remote sensing

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Review

Marine Infrastructure Detection with Satellite Data—A Review

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Abstract: A rapid development of marine infrastructures can be observed along the global coasts. Offshore wind farms, oil and gas platforms, artificial islands, aquaculture, and more, are being constructed without a proper quantification of these human activities. Therefore, effective monitoring is required to maintain transparency towards environmental standards, marine resource management, inventorying objects, and global security. This study reviews remote sensing-based approaches to offshore infrastructure detection over the past 12 years. We analyzed 89 studies from over 30 scientific journals, highlighting spatial and temporal trends, methodological approaches, and regional and thematic research foci. Our results show a significant increase in research interest, especially since 2019. Asia, and especially China, is the predominant focus region in terms of first authorship, funding, and areas of investigation. Aquaculture is the most studied infrastructure, followed by platforms, offshore wind farms, and artificial islands. Gaofen, Sentinel, and Landsat are the most used satellite sensors for detection. The apparent shift towards automated detection methods, especially Deep Learning algorithms, reflects advances in computer vision. This study highlights the key role of earth observation in the field of off-shore infrastructure detection, which can contribute towards outlining effective monitoring practices for marine activities, as well as highlighting important knowledge gaps.

Keywords: remote sensing; earth observation; detection; offshore; infrastructure; aquaculture; platform; artificial island; windfarm; review

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1. Introduction

1.1. Offshore Activities

The exploitation of marine natural resources has for centuries driven economic expansion at a local and global scale. Advances in technology have contributed to the rapid increase in offshore industries, including aquaculture, wind power generation, and oil extraction [1]. Today, almost 30% of the world's oil is drilled in offshore fields [2]. This 1.5–2.5 trillion dollar offshore economy is growing faster and more uncontrollably than the global economy as a whole and is expected to exceed 3 trillion US dollars by 2030 [1,3]. However, this also has ecological consequences. An estimated 30–50% of critical marine habitats have been lost due to human activities [4–6].

The global extent of marine man-made construction was estimated to be at least 32,000 km^2 in 2018 and is expected to reach 39,400 km^2 by 2028 [7]. The growth of marine construction is being driven by the extraction and transportation of gas and oil and the rise of the renewable energy industry, alongside the growth of coastal cities and rising sea levels [7]. Marine infrastructure includes structures such as energy production and energy resource extraction (e.g., offshore wind farms (OWF), oil, and gas platforms), fisheries (e.g., aquaculture facilities) as well as other man-made structures such as bridges, airports, harbors and artificial islands on atolls. In the last decade, the construction of artificial islands has become increasingly important. Land reclamation by filling in sand on atolls or near the mainland for industrial and storage facilities or ports and airports is increasing rapidly [8,9]. Transparency in monitoring this rapid development of all offshore infrastructure is crucial to prevent environmental degradation and the overexploitation of fisheries and marine resources, and to quantify the development of offshore energy [4]. Through open information, countries will also be better able to effectively manage vital marine resources as well as space and energy development. This information can provide insight into the environmental footprint created by the construction, maintenance, and use of these structures, helping decision-makers. It can also help to localize sources of oil spills and other marine pollution. While detailed maps and regularly updated datasets are available for almost every road, house, and industrial building on land, information on the development of offshore infrastructure often remains concealed [10]. The ongoing expansion of human activities offshore remains largely unquantified [11].

Due to the vastness of the ocean and the distance from urban infrastructure and monitoring facilities, the comprehensive monitoring of infrastructure development at sea on a worldwide scale is difficult. Some offshore structures, such as oil platforms and wind turbines, are equipped with so-called automatic identification systems (AIS) [12]. These systems automatically transmit identity and location data to nearby ships, transponders on land, or satellites to intensify surveillance and minimize ship collisions at sea. In addition, institutional directives such as the EU's Environmental Impact Assessment (EIA) ensure that offshore installations are subject to mandatory reporting. For example, aquaculture facilities have to pass through Maritime Spatial Planning [13]. Nevertheless, such guidelines do not exist in all countries and continents of the world or there are legal loopholes and in some cases, the location data of offshore installations are incomplete or outdated [11,14]. The existing methods therefore do not adequately record marine infrastructure on a global scale.

1.2. Remote Sensing

In contrast to small-scale in-situ measurements, data from satellite systems can provide global coverage with continuous measurements over long periods. The availability of high-resolution optical, multispectral, and radar images provides a source of information for detecting infrastructure at sea. Earth observation (EO) data are often made free to access for the public. Vast open archives such as those of the Moderate Resolution Imaging Spectroradiometer (MODIS) (with about 250 m spatial resolution), Landsat (with about 30 m spatial resolution), or the Sentinels (with about 10 m spatial resolution) enable research in a wide range of applications, from a local to global scale, and with high temporal resolution. The temporal resolution depends heavily on the selected data source. For example, long-term analyses at a medium spatial resolution (30 m) are possible with optical Landsat data (since 1972). Sentinel data offer a better spatial resolution, but the data are only available from 2014 onwards. If commercial satellite data are used, such as PlanetScope, QuickBird, Gaofen, and WorldView, very high-resolution data with less than a 3 m spatial sensor resolution become accessible, although the temporal scale is usually limited to the 21st century [15,16]. Due to the trend towards opening up archives for EO data, the amount of high-resolution remote sensing data is expected to continue to increase significantly in the near future—not only in terms of the versatility of the data due to the development of new and better sensor systems, but also in terms of temporal coverage and the overall continuity of coverage [16]. High-resolution data has been used for over 10 years for airborne and spaceborne earth observation applications, such as the detection or segmentation of structures like ships or offshore platforms (e.g., [17,18]). Today, the applications in earth observation research are wide-ranging and no longer limited to RGB images. The number of technical concepts for recognition, some of them automated, in earth observation continues to grow and shows new trends and possibilities for analyzing remote sensing data.

Analyzing the time series of different data sets can potentially identify long-term trends in marine infrastructures. Earth observation has benefited significantly from advances in computer and data science in recent years, as analyzing multi-temporal and multi-dimensional raster datasets has always been a computational challenge. For example, cloud computing platforms such as Google Earth Engine can process large datasets without the need to download and store terabytes of EO data on local computers [19]. In addition, innovative Machine Learning methods are enabling new data-driven insights into the constantly growing volume of geoscientific data. Deep Learning in particular shows the potential to utilize the spatio-temporal information stored in EO datasets for the precise detection of structures and processes on the land or sea surface [20].

1.3. Literature Review

This article provides an overview of the existing literature from the last 12 years on the topic of EO data-based detection of offshore infrastructure. The infrastructures to be analyzed include any man-made structures that are located offshore; therefore, those that are not firmly connected to the land via a shelf (see Figure 1). The five most prominent infrastructures categorized are offshore wind farms (OWF), bridges, aquaculture, oil and gas platforms (which can also include research platforms, for example) and artificial islands. Artificial islands include any structures that are not directly connected to the land. These are, for example, seaports and airports, sand fill on atolls to establish infrastructure, such as in the South China Sea, and sand fill near the mainland for industrial and storage purposes. Therefore, artificial sand filling for land expansion, such as the palm trees in Dubai, is not considered, as it is directly connected to the land.

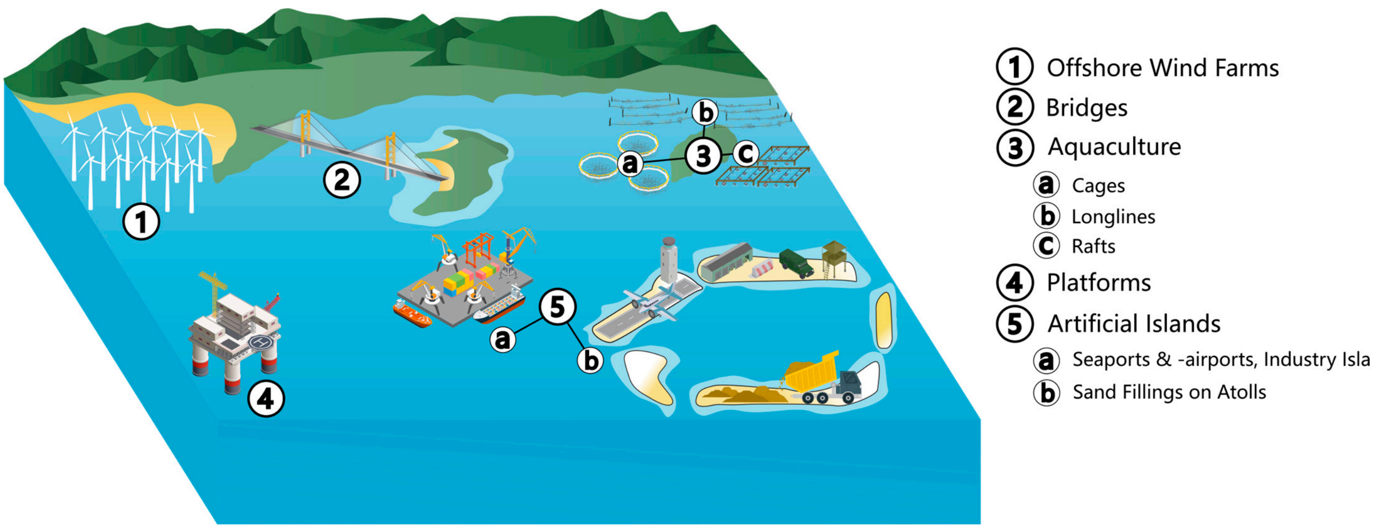


Figure 1. Overview over marine man-made stationary infrastructures above water: (1) offshore wind farms (OWF), (2) bridges, (3) aquaculture (a: cage, b: longline, c: raft), (4) oil and gas platforms and artificial islands (a: seaports, b: sand filling on atolls). The graphic is based on a combination of symbols, some of them modified, from the courtesy of the Integration and Application Network, University of Maryland Center for Environmental Science, as well as https://www.freepik.com/, accessed on 17 November 2023.

To our knowledge, no review covers all available EO-based detection methods for all applications in the open ocean. Therefore, this review aims to provide the first comprehensive overview of the application of EO data for the spatial and temporal mapping and monitoring of ocean surface dynamics in the form of infrastructures and to identify potential research gaps. We will address the following research questions:

- What types of infrastructures have been detected using EO data and is a trend emerging?
- In which countries are researchers particularly focusing on the topic?
- Where and at what spatial scales have the detections been made?
- Is there a clear trend in which regions certain infrastructures are detected?
- Which countries are interested in which areas of investigation and support research?
- What is the temporal resolution of the investigations?
- Is there a trend towards time-series investigations?

- Which sensors are most frequently used in the detections and for which types of infrastructure?
- What role does the resolution of the sensors play in detection?
- Which detection methods were used and for which applications?
- Is there a trend towards the use of certain detection methods?

Our review methodology is outlined in Section 2. We then present the results of the literature review in Section 3: First, we provide an overview of the infrastructures in the field of EO-based detection and to what spatial extent and by whom they have been carried out. We provide a brief insight into which regions are particularly in demand and which institutions provide financial research support there. We then present the temporal scope of the studies analyzed and the use of sensors, including technical aspects such as spatial sensor resolution. Finally, we categorize and briefly present the detection methods identified. Our results are discussed in Section 4 and finally summarized in Section 5.

2. Materials and Methods

In this study, we analyze scientific studies that attempted to detect marine infrastructure using EO data. A visualization of the review methodology can be found in Figure 2. With this review method, we follow the common and well-accepted methods also presented by Baumhoer et al., Uereyen et al., Holzwarth et al., Zhang et al., and França e Silva et al. [21–25]. The literature search for Science Citation Index (SCI) papers was based on the bibliographic database of Web of Science (WoS) (last accessed on 31 October 2023). A search string was defined to filter the literature based on English research articles or reviews published since 2012 and covers the following four topics (see Table 1):

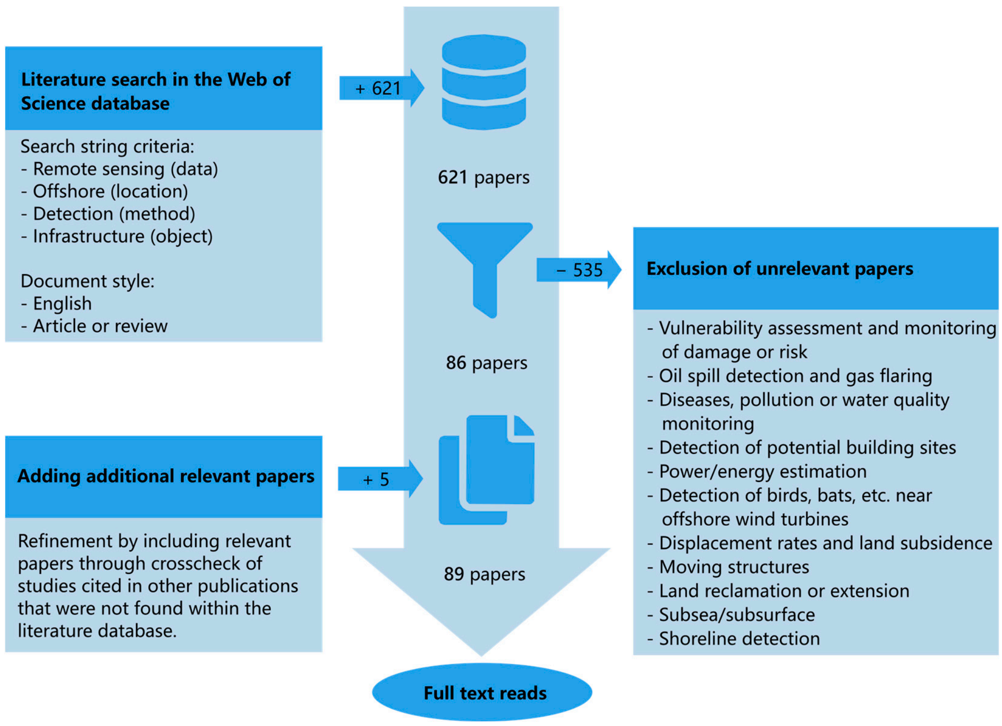


Figure 2. Summary of the literature search and sorting out process that ended with 89 papers for this review.

Table 1. Overview of the constructed search string. This consists of four main topics, each with a large number of search terms, which are listed here in the Table as examples. By adding a left or right truncation to the search term, the product can return terms in the plural and singular or word extensions. For example, *shore also returns shoreline, shore* also returns offshore, and *shore* returns both. Using quotation marks finds exact phrases and turns off lemmatization or the product's internal synonym finder. For example: "offshore" finds offshore but not off-shore. The complete search string is attached to the Supplementary Material S1.

Topic	Search Terms
Remote Sensing (Data Source)	"remote * sens *" OR "eo" OR "satellite *" OR . . .
Offshore (Location)	offshore OR marine * OR ocean * OR . . .
Detection (Method)	segmentation OR "object detection" OR monitor * OR . . .
Infrastructure (Object)	"wind farm *" OR rig OR aquaculture * OR . . .

We give each of the four topics numerous variations in search terms to find the maximum number of relevant articles. For the first three topics, the search terms had to be included either in the title, abstract, or keywords, while for the infrastructures the search terms could only be in the title. We made this decision because the absolute majority of relevant publications in this field of research have the object that is detected in the title (example: "Object X is recognized using Y") and this step avoided a large number of irrelevant publications in the search results. To list all possible infrastructures that may occur on the sea in the search terms, extensive research and iterative processes were carried out in advance. We have set the publication search for the time period between 2012 and the end date of 31 October 2023. The decision to analyze articles from the last 12 years was driven by the significant advances in earth observation technology and image processing methods during this period. The accessibility of EO archives and the proliferation of EO data sources have greatly expanded research opportunities in the field of EO-based detection, especially in the last decade with the satellite launches of the Gaofens and Ziyuans (launches from 2011) and the Sentinels (launches from 2014) [15]. Furthermore, the opening of the Landsat archives has had a huge impact on data availability for the research community [26]. In addition, the initial introduction of Convolutional Neural Networks (CNNs) for image processing [27] by Krizhevsky et al. has revolutionized detection approaches and opened new ways for research. Our decision to start with 2012 reflects the emergence of these crucial developments, which have had a profound impact on the field. The complete search string with all search terms is attached to the supplementary material S1 to enable complete verifiability and replicability. We chose this extensive and detailed search string with many search terms in order not to omit any relevant publications and to minimize the subsequent manual sorting of irrelevant publications. Our literature search using the search string yields a total of 621 publications by the imposed end date of 31 October 2023.

We then manually screened and filtered these by title and abstract according to certain criteria to exclude irrelevant papers. The criteria are listed in Figure 2. For example, we had to omit papers that were dealing with moving structures because there are hundreds of papers that are dealing with ship detection alone. The final filtering gave 84 candidates. Five articles were added manually by the crosschecking of studies cited in the 84 relevant publications that were not found within the literature database. This manual process resulted in 89 relevant scientific publications dealing with the detection of marine infrastructures, which we scrutinized in this study.

The review was based on these 89 papers selected by full-text reading, looking for attributes such as the publication date, the nationality of the author, the funding received, the area of application, the spatial scope of the study, the detection methods used, the temporal scope of the study and its EO data used, and other technical aspects. (The complete table of all 89 papers analyzed with the identified attributes can be found in the Supplementary Table S1 in .csv format.). We have decided against filtering by specific scientific journals. The range of topics relating to offshore infrastructures does not allow for this. Depending on the infrastructure, the topics may range from Remote Sensing to Energy and Fuels, Engineering, Electrical and Electronic; Oceanography, Water Resources, Chemistry, Physics, Biology, and more. The number of reviewed articles per journal is listed in Table 2. The table also provides information on the impact factor and research focus of the journals. Accordingly, the research focus of the journals is primarily on EO and geosciences, but environmental sciences and marine engineering and science are also very prominent, and the number of multidisciplinary journals shows how broad the range of topics is. The 89 publications have an average impact factor of 5.2.

Table 2. List of covered journals, the number of articles per journal reviewed, and their respective impact factor.

Journal Title	Number of Reviewed Articles	Impact Factor 22/23	Scientific Field
Remote Sensing	23	5.0	Remote Sensing, Geosciences & Environmental Science
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	7	5.5	
Remote Sensing of Environment	5	13.5	
International Journal of Remote Sensing	4	3.4	
International Journal of Applied Earth Observations and Geoinformation	3	7.5	
Sustainability	3	3.9	
Journal of Coastal Research	3	1.1	
ISPRS Journal of Photogrammetry and Remote Sensing	2	12.7	
Earth System Science Data	2	11.4	
IEEE Transactions on Geoscience and Remote Sensing	2	8.2	
Anthropocene	2	5.1	
Journal of Applied Remote Sensing	2	1.7	
Landscape and Urban Planning	1	9.1	
Geocarto International	1	3.8	
ISPRS International Journal of Geo-Information	1	3.4	
Remote Sensing Letters	1	2.3	
IEEE Journal of Oceanic Engineering	3	4.1	Marine Engineering & Science
Journal of Marine Science and Engineering	2	2.9	
Ocean and Coastal Management	1	4.6	
Frontiers in Marine Science	1	3.7	
Marine Environmental Research	1	3.3	
Journal of Oceanology and Limnology	1	1.6	
Marine Technology Society Journal	1	0.8	
Scientific Reports	2	4.6	Multidisciplinary Science
Sensors	2	3.9	
Scientific Data	1	9.8	
PLOS Biology	1	9.8	
Journal of King Saud University—Computer and Information Sciences	1	3.8	
Entropy	1	2.7	
PeerJ	1	2.7	
Applied Sciences-Basel	1	2.7	
Renewable and Sustainable Energy Reviews	1	2.5	
International Journal on Artificial Intelligence Tools	1	1.1	
Information Processing in Agriculture	1	n.s.	
	∑ 89	Ø 5.2	

3. Results

3.1. Development of Research Interest over Time

After our detailed analysis of the 89 reviewed publications, it becomes clear that aquaculture is the predominant type of infrastructure observed. Figure 3 shows the research interest over time and which infrastructure type was observed, and for the comprehensive character of the review, we conducted a citation analysis using the literature tool litmaps in Figure 4. It visualizes the citations of the authors among each other and between the different fields of offshore infrastructure observation.

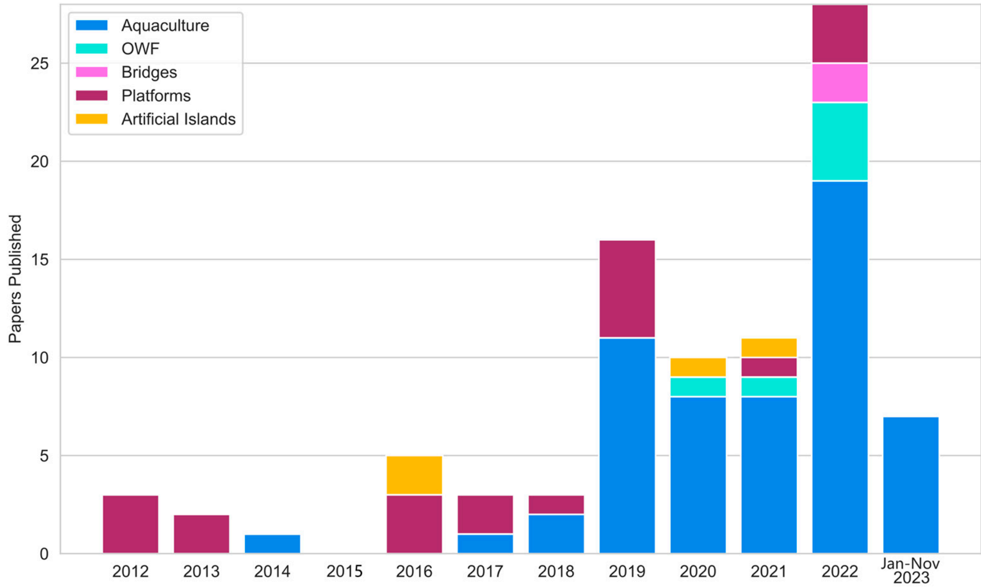


Figure 3. Research interest over time with a huge increase in 2019 and the peak in 2022. The color coding gives an indication of the thematic focus (observed infrastructure). Aquaculture was the most commonly studied infrastructure type.

We can see a positive trend in terms of the general research interest in this topic since 2012. In the years 2012 to 2018, no more than five peer-reviewed studies were published per year; in 2015, there were none at all. What is noticeable in the graph is that there was a rapid increase in publications in 2019 (16 studies) and 2022 (peak of 28 studies) and a decrease right after that. We suspect that the significant reasons for the increase in 2019 are due to the greater availability and accessibility of high-resolution satellite data that preceded satellite launches between 2013 and 2017 (e.g., the European Sentinels 1-2 and Chinese Gao Fen 1-3) and the continuous annual coverage of this data thereafter. The fact that the data could be easily processed using the Google Earth Engine (GEE) will also have had an impact. As 2019 was followed by the COVID-19 pandemic in 2020, this could have certainly had an impact on the number of publications in the following two years, albeit a small one. Also, far fewer new projects were applied for during the pandemic [28]. The fact that many more studies were suddenly published again in 2022 could be a consequence of this. Many of the studies that would have been completed in previous years without the pandemic were then completed and published in 2022. This could also explain the decline in 2023 and make it appear less drastic. However, it must be emphasized here that we have set the deadline for the inclusion of additional papers in the review at the end of October and therefore the publications for November and December 2023 are not included. However, the reasons for the increases can be many and varied, ranging from technological advances such as the new sensors to global events or challenges, increased funding, or policy changes.

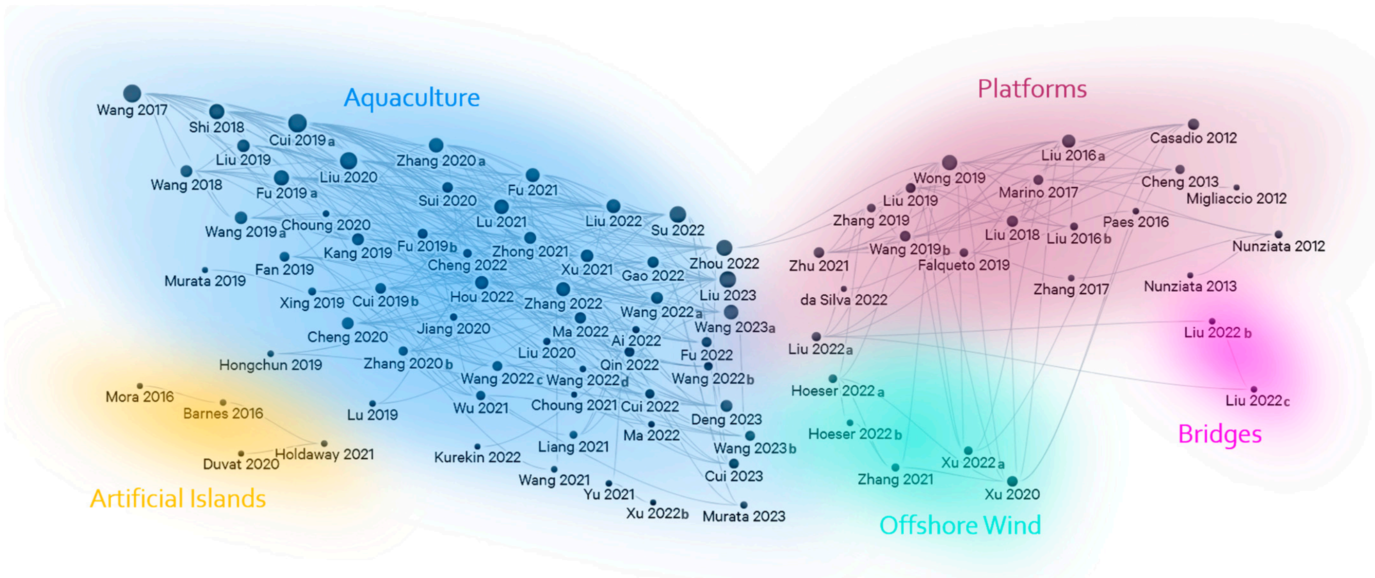


Figure 4. Reviewed articles illustrated with https://www.litmaps.com (accessed on 24 April 2024), visualizing the citations of the authors among each other. The larger a node, the more often the author was cited. Authors are grouped based on the infrastructure they observed. Due to multiple authors with the same surname or publishing in the same year, the following designation mapping is used: Liu 2016a [29], Liu 2016b [30], Cui 2019a [31], Cui 2019b [32], Fu 2019a [33], Fu 2019b [34], Liu 2019a [35], Liu 2019b [36], Wang 2019a [37], Wang 2019b [38], Zhang 2020a [39], Zhang 2020b [40], Hoeser 2022a [41], Hoeser 2022b [42], Liu 2022a [43], Liu 2022b [44], Liu 2022c [45], Liu 2022d [46], Wang 2022a [47], Wang 2022b [48], Wang 2022c [49], Wang 2022d [50], Xu 2022a [51], Xu 2022b [52], Wang 2023a [53], Wang 2023b [54].

Concentrating on thematic foci, aquaculture was investigated in 57 publications and was therefore the most commonly studied infrastructure type in this review. Raft aquaculture was the most studied (46%) [31,32,37,39,46,50,55–73] and 12% of aquaculture studies looked specifically at cages [40,52,74–77]. The remaining 42% investigated different types of aquaculture including raft, cage or longline in combination [33–35,47–49,53,54,78–93]. Especially since 2019, the interest in observing aquaculture has increased enormously. The second most frequently investigated topic is the platforms [14,17,29,30,36,38,43,94–106], which have been the subject of continuous interest since 2012 when Casadio et al. observed this type in the North Sea by their characterization of night-time gas flaring [101]. Since then, 20 studies were published detecting platforms offshore. Recognizing bridges at sea using EO data was carried out in 2022 by the same first author Chun Liu [44,45]. We assume that this is a niche topic and has therefore only been investigated twice and only by the first author. Bridges are generally also detected on the mainland and not specifically only "sea-crossing" bridges. OWFs were investigated six times from 2020 on by four different author groups [41,42,51,107–109]. and are assumed to continue to be investigated. There are only four studies on artificial islands that deal with their detection. Two author teams, Mora et al. and Barnes et al. [110,111], observed sand filling activities on atolls in the South China Sea in 2016. In 2020, Duvat investigated the human-driven atoll island expansion in the Maldives [112] and one year later Holdaway et al. focused on a global observation of artificial islands on atolls [9].

All these low numbers of publications show that it is difficult and should be treated carefully when making assumptions or predictions. At the same time, however, it also makes it clear that not much research has been carried out in this area thus the need for further research.

3.2. Country of First Author

The data presented in Figure 5 show that around 80% of the first authors are of Asian descent. Among them, 74% are exclusively from China. European and American institutions account for approximately 11% and 9%, respectively. Only one study is published by authors from New Zealand [9]. The high number of publications by Chinese authors can be attributed to a greater emphasis on methodological research and presumably a larger amount of funding.

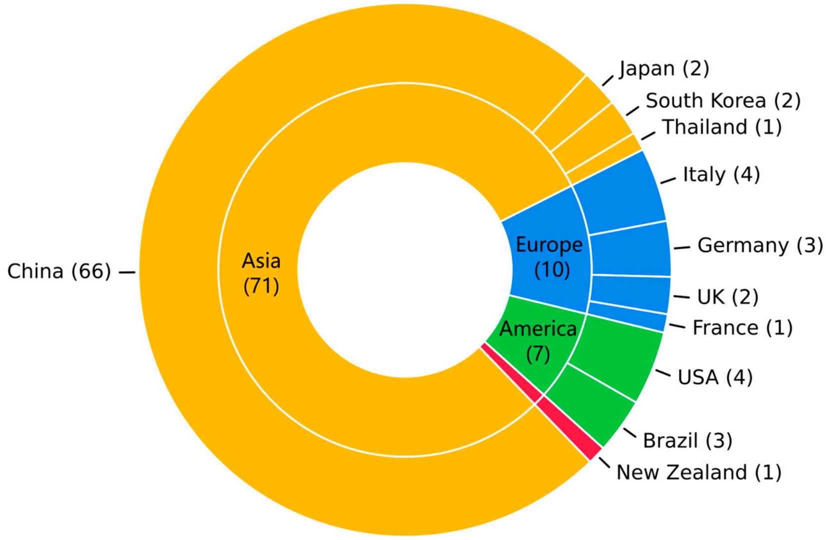


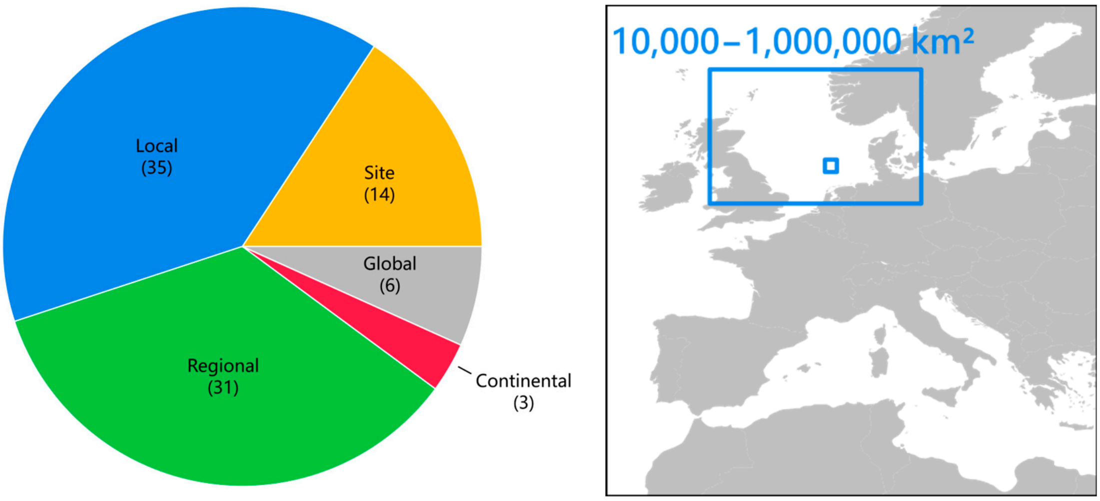
Figure 5. The distribution of the country and continent of first authorship is as follows: Asia has the largest share with 80%, followed by Europe with 11% and the Americas with 8%. Among the countries, China has the largest share with 74%, while the USA, Italy, Germany, and Brazil each have less than 5%. The number of reviewed articles is displayed in parentheses.

3.3. Areas of Investigation

Further details become clear when looking at the distribution and size of the study areas in Figure 6. A total of 16% of the studies conducted their research on the site scale with less than 100 km^2 and about 39% at a local level (100–10,000 km^2). In other words, studies that only examine a small area with usually only a few structures and only one type of structure, such as specific wind farm sites in the North Sea. This is a further indication of many studies that have a stronger methodological focus. The proportion of regional studies (10,000 and 1,000,000 km^2) is about 35%, which is roughly equivalent up to a study area of the North Sea.

The third category, Continental, concerns any studies that have examined a larger area than that and that do not cover the entire world, which in this case belongs to the last category which we named "Global". These last two study region sizes of continental and global include 3% and 7% of the studies, respectively. These are less method papers but are almost exclusively multi-temporal and time-series studies (e.g., [108,109]), which examined the distribution and a trend or development of the examined infrastructure and presented their work more as a product than, for example, the testing of a new method.

We have created a visual representation of all the study areas in Figure 7. Each study area is represented as a bubble, and the size of the bubble indicates the number of studies conducted in that region. The color of the bubble corresponds to the type of infrastructure that was investigated in that area. Additionally, we have linked this information to the countries of first authorship. We have labeled the number of publications to the corresponding country. It is worth noting that a large number of the study regions are located in East and Southeast Asia. To provide a closer and clearer examination of this area, we have zoomed into it (Figure 8).



(**a**) (**b**)

Figure 6. The range of study area sizes. The study areas are divided into five categories based on the hierarchy of spatial scale for marine environments of Stevens et al.: site (<100 km^2), local (100–10,000 km^2), regional (10,000–1,000,000 km^2), and continental (1,000,000 km^2—global) [113]. (**a**): Distribution of the study area size, number of reviewed articles in parentheses; (**b**): example of the regional (blue) scale in Europe.

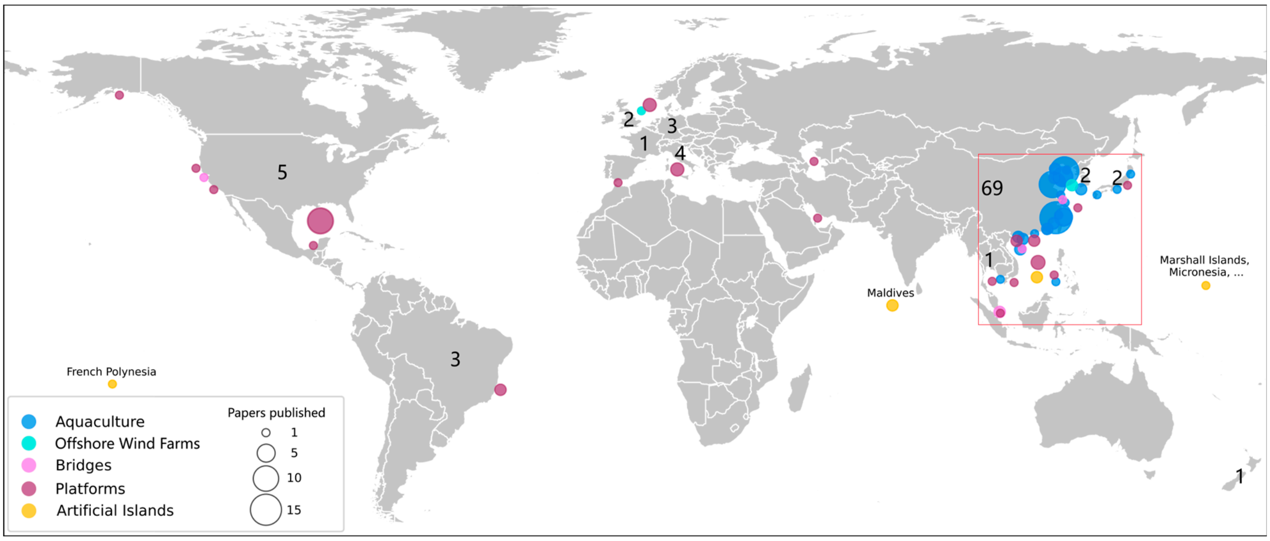


Figure 7. Spatial distribution of first authorships (quantification) and study areas (bubbles) with thematic focus (coloring). The numbers in black indicate the number of publications in the corresponding country.

It is important to note and consider that the six global studies are not shown here. One was dealing with the detection of platforms [36] while the remaining five detected OWFs [41,42,107–109]. In addition to the global studies, OWFs were also investigated in the Yellow Sea near China and the North Sea [51].

When looking at the maps, it is also noticeable that all of the aquaculture studies were conducted in East and Southeast Asia. Platforms, on the other hand, are observed all over the globe, particularly in oil and gas-producing regions such as the Gulf of Mexico, Caspian Sea, Persian Gulf, North Sea, Southeast Asia, but also in the Campos Basin in Brazil, the west coast of the USA and the Gulf of Alaska. Artificial islands have been examined in the Maldives [9,112], on atolls in the Indian and Pacific Oceans [9], and in the South China

Sea [9,110,111]. The two studies that looked at bridges on the open sea did so in San Francisco, Singapore, Fuzhou, and Hainan [44,45].

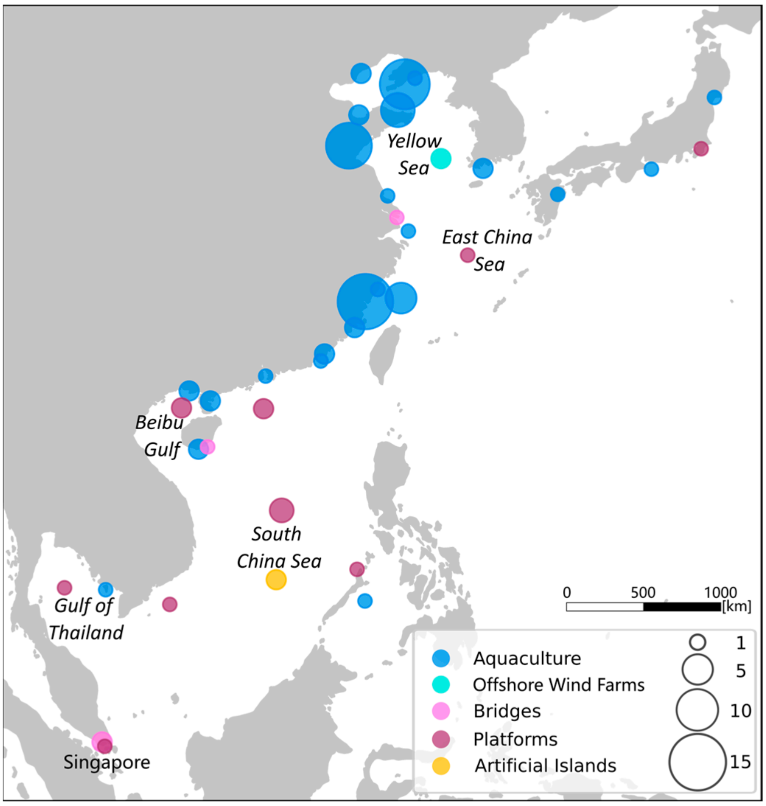


Figure 8. Zoom in on East and Southeast Asia.

In general, 73 of the 89 papers (82%) dealt with Asia as an area of research, 57 of them in China; 52 (58%) even have their study area exclusively in China (88% of them aquaculture studies). The zoomed-in map (Figure 8) of East and Southeast Asia clearly shows that aquaculture is being studied along the entire Chinese coast. The hotspots here are Sansha Bay in Fujian Province (16 studies) [33–35,37,47,49,56,65,69,73,76,80,83,85,86,88], the offshore area around Dalian in Liaoning Province (13 studies) [37,39,49,50,53,57–60,62,67,68,73], and Haizhou Bay in Jiangsu Province (9 studies) [31,32,55,61,63,66,71–73]. Further site and local studies of aquaculture were carried out on the coast of Japan [59,70,93,106], on the south coast of South Korea [81,82], the south coast of Vietnam [43,78], and Palawan in the Philippines [74]. It is also noticeable that there have been local studies on platforms in almost every sea in Southeast Asia [14,29,30,38,43,95,96,103].

Concluding, it can be said that apart from a few exceptions (e.g., Maldives, Persian Gulf, Caspian Sea, and New Zealand), hardly any studies were carried out in regions which also did not publish studies on their own.

3.4. Funding of Studies

To gain more insight and identify the institutions or countries that are interested in conducting studies in certain regions, we examined the funding sources of all articles (See Figure 9). The country where the funding came from is displayed on the left side, while the study region is on the right. The color coding indicates the continent from which the funding comes and where the study region is located: yellow for Asia, blue for Europe, green for America, and red for Oceania. Studies published without funding are shown in gray, and studies with a global study region are displayed at the bottom in black.

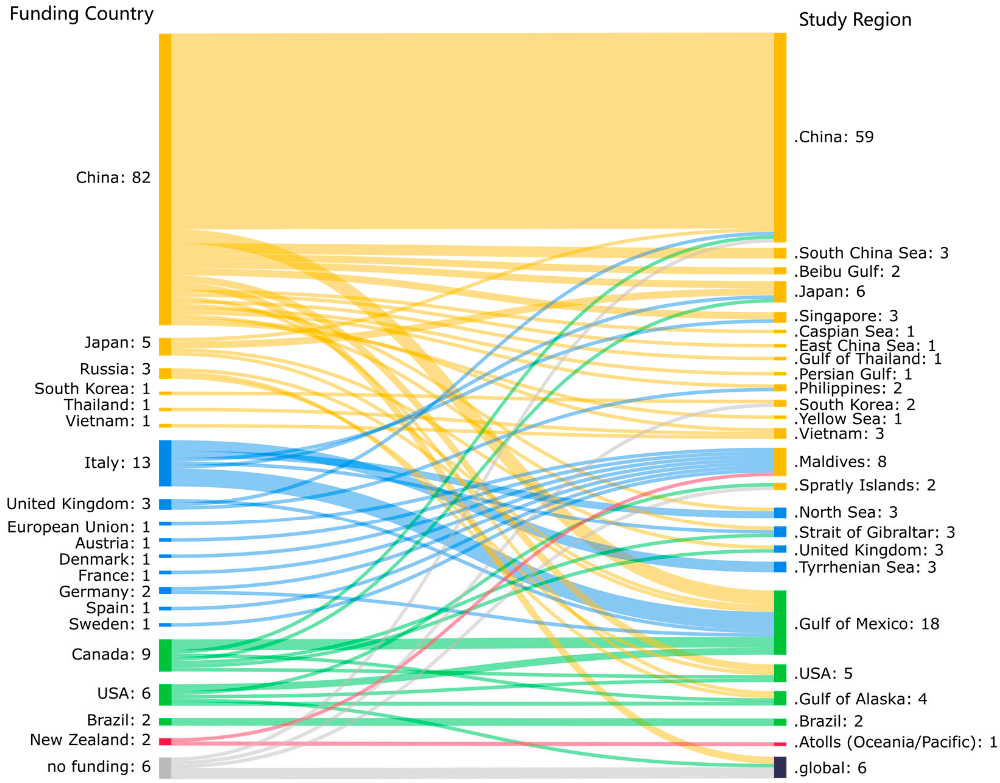


Figure 9. Visualization of the funding (funding country) going into specific study regions. The color indicates the continent from which the funding came and where the study region is located: yellow for Asia, blue for Europe, green for America, and red for Oceania. Studies published without funding are shown in gray, and studies with a global study region are displayed at the bottom in black.

It is important to note that the numbers displayed on the graph do not represent the number of publications. Rather, they indicate instances of funding that have been allocated to studies within specific regions. It is common for a single study to receive funding from multiple countries, and to examine multiple regions.

Since the majority of all publications (67 of 89–75%) come from China, it is not surprising that China also plays a major role in the funding. However, a look at the study regions is interesting. While the majority of China's financial support is allocated to research within its borders, it is apparent that China is also quite interested in research outside its borders. The areas of particular interest seem to be less in Europe but in the US, the Gulf of Mexico [29,94,97,106] and the east and west coasts of the USA [45,97], countries and waters close to China (Japan, Singapore, the Philippines, and Vietnam; South China Sea, Beibu Gulf, East China Sea, and Yellow Sea) [29,43–45,59,106] as well as the Persian Gulf [29] and the Caspian Sea [102].

It is worth noting that many countries and institutions are interested in studying regions outside of their own. For instance, some European countries are interested in the Maldives [112] and the Gulf of Mexico [17,98,104–106]. The USA and Canada are also interested in the Gulf of Mexico [14,94,97,106]. Canada has financially supported a total of three studies in nine study areas, even though none of the first authors were from Canada. Apart from the Gulf of Mexico, funding was also given for studies in China, Japan, the Spratly Islands, the Strait of Gibraltar, the United Kingdom, and the USA [14,106]. Interestingly, almost no funds from Western countries flow into studies on the Chinese coast or the surrounding area. Global studies were funded from China and the USA [36,109], as well as three studies on OWFs without funding [41,42,108].

3.5. Temporal Scope of the Reviewed Articles

Figure 10 shows the overall distribution of the temporal resolutions (pie chart) as well as the development of the duration of the studies from older to newer publications with color coding which infrastructure was detected. The following definitions are worth pointing out: Mono-temporal refers to studies that only deal with a single time instant, for example, a satellite image on a specific date. In contrast, studies that look at at least two different points in time are referred to as multi-temporal studies. Time series examine multiple points in time that are spaced at regular intervals to investigate a trend or pattern. Therefore, all stand-alone points in the graph are mono-temporal studies and all pairs of points connected are studies that are multi-temporal and time-series.

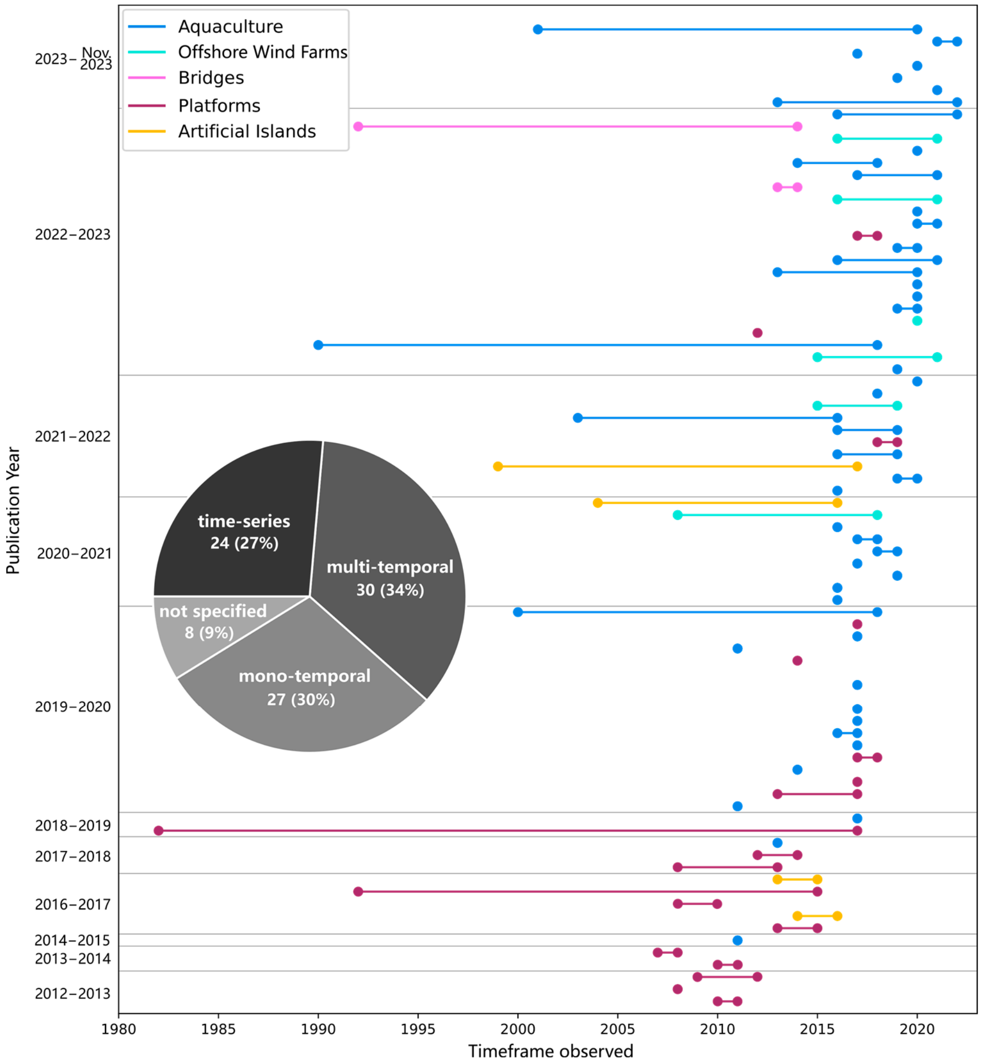


Figure 10. Timeline visualizing the temporal resolution of the research articles over the course of publication years. The integrated pie chart displays the distribution of the temporal resolution across all reviewed articles.

Significantly, more than half of all studies (61%) deal with more than two different dates for their investigation. In total, 34% of these deal with multi-temporal studies and 27% with time-series. This means that the majority of reviewed articles deal with study areas where a certain comparison or trend is to be derived. The majority (82%) of the multi-temporal and time-series studies cover a period of less than 10 years, 71% of them even less than 5 years. Of the time series, 18% are longer than 10 years [30,48,58,94,109] and 7% cover more than 20 years [30,48,94]. The time series ranges from one year [46] to 38 years [48] with an average length of almost 6 years.

Due to the wide availability of high-resolution satellite archives and the associated continuous coverage, it could be assumed that time-series studies have increased considerably over the years. However, this cannot be confirmed in the graph. A small trend towards time-series or multi-temporal can be recognized, but certainly not a significant trend. This can be explained by the fact that a large proportion of the reviewed publications are method papers, which primarily deal with the presentation and testing of a new method or model (e.g., [40,50,60,65,72,80]). A satellite image of one or at most a few time points is usually sufficient for this. Just under a third of the reviewed papers are mono-temporal studies, most of which are method-oriented.

To our surprise, eight studies named the sensor they used for their study, but did not provide any detailed information about which years the images were from and some also do not mention how many satellite images they used for their research [39,49,50,57,90,91,103,114].

When the infrastructures that were detected are closely examined, it is noticeable that many of the mono-temporal studies also dealt with aquaculture, while not a single mono-temporal study was carried out on bridges or artificial islands. This makes sense, particularly in the case of artificial islands, as the focus here is on the development of these structures. OWFs and platforms are also primarily observed based on long-term studies. For the detection of these fixed metallic infrastructures at sea, this also makes sense to eliminate all moving targets such as ships by creating a median image (which can only be created using several satellite images of the same location but at different times) that could otherwise interfere.

3.6. Employed Remote Sensing Sensors

Figure 11 shows the distribution of the platform and sensor type across all the articles examined. When looking at the reviewed articles and the data used, it quickly becomes apparent that almost exclusively spaceborne platforms were used (95%). Only two studies used airborne platforms [93,114]; one study used airborne in combination with spaceborne [45] and another one used a UAV in addition to spaceborne [84]. Based on the findings from Section 3.3 and the previous figure that most publications focus on smaller proof-of-concept and method development studies rather than large-scale applications, it would have been assumed that some more of the studies would use airborne platforms. However, this is not the case. The 95% of publications that use space-based platforms ought to have the potential to examine larger scales beyond regional and national data collection projects. Nevertheless, the majority investigate local, single scenes or smaller sections scattered across multiple scenes and also focus on proof of concepts or method development.

The sensor type also shows that almost all studies used multispectral or radar data, except for one that used hyperspectral data [64]. The proportion of multispectral applications is 59%, with radar at 40% and hyperspectral at just under 1%.

The most frequently used satellite missions include the American Landsats 4–8, the European Sentinels and RadarSat 1–2, and the Chinese Gao Fen 1, 2, 3 and 6. Together, these four satellite families account for 86% of all reviewed articles and 76% of use cases. These sensors are all characterized by a long mission duration of over 10 years with continuous data and thus create optimal conditions for a huge variety of applications, periods and long-term studies.

The Landsats 4-8 were used a total of 34 times in 19 of the reviewed articles with the highest proportion of Landsat-8, OLI with over 18 applications. This means that many studies used data from several Landsat missions instead of only one for their research (e.g., [30,48,58,94,109]). The Landsat-4 was launched in 1982 and was continued with the 5, 7 and 8. Together, they provide over 42 years of continuous multispectral satellite data coverage, which is also freely available from NASA and therefore particularly appealing to many researchers. Sentinels 2 for multispectral applications and 1 for radar applications are also freely available and widely used. Since their launch in 2014, they have now provided over 10 years of data. Sentinel data were used a total of 29 times in 23 of the reviewed articles. The RadarSat-1 and 2 have a total operational lifetime of 29 years to date and provide continuous radar data. Nine of the reviewed studies used data from RadarSat-2 [38,43–45,49,59,97,105,106] and one of the reviewed articles used data from RadarSat-1 [94]. With the Gao Fen missions, the Chinese remote sensing missions are leading in the field of data acquisition. The first Gao Fen satellite was launched into space in 2013. Gao Fen 2 and 3 followed in 2014 and 2016 and the sixth in the series in 2018. Together, they provide over 11 years of high-resolution multispectral and radar data to date. The data are not all freely available; most of them are restricted and in our reviewed articles these data are used exclusively by Chinese first authors, comprising 25 studies in total.

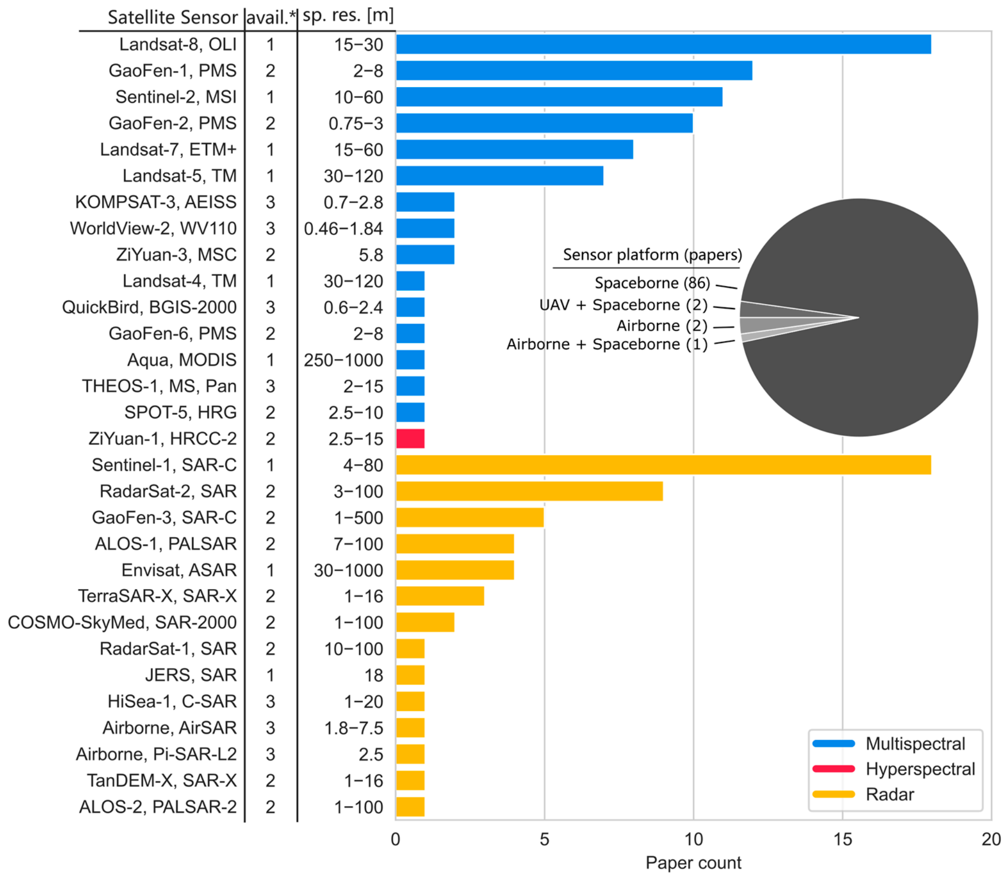


Figure 11. Used satellites and sensors for offshore infrastructure detection in all 89 reviewed articles. Color coding indicates sensor type. Many studies use multiple sensors and sensor types. Information on the sensors is provided in tabular form on the left-hand side: information on data availability (* 1 = free data, 2 = free for set areas, dates, or products, 3 = commercial) and on the range of the spatial resolution of the sensor.

Despite that over 80% of the publications come from the Asian region and 74% from China alone, only around 32% of all the articles examined are based on Chinese satellite data. Most of the studies are based on European satellite data (43%), followed by American satellite data used in 25% of all reviewed articles. This imbalance can be attributed in part to the open data policy of ESA and NASA, which aims to make high-resolution satellite data freely available to researchers and also to the general public.

In Figure 12, we have examined the extent to which the sensor type selected for the study is related to the infrastructure examined. Table 3 gives additional information about the bands used for offshore infrastructure detection. First of all, it is noticeable that 81 of the 89 reviewed articles were limited to just one sensor type. Only nine authors used multispectral data in combination with radar data as the basis for their studies. Of these nine, seven dealt with aquaculture [46,53,65,66,73,74,79] and two with platforms [30,94]. A total of 47 of the 89 studies (53%) dealt with the detection of offshore infrastructure based on multispectral satellite data. Of these, 40 focused exclusively on the detection of aquaculture. Four studies dealt with the detection of platforms [29,36,102,103], four with artificial islands [9,110–112] and one with OWFs [109]. The fields of application and infrastructures detected with radar data are diverse. Of the total of 32 reviewed articles (35%), aquaculture was identified in 11 [39,49,50,59,62,67,68,70,93,114,115], platforms in 18 [14,17,38,43,95–101,104–106], OWFs in five [41,42,51,107,108], and bridges in 2 [44,45]. The one study that used hyperspectral satellite data used them to detect aquaculture [64].

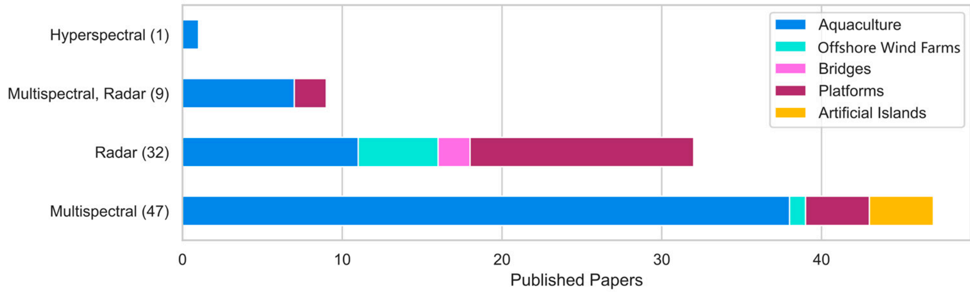


Figure 12. The type of sensor used versus the type of infrastructure studied. The number of reviewed articles is displayed in parentheses. Ten studies use several sensor types in combination, which is considered in this figure.

Table 3. List of bands used for offshore infrastructure detection. The color scheme provides information about the continent of investigation: Asia (Yellow), Europe (Blue), America (Green), Oceania (Pink), and Global (Black).

Bands	Aquaculture	Offshore Wind Farms	Bridges	Platforms	Artificial Islands
RGB	24				3
NIR	16	1			
SWIR				1	1
Multi	21			2, 3	1, 2, 1
Pan	12			1	1
X			1, 2	3, 2, 2	
C	16	1, 1, 4	1, 2	7, 7, 4	
L	2		1, 1	3, 2, 2	

It can be concluded from the graph that multispectral satellite data in particular were used for the detection of aquaculture. A total of 45 out of 57 articles (79%) that dealt with the detection of aquaculture were based exclusively on multispectral data or in combination with it. The structure of offshore aquaculture (cages, rafts, longlines) can be successfully identified based on spectral features. As the reviewed articles detecting aquaculture primarily focus on East and Southeast Asia, it is no surprise that only 18 of the 57 articles (31%) used radar data because in comparison to regions, e.g., in Alaska or Northern Norway, the maritime conditions, such as wind, waves, rain, and fog are not that impactful.

The development and detection of artificial islands are being investigated in four scientific investigations [9,110–112] and always use multispectral satellite images. All four studies do not attempt to identify all artificial islands in a large study area but rather investigate the development of a specific smaller region or even an atoll in the context of artificial islands mainly through band operations and visual inspection.

In contrast to aquaculture, the situation is completely different when it comes to identifying metallic infrastructure offshore. OWFs, platforms, and bridges, in general, are detected using radar images in particular. In total, 80% of the platform studies, 83% of the wind farm studies, and all (100%) of the bridge studies exclusively or partially detected the respective infrastructures on radar images. This is because metallic structures are particularly well distinguishable from the sea surface on radar images due to their backscatter characteristics.

In Figure 13, we have compared the spatial sensor resolution with the study region and the infrastructure investigated. The *x*-axis represents the size of the study region in km^2. The division into site, local, regional, continental, and global from Section 3.3 and Figure 6 is shown here with background zones in shades of gray. The *y*-axis shows the resolution of the sensor in meters. Both axes have logarithmic scales. The color code provides information about the infrastructure investigated. It is important to note that each bubble does not necessarily represent a study but a sensor used in a study. Therefore, there are several bubbles if different sensors were used in a study. The bubble size is increased if several sensors detect the same infrastructure in the same or a similar size study area. Studies that provided no information about the sensors used or the study area could not be included in the figure (e.g., bridge detections).

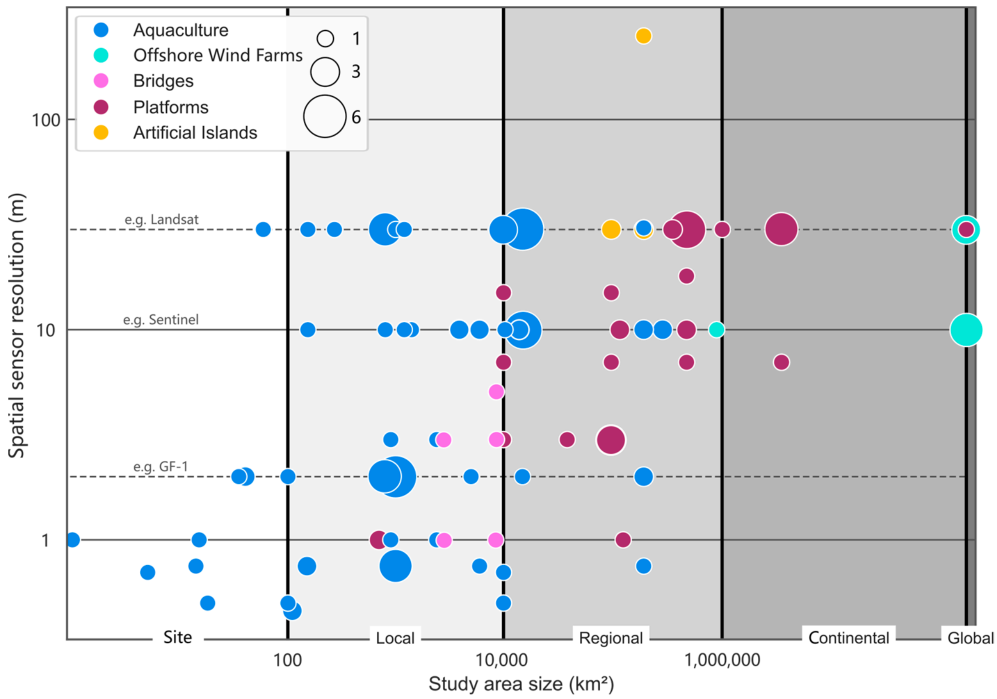


Figure 13. Spatial sensor resolution compared with the study area size. All sensors used in the reviewed articles are plotted as a dot. There may be several dots per publication if different sensors were used. The dot size is increased if there are multiple sensors of the same resolution, study area size and observed infrastructure. The color code indicates which infrastructure was observed.

The findings from Section 3.3 that more than half of the studies take place at a site or local level can also be found in this figure. It also shows that almost 90% (88%) of all site and local studies investigate aquaculture. The highest resolution data used were WorldView-2 data from the WV110 sensor to identify aquaculture with a resolution of less than half a meter [33,34]. The lowest resolution data came from the Aqua satellite and the MODIS instrument with a resolution of 250 m [111]. The latter was used in combination with Landsat-8 data to observe artificial islands and makes a clear exception. All other 90 studies use sensors with a resolution of 30 m or finer. The figure shows that many of the studies used sensors with a resolution of 30 m, 10 m, 2 m, or below 1 m for their research, highlighting the Landsat missions, ENVISAT ASAR, SRTM, and ZiYuan-1 (30 m), the Sentinel missions and RADARSAT-1 (10 m) and the very high-resolution Gao Fen, ZiYuan, QuickBird, WorldView etc. (<3 m), respectively.

In general, a slight pattern can be seen that many of the studies with large study areas (regional to global) used lower-resolution sensors (10 m or above), while the high-resolution sensors (3 m or under) were mostly used when looking at site or local study areas. Another observation is that the smaller the infrastructure investigated, the higher the resolution of the sensor. Site and local studies as well as smaller structures such as aquaculture are usually detected with high-resolution sensors. Aquaculture, whether cage, raft, or longline is relatively small. Individual cages, for example, are often less than 3×3 m in size. Of course, these cages are arranged in a group of multiple cages at the same time and therefore form a larger overall structure, but the authors' aim is also to recognize individual cages and their exact boundaries. To achieve this, very high-resolution data must be used which are mostly commercial such as WorldView, QuickBird or some of the Gaofen family of satellites. Over half of all sensors used for aquaculture detection have a resolution of 3 or less than 3 m and over 80% of all sensors with resolutions of 3 m or less have been used to detect aquaculture.

On a larger regional, continental, and global scale, mostly larger infrastructures like platforms, artificial islands, and OWFs are detected. Satellites that provide at best a global coverage of the earth are used for this purpose. The figure shows that most studies use Landsats (30 m) or Sentinels (10 m). Over 72% of the sensors used in the aforementioned infrastructures have a resolution of 10 m or coarser, and almost 50% even have a resolution of 30 m or coarser. However, the infrastructures are also many times larger than aquaculture structures. Wind turbines with their sockets and platforms are more than 20 m^2 in size and bridges and artificial islands are even much larger.

It has been observed that there are only six global applications, out of which one examines platforms [36] while the remaining five are focused on OWFs [41,42,107–109]. Out of these five, three are based on the same approach and authored by Thorsten Höser [41,42,108]. This indicates a lack of diversified studies, authors, and infrastructure, which leaves only four independent studies. This highlights a significant research gap in identifying offshore infrastructures on a global level. Applications that are not about the method itself but rather about the product can then be updated in subsequent years to observe the further development of the infrastructure in subsequent years.

3.7. Methods Used

The different marine infrastructures have characteristic remote sensing features that facilitate their identification. All structures have the common characteristic that they are stationary. This means that a temporal satellite image analysis, for example using a median composite image, filters out any temporary or moving structures such as ships. In addition to their stationary character, aquaculture is characterized in particular by their specific shapes (cages, rafts, longlines) and can be recognized by spectral features and detection methods such as edge detection. Any structures with a metallic character such as offshore wind farms, bridges, and platforms are particularly well distinguishable from the sea surface on radar images due to their backscatter characteristics. The OWFs can be well distinguished from platforms on radar images due to their typical pattern of layover and double bounce effect [41]. Bridges are characterized in particular by their linear structure that connects two parts of land. Artificial islands are a special case, as they are also man-made structures on the sea, but they are very large structures. The focus of the studies is not on detecting all artificial islands in a large study area but rather on investigating the development of a specific smaller region or even an atoll in the context of artificial islands mainly through RGB or band operations and visual inspection. Considering the diverse characteristics of marine infrastructures, the publications reveal a range of methods employed to detect these features and structures effectively.

The detailed analysis of the methods in the literature analyzed (Figure 14) illustrates the variety of approaches used by the authors to detect offshore infrastructures. These techniques can be roughly divided into the main methods of Information Enhancement and Pixel-based Extraction, Object-oriented or Object-based Image Analysis (OBIA), Traditional Machine Learning, and Deep Learning, as shown in the inner ring. The outer ring shows the sub-methods, techniques, or algorithms that were used in the studies. In the figure, the authors' target-leading method is listed, which means that if both Deep Learning was used for detection and Information Enhancement for preprocessing or the creation of land-water masks, only Deep Learning was included in the figure because it was the target-leading method. However, if two different Deep Learning algorithms were used for detection, both were included in the figure.

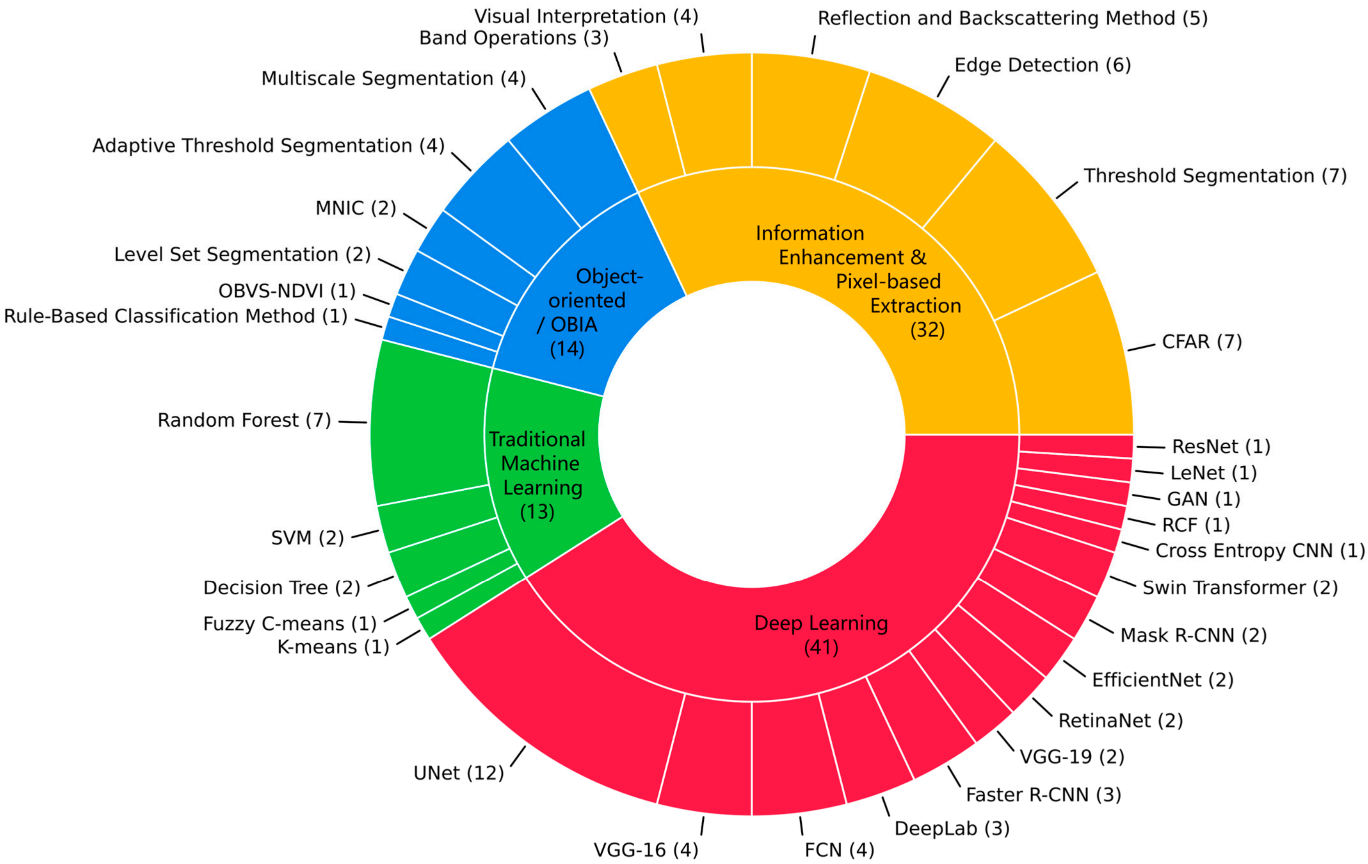


Figure 14. Visualization of the target-leading method the authors used for offshore infrastructure detection. The number of reviewed articles is displayed in parentheses. In the studies examined, 32% of the publications employed Information Enhancement and Pixel-based Extraction as the primary method to detect offshore infrastructures. Object-oriented/OBIA was used in 17% of the studies. More than half of the studies (52%) used a Machine Learning approach to identify offshore infrastructures, with over 40% of the studies relying solely on Deep Learning algorithms.

In general, the main methods can be divided into the traditional tools of Information Enhancement and Pixel-based Extraction and Object-oriented or OBIA and Machine Learning algorithms.

A total of 32% of the publications used Information Enhancement and Pixel-based Extraction as their target-leading method to detect offshore infrastructures. Thresholding methods [14,29,30,36,74,102,107] and Constant False Alarm Rate (CFAR) [17,38,95,96,101,104,106] are predominantly used here. Edge detection was used six times for detection [37,46,48,58,63,89]. These were followed by Reflection and Backscattering mechanisms with five applications [70,93,98,105,107], Visual Interpretation with four [70,93,110,112], and Band Operations with two [110,111]. Object-oriented or OBIA was used in 14 of the studies (15%). These used multiscale [40,55,75], adaptive threshold [90,94,109,114], rule-based [78] or level-set segmentation [44,45]. In two cases, multi-scale-based neighbor information classification

(MNIC) [34,86] and in one case object-based visually salient (OBVS) NDVI [56] were used as a thresholding technique.

Just over half of all studies used Machine Learning algorithms, with over 40% using Deep Learning approaches alone. With seven applications, Random Forest accounts for the majority of Traditional Machine Learning approaches [51,53,54,65,66,79,81], followed by Support Vector Machine [9,65] and Decision Tree [64,65] (two each) along with Fuzzy C-means [59] and K-means [81] (one each). This indicates that Random Forest plays a prominent role in recognition due to its flexibility and adaptability. The largest share of Deep Learning approaches was represented by the encoder–decoder architecture UNet. With 12 applications [31,39,50,62,67–69,72,73,80,83,115], UNet is the most frequently used technology of all the articles reviewed. The U-Net model, originally developed for biomedical image segmentation [116], gained considerable attention due to its outstanding performance when published and its clear, structured design. Through continuous research and modifications, UNet has established itself as a robust model for the detection of offshore infrastructures [20]. In addition to UNet, various algorithms have been used for image segmentation or object detection, including VGG [33,57,99,100], FCN [32,87,91], DeepLab [60,84,92], and R-CNN-based models [41,42,47,77,108], to name a few. This diversity illustrates the ongoing search for optimal solutions and the adaptation to the specific requirements of offshore detection.

Figure 15 shows the link between the target-oriented methods used and the infrastructure examined. The percentage share of the main methods is shown. As previously mentioned, Deep Learning was used most frequently as the target-leading method. It is now clear that this method was used in around 50% of all aquaculture (e.g., [52,77,87,92]) and OWF (e.g., [41,42,108]) studies. The remaining 50% is distributed roughly equally among the other three methodological approaches. Every fifth study investigating platforms used a Deep Learning approach for detection (e.g., [43,99,100]). In the remaining platform studies, Information Enhancement and Pixel-based Extraction (75%) (e.g., [14,95,96]) and OBIA (5%) ([94]) were used. The two publications that dealt with the detection of bridges both used an Object-oriented or OBIA method ([44,45]). Traditional Machine Learning was used to detect artificial islands in one of the four studies ([9]) and Information Enhancement and Pixel-based Extraction in the other three studies ([110–112]).

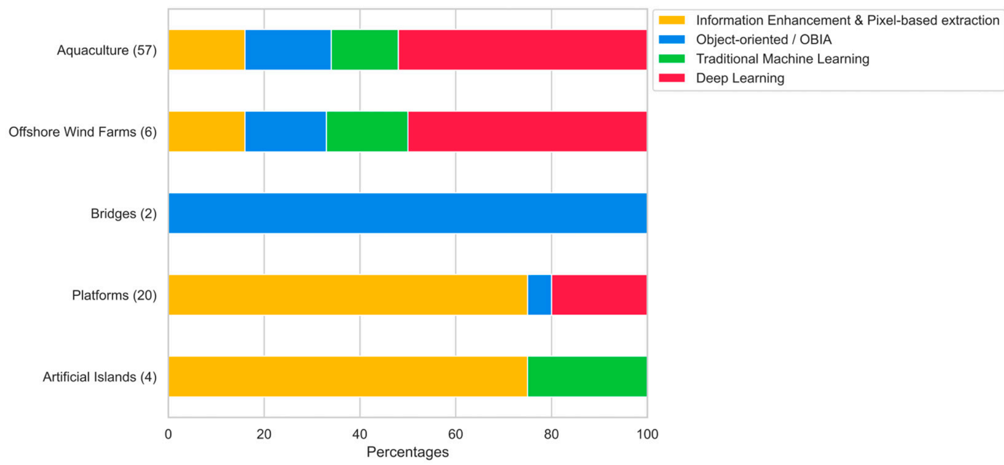


Figure 15. Relation between the main target-leading methods used and the infrastructure examined. Percentage share of the four main methods "Information Enhancement and Pixel-based Extraction", "Object-oriented/OBIA", "Traditional Machine Learning" and "Deep Learning" on the detection of the six infrastructure types. The number of reviewed articles is displayed in parentheses.

Figure 16 compares the use of the four main methods with the publication date of the reviewed articles. It is evident that until 2017, Information Enhancement and Pixel-based Extraction was used almost exclusively (91%). It was only from 2017 onwards that authors increasingly began to use Object-oriented or OBIA. OBIA has several advantages over traditional methods. It focuses on identifying and classifying objects within an image, rather than analyzing individual pixels. This results in faster processing times and lower computational requirements. Additionally, OBIA is better equipped to process complex objects with irregular shapes or textures and can group pixels into objects, resulting in higher accuracy. These benefits make OBIA an ideal choice for analyzing images with complex backgrounds or objects with similar appearances.

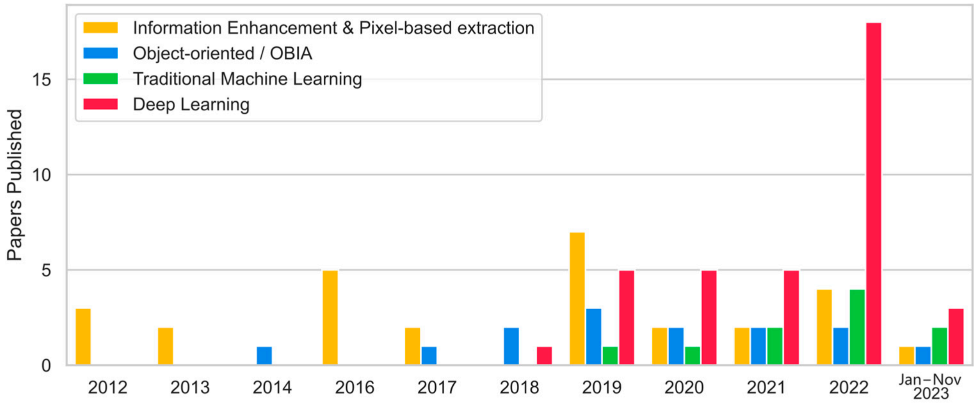


Figure 16. Method used for offshore infrastructure detection with regard to the year of publication.

From 2018 to 2019, Machine Learning approaches were used for the first time to detect infrastructures at sea. While 2019 was the peak of information enhancement and Pixel-based Extraction and Object-oriented/OBIA approaches, the use of Machine Learning applications continued to increase until 2022. In 2022, 66% of all studies used Deep Learning models to detect infrastructure at sea. Machine learning and Deep Learning clearly show their strengths when a lot of training data are available and the necessary computing power is available to enable intensive model training. This has become increasingly possible over the last ten years, as the availability of freely available training data sets and satellite image archives has continued to expand and the development of technology has driven computing power forward. Problems that were considered unsolvable are now being solved with extremely high accuracy. Machine Learning and Deep Learning models are dominating the field of computer vision due to significantly better performance compared to traditional methods. Traditional and manual tools are still often used when there is a lack of labeled data or insufficient storage and processing power. It can also be a more cost-effective solution. In addition, a lot of expertise is available here. Nevertheless, the Figure shows a clear trend from the more traditional image processing and image processing techniques towards Machine Learning models. Even if there have still been studies in recent years that have not used Machine Learning, it is evident that Machine Learning and Deep Learning in particular will continue to push back the traditional techniques.

4. Discussion and Future Prospects

4.1. Discussion

The huge economic and political potential of the ocean has been recognized by states and private companies for decades. Offshore construction is developing rapidly and uncontrollably, while information about these structures is often withheld. Science and research are only partially able to keep up with this pace and create transparency in monitoring this rapid development. Although research interest in the topic of offshore infrastructure is increasing, this review shows that there is still a need in this area. It was surprising that there were relatively few studies on the topic in our defined search period of 12 years. However, it can be assumed that not every satellite-based analysis that is being undertaken to investigate offshore infrastructure developments is really published in scientific journals.

Most of the studies we reviewed deal with method development or proof-of-concept studies rather than large-scale geoscientific research questions that aim for global detection and analyze the dynamics of these objects and their impact on the environment or land surface. We conclude that it is necessary to close this scientific research gap. A strong relationship was found between the country of first authorship and the regions they studied, probably due to research funding, the location of field sites and the availability of local reference data. About 80% of the first authors are from Asia, 74% of them exclusively from China. The high number of publications by Chinese authors and the funding from China can be partly attributed to an increased interest in research, but this should not be over-interpreted, as the country accounts for almost 20% of the world's population.

Distinct study clusters of the reviewed articles are located in the East and South China Seas in particular. All aquaculture studies in our literature review were conducted in this region. This can be explained by the fact that Asia dominates the global aquaculture sector, producing almost 90% of the total annual global production. The value of marine and coastal aquaculture is in fact slightly above 90% [117,118]. Although Asia dominates the global aquaculture sector, we noticed that offshore aquaculture, for example in Norway or Chile, has received little to no attention so far. While offshore aquaculture in general has been extensively studied, no study monitors aquaculture globally resulting in another research gap that needs to be filled. It is particularly clear how few studies have investigated other infrastructures than aquaculture. Only a few studies have been published on artificial islands. Even though this type of infrastructure is still relatively new in history, its development can be observed, for example, in the South China Sea over the last decade. Although this fact is present in the media, it is obvious that this rapid development of these infrastructures has hardly been studied in scientific journals.

Although the Persian Gulf is the largest single source of oil in the world, only one study has investigated offshore platforms in this area. There is only one study monitoring offshore platforms on a global scale and that is over five years old. Most studies focus on specific regions and methodological aspects rather than spatial or developmental analysis.

The detection of OWFs has been studied in only six research papers so far. Despite this, there are already successful global applications. However, because the most recent study was conducted several years ago, it is necessary to update the inventory to fully understand and evaluate this fast-developing sector.

To fully capture and assess the global and long-term developments of offshore infrastructure, analyses on larger scales with high temporal and spatial resolution and long-term temporal coverage are required. So far, however, only less than 7% of the articles reviewed have conducted their analyses on a global scale. Rather, the majority of articles (55%) have focused on site or local studies. In 70% of infrastructure detection studies, the area covered is even less than 100,000 km^2.

Since 2018, more and more studies have discovered and utilized the potential of Deep Learning for offshore infrastructure detection. The first successful Deep Learning implementation was conducted by Shi et al., who presented an automatic method for the pixel-wise labeling of aquaculture rafts based on a fully convolutional network (FCN) [57]. In 2022, publications of studies using Deep Learning increased by a significant amount. Hoeser et al. automated the detection of offshore wind energy infrastructure locations by applying Deep Learning-based object detection with two cascading neural networks to screen the Sentinel-1 archive on a global scale [108]. The two consecutive CNNs used synthetic training examples to recognize offshore wind energy infrastructures in real images. Another study is worth mentioning, published in early 2024 [11]. Paolo et al. used the Sentinel-1 product Ground Range Detected (GRD) Level-1 as well as the RGB and NIR bands of the Sentinel-2 product Level-1C to detect moving infrastructure such as ships, but also fixed infrastructure such as wind turbines and platforms worldwide. Even though this study by Paolo et al. falls outside our review investigation period, we wanted to mention it here as an exception due to its particular significance.

4.2. Prospects

Current research in the field of maritime infrastructure detection faces several challenges, such as time-consuming processing and high computing power requirements, especially for large-scale applications or global monitoring. Addressing these challenges necessitates the development of more precise and robust models capable of discerning smaller infrastructures and their boundaries, thus mitigating the risk of extraction inaccuracies. Moreover, the accessibility of very high-resolution open-access data remains as the financial constraints associated with data acquisition often impede progress. Further enhancements in data processing platforms, such as GEE, are imperative to facilitate the seamless handling of vast data, fostering more efficient analysis. The acquisition of proficient ground truth data is indispensable for the rigorous training and validation of detection methodologies. Training models is another ongoing challenge and requires a significant amount of labor and time for comprehensive and well-labeled data. In addition, with higher accuracy requirements and demands for identification by even more different types of objects or classes come more misclassifications, especially for structures near the coast or in regions with dense object populations. Recognizing trends on a broader scale and extending the applicability of the methodology to other areas is another important point.

In the future, our understanding of marine infrastructure dynamics will continue to advance due to the increasing availability of satellite data and advanced computing platforms, enabling long-term analysis and detection at larger scales. Although Deep Learning algorithms currently play an important role and are expected to continue to be used in future studies, they will likely eventually be replaced by new, more advanced methods. The ongoing transition from traditional detection methods to automated methods such as Deep Learning will continue and change the focus of studies. This will lead to an increase in studies investigating offshore infrastructures on a larger scale. Method papers and proof-of-concept studies are likely to continue due to the rapid developments in computer vision. Method development will remain a challenging and actively investigated topic.

Other types of infrastructure at sea are already planned or under construction. These include, for example, floating solar panels such as those in Singapore [119], energy islands such as those planned in the North Sea and Baltic Sea [120], oil infrastructure and storage islands such as those already built in the Persian Gulf [121] and further sand fillings on atolls for the construction of offshore infrastructure [8]. Offshore oil and gas platforms likely will expand into the Arctic and Antarctic regions as the ice melts [6]. It is expected that certain applications will continue to dominate due to their interest in research and practice. These applications will be in areas where people interact and are economically active.

By detecting these infrastructures, the dynamics can be accurately monitored and quantified. This will not only provide valid data for research and policymakers but also for everyday economic managers deciding on short-term strategies on a regional and global scale. Therefore, a comprehensive inventory of things is essential to compare the current situation with the past and to make and manage predictions in near real-time.

4.3. Limitations of This Review

This review focused on the detection of offshore infrastructures using remote sensing. A total of 89 articles from more than 30 international journals were analyzed. We made a conscious decision not to limit ourselves to journals from exclusively EO journals, as the subject area of offshore infrastructure is broadly diversified and, for example, also covers a lot of marine engineering and marine science.

We are aware that there is a large number of infrastructures on and in the sea and, above all, at the interface between sea and land. We have decided not to include the very intensively studied topic of ship identification, infrastructures that are located below the water surface or are not permanently installed (ships and garbage patches) as well as infrastructures with shelf connection to the mainland (e.g., Palms, Dubai) in order not to go beyond the scope of this review. For the same reason, we have not included non-English articles. We have decided the focus of the reviewed articles to be on the detection of man-made, permanently installed infrastructure offshore without a shore connection to the mainland. This also includes the filling of uninhabited atolls with sand to establish infrastructure, e.g., bases or military bases.

This approach called for a detailed search string covering the four main topics under consideration for this review: Remote Sensing, Offshore, Detection, and Infrastructure, which we presented in Section 2. We are aware that by narrowing this down, other relevant studies may have been published that deal with relevant applications but do not include one of the keywords in the search string and may therefore fall out. Through an extensive iterative process, we have optimized and expanded the search string and the keywords it contains several times to include as many relevant studies as possible.

We are aware that due to the limitation of the study period from 2012 onwards, possible relevant studies before this year cannot be included in our review. We argue this decision with the increase in earth observation research due to the proliferation of archives and data sources, which coincided with the introduction of CNNs by Krizhevsky et al. in image processing and opened up new possibilities for recognition models.

After filtering through the search string, our literature search returned 621 results. We further filtered the results manually by excluding studies that did not deal with the detection of the infrastructure itself, but for example with its vulnerability or risk. By including all international journals and a well-thought-out search string and filtering process, we believe we have captured a representative representation of available articles dealing with the detection of offshore infrastructure.

5. Conclusions

We provide a comprehensive overview of EO-based offshore infrastructure detection over the last 12 years. For a total of 89 studies from over 30 scientific journals, we examined the spatial distribution of research foci, the temporal resolution and the time period investigated, the sensors and sensor types used, the methods for detecting offshore infrastructures and the thematic foci. In the following, we briefly summarize our main findings on the defined research questions from Section 1.3:

- The marine infrastructures covered in the articles examined can be categorized into aquaculture, OWFs, bridges, platforms and artificial islands. Aquaculture is the most frequently observed infrastructure with 64%, followed by platforms with 23% and OWFs with 7%. Artificial islands have a share of 4% and bridges 2%. We have seen an increase in research activity over time on the EO-based detection of offshore infrastructure over the last 12 years, with particular growth since 2019. The number of publications in 2019 alone already exceeded the total number of all publications to that year and peaked in 2022.
- The research hotspots are primarily located in Asia. China alone accounted for 59% of publications. When including the studies in which research was carried out in China and other countries, as well as global studies, the figure is as high as 71%. Other areas in East and Southeast Asia are examined in 16% of the reviewed articles. The study areas in Asia are in particular aquaculture areas on the coast of China (56%), platforms in the East and South China Sea, Beibu Gulf, Gulf of Thailand, and near Singapore (9%), and artificial islands in the South China Sea (2%). A high concentration of studies on the detection of platforms, and OWFs were also found for the Gulf of Mexico (11%), the North Sea (4%) and Tyrrhenian Sea (3%). The majority of studies detected infrastructure at the site or local level (55%), 35% at the regional level and 3% at the continental level. Only a small number of studies investigated the detection of offshore infrastructures on a global scale (7%).
- The most first authorships come from China (74%), Italy (4%), Germany, Brazil and the USA (3% each). China provided financial support in 75% of all studies. Of these, the study region was outside China in 20% of these studies and in all but one of these studies the first author was from China. European countries funded or co-funded 10% of all studies, particularly for studies investigating the Gulf of Mexico,

the Mediterranean, the North Sea or the Maldives. The USA, Canada and Mexico almost exclusively funded studies conducted on the American continent. Overall, these countries contributed financially to 9% of all reviewed articles.

- At the temporal level, we differentiated between mono-temporal, multi-temporal and time-series. While 30% of the studies used only a single satellite image on a specific date, 61% used more than two different dates for their investigation. Of these, 34% dealt with multi-temporal studies and 27% with time series. This means that the majority of the articles examined deal with study areas from which a specific comparison or trend is to be derived. The majority (82%) of multitemporal and time-series studies cover a period of up to 10 years. Contrary to expectations, there is only a small trend towards time series or multitemporal studies over the years, but not a significant trend. Many of the mono-temporal studies deal with aquaculture, while the larger infrastructures such as artificial islands, OWFs, platforms, and bridges are mainly monitored on the basis of long-term studies.
- For the detection, spaceborne platforms are used almost exclusively (95%). Except for one study that used hyperspectral data, all others used multispectral (59%) and radar data (40%). In total, 89% of studies used one type of sensor rather than a combination of several. Multispectral data were used in particular for the detection of aquaculture and artificial islands, while radar data were mostly used for the detection of metallic structures such as OWFs, bridges and platforms. The most frequently used satellite missions include the Chinese Gao Fen 1, 2, 3 and 6 (28%), the European Sentinels (25%) and RadarSat 1–2 (11%) as well as the American Landsats 4–8 (21%). Together, these four satellite families account for 86% of all articles reviewed and 76% of use cases. These sensors are characterized by a long mission duration of over 10 years with continuous data.
- The analysis of the spatial sensor resolution in relation to the study area size and the infrastructure observed revealed that aquaculture was studied almost exclusively at a site or local scale and using high- and very high-resolution sensors, while the larger infrastructures such as platforms, OWFs and artificial islands were studied almost entirely at a regional and continental scale or beyond and with also lower resolution sensors.
- A total of 32% of the publications used Information Enhancement and Pixel-based Extraction as the target-leading method to detect offshore infrastructures. Object-oriented/OBIA was used in 17% of the studies examined. Most studies used a Machine Learning approach to identify offshore infrastructures (52%), with over 40% of studies relying solely on Deep Learning algorithms. Traditional Machine Learning models were dominated by Random Forest applications (8%), while UNet was the most commonly used Deep Learning algorithm (13%). In addition to UNet, however, a large number of other different algorithms were used to detect infrastructures. A trend from traditional detection methods to automated methods such as Deep Learning is particularly evident from 2019 onwards, with Deep Learning accounting for almost two thirds of all detection approaches in 2022.
- To fully capture and assess the global and long-term developments of offshore infrastructures, analyses on larger scales with high temporal and spatial resolution are required. So far, however, only less than 7% of the articles examined have conducted their analyses on a global scale. Here we see a clear research gap. Although offshore aquaculture is the most studied infrastructure, there is no global research on this type of infrastructure. In addition, there is a great lack of research on artificial islands. Although their development has been observed for a decade in the South China Sea, for example, this rapid development of these infrastructures has hardly been studied in scientific journals, let alone large-scale studies or even global applications. Offshore wind farms and offshore platforms have already been mapped worldwide, but these studies are few and several years old. It is therefore necessary to update the inventory in order to fully understand and assess this rapidly developing sector.

Our review complements existing research on the detection and dynamics of marine infrastructures by providing the first comprehensive overview of this field. We have examined the authors' research foci and the different study regions and presented important developments in the methods and applications used. We have highlighted current approaches of offshore infrastructure detection and give our predictions for possible future developments. Considerable progress has already been made in the field of marine activity and infrastructure monitoring. However, the development of marine activities and structures continues unabated and uncontrollable, and the challenge is to monitor this rapid construction boom transparently and, where possible, in real time. Future efforts therefore remain necessary to solve these challenges and effectively manage vital marine resources, space and energy development.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16101675/s1, Material S1: Web of Science Search String; Table S1: Overview of Reviewed Publications.

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