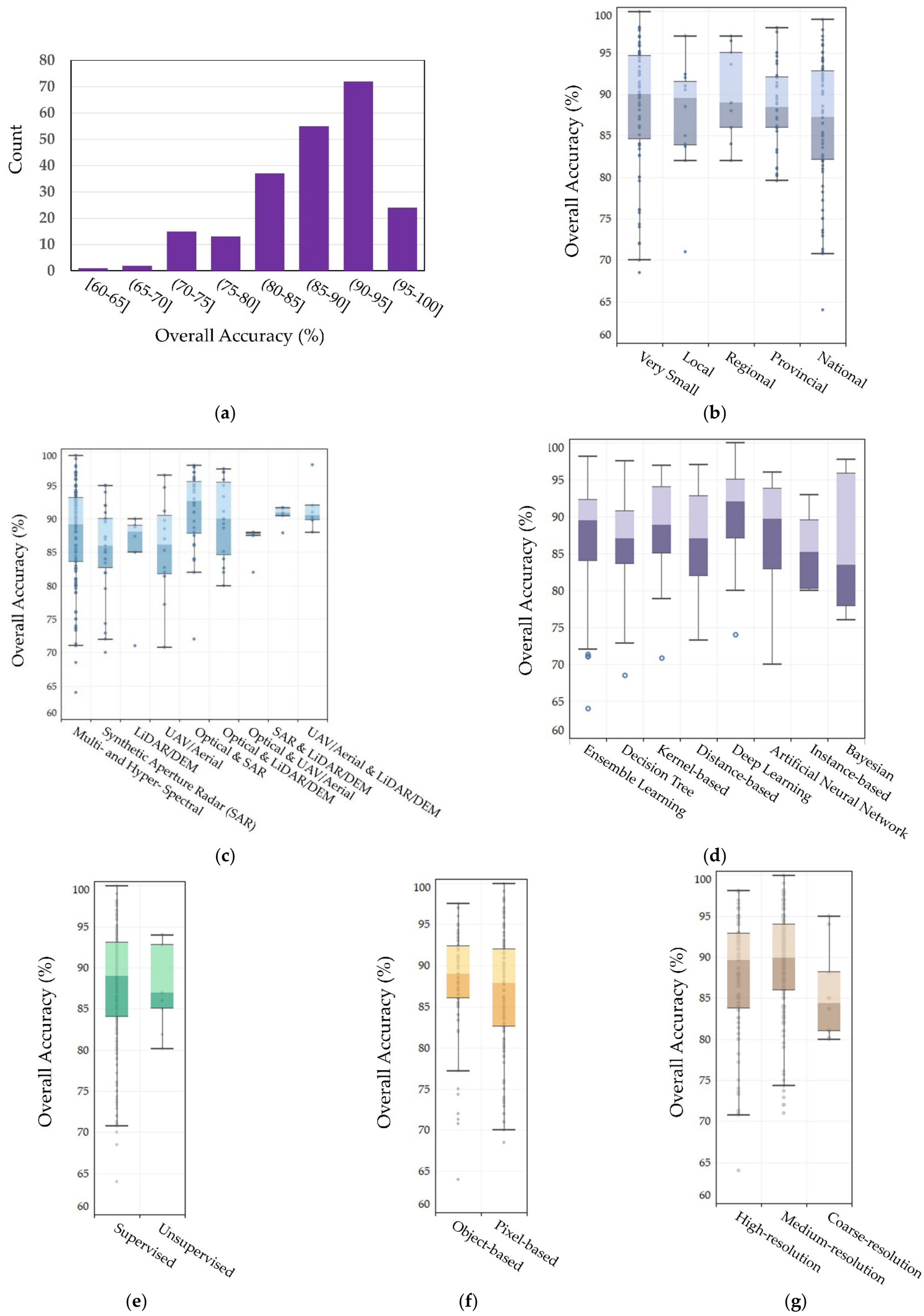


Figure 19. (**a**) The histogram of the overall accuracies reported in wetland classification papers. Box-and-whisker plots displaying the overall accuracies reported in RS-based wetland classification studies according to the (**b**) study extent, (**c**) utilized data type, (**d**) type of employed ML algorithm, (**e**) supervised or unsupervised models, (**f**) pixel-based or object-based methods, and (**g**) selected image resolution.

Figure 20. The main tools used for data preprocessing and processing in wetland studies. The larger the text, the more frequently the tool used in papers.

4. Future Perspective

As a part of the systematic review of the literature, this study also proposes the following three general suggestions for future research in order to shed light on issues identified during the review process (Figure 21). Considering the ever-increasing stresses upon and loss of wetland areas, implementing the following suggestions in the future seems both appropriate and necessary, and has a high potential to make a difference to practitioners and policymakers.

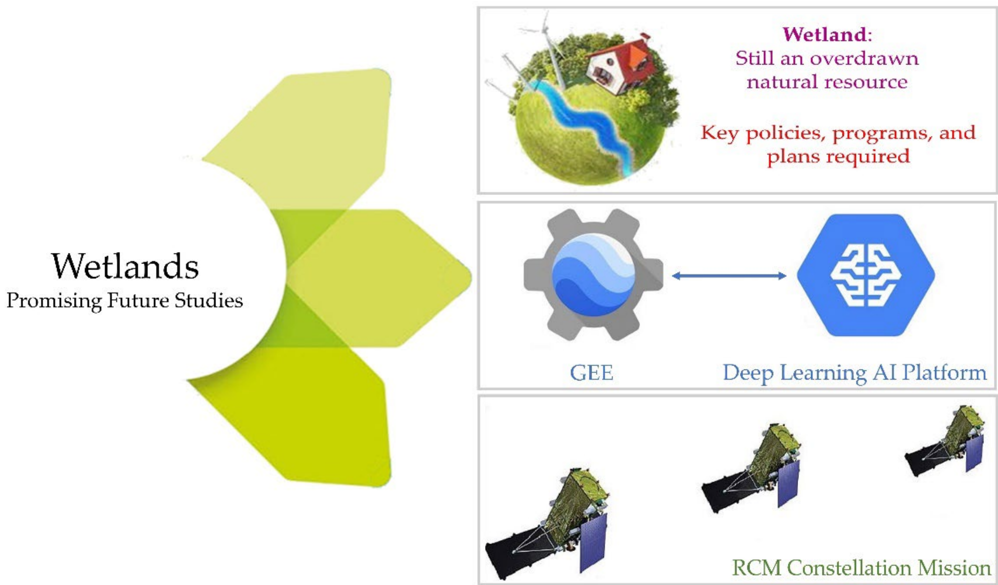


Figure 21. General overview of key recommendations for future studies to combat the challenges of wetland monitoring.

(1) Wetland sustainability policy: wetlands are at risk, and those around agricultural land or near urban areas have suffered huge losses with extended cultivation and urbanization. This indicates that upgrades and reinforcements of existing legislation,

policies, programs, and strategic ecosystem plans are seriously required to protect and preserve wetlands habitat. Land use decisions are mostly influenced by agricultural policies and urban planners. On the one hand, agricultural policies try to act as an economic stimulus (economic gain trumps) for crop production and cultivation expansion, which constitutes an encroachment on wetland areas. On the other hand, with the expansion of urbanization around wetlands, many people now live in and around wetlands and rely on their resources for their livelihoods. Moreover, wetlands near urban centers are under increasing developmental pressure for residential purposes. Accordingly, educating the community about the importance and benefits of wetlands and encouraging volunteer monitoring programs are perhaps the best ways to protect them. Indeed, developing community advocacy that is persistent, watchful, and active to empower communities to be more active stewards of wetlands would be wise to preserve wetlands. Doing so could minimize the adverse/negative effects of agricultural activities and urban expansion on neighboring and adjacent wetlands. As a consequence, decisions by local communities are critical to the successful sustainable management of wetlands.

(2) The use of state-of-the-art DL models combined with GEE has the potential to make substantial progress toward wetland status monitoring, which has remained undocumented in the literature. Utilizing such a system would allow a large area of wetlands, whether globally or nationally, to be studied for automatic and efficient monitoring, thereby minimizing human involvement in data processing and enhancing the accuracy of monitoring results. Therefore, intelligent monitoring and assessment of wetland status are essential for wetland management and strategy formulation.

(3) Based on Figure 19c, SAR images show high potential for wetland monitoring. The recent deployment of SAR systems in RS, such as in the RADARSAT Constellation Mission (RCM), has resulted in a number of new applications [188]. This mission is a continuation of RADARSAT-1 and RADARSAT-2 and is conducted by the Canadian Space Agency (CSA) under the RADARSAT project. It offers a variety of imaging modes from 100 m low resolution to high 3 m resolution [188,189]. As noted before, the primary advantage of SAR is that it provides repeatable data acquisition while being relatively unaffected by atmospheric effects, making it a reliable data acquisition technology. In the ongoing efforts to inventory wetlands and monitor their changes, RCM is expected to provide an essential source of C-band SAR data. Although the RCM is a Canadian commercial mission, given the high number of papers affiliated with Canadian researchers, it is somewhat strange that the RCM compact polarimetry data have not yet attracted the interest of wetland researchers. This is partly due to the lack of a suitable standard coverage, but one has been added by the CSA to improve the availability of suitable data. This study highly recommends the employment of promising new technologies and data for future wetland inventory and monitoring, including the upcoming NISAR mission.

5. Conclusions

In this study, the trend of worldwide RS-based wetland monitoring studies was established, exploring 344 papers published in the last three decades. Over fifteen sub-fields were summarized and highlighted, including ML approaches and their accuracies in wetland studies, RS data types and their corresponding accuracies, journals/conferences/publishers, authors affiliations, publications per year, the geographical distribution of case studies and the corresponding study extent, and paper citations. Through this, a comprehensive meta-analysis was used to discuss the utilization of RS and ML tools in these subfields. Consequently, this paper addresses the role of RS and ML tools in supporting global wetland monitoring. Research opportunities and directions for further supporting wetlands studies were also presented in the paper. In summary, the general findings of this review paper concerning both technological and substantive viewpoints are as follows:

- A total of 88 journals have published the papers summarized in the present meta-analysis (with a share of 89%). The papers from the IGARSS conference, as well as a few from other international conference proceedings, were also included. About 67% of these publications were published between 2018 and 2022.
- More than half (51%) of the reviewed publications investigated wetlands from the perspective of classifying wetland zones, while 14% analyzed the changes within the wetlands. Wetland vegetation mapping and wetland extent recognition are in third and fourth places, with a share of 12% and 7% among all reviewed papers.
- Over 70% of the research studies have been conducted in China, the USA, and Canada, illustrating the need for wider international efforts to be undertaken in other countries in order to have consistent monitoring of wetlands across the globe. Over the past few years, the number of wetland studies has increased. In light of the increase in quality RS data availability, the launch of new RS platforms, as well as increased computing capabilities, and the growing interest in wetlands as part of climate change research, it is likely that this trend will continue.
- Slightly more than three-quarters of the studies have been conducted at areas with very small and local scales, whereas a few national-scale research papers have been published. More large-scale (e.g., continental-scale) studies are likely to be conducted as the number of satellites continues to increase and data become more widely available. The very recent ability of GEE to apply DL models has also opened up new possibilities for large-scale wetland classification research.
- The largest number of studies have been conducted on optical sensors using the Landsat archive (with 201 studies) and Sentinel-2 (with 54 studies), while SAR-based studies mostly employed data from Sentinel-1 (with 45 studies) and RADARSAT-2 (with 31 studies) missions. This is likely partially due to the relatively long history of these datasets and low/no cost availability.
- Reviewed studies indicated that optical images had most often been used in the wetland monitoring tasks with 247 studies, followed by SAR datasets with 116 studies. A fusion of data types, including optical and SAR data, increases overall accuracy compared to each data type separately.
- A review of the published literature from the methodological viewpoint found that 152 studies adopted ensemble learning methods, 70 employed DT-based methods, and 68 utilized kernel-based methods. Further, among different classification approaches, CNN as a DL model, as well as RF as a ML model are the most successful classifiers for wetland mapping.
- As expected, spatial resolution was highly correlated with the overall accuracy of the wetland classification. This shows that wetland mapping may be improved by high/medium resolution RS imagery, at least until some minimum resolution threshold is reached.
- In comparison to pixel-based and unsupervised methods, object-based and supervised methods were mostly preferred for mapping and delineating wetlands owing to their simplicity and higher accuracy. On a national or continental scale, however, employing object-based analysis can be challenging.

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Abbreviations

RS	Remote sensing
ML	Machine learning
DL	Deep learning
CNN	Convolutional neural network
CD	Change detection
RF	Random forest
DT	Decision tree
SVM	Support vector machine
GEE	Google Earth Engine
CSA	Canadian Space Agency
RCM	RADARSAT Constellation Mission
LULC	Land use and land cover
SAR	synthetic aperture radar

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