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Mapping the fine spatial distribution of global offshore surface seawater mariculture using remote sensing big data

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ABSTRACT

Against the backdrop of near-saturation in global marine capture fisheries, current mariculture production now exceeds one-third of capture production and continues to hold significant growth potential. However, the lack of spatially detailed global offshore surface seawater mariculture (OSSM) data hampers scientific understanding and management from a spatial perspective. In this study, utilizing multi-source remote sensing time-series imagery, we achieve the world's first spatially detailed mapping of both raft and cage mariculture types. The results show that (1) in 2020, the total global OSSM area was 20,079.97 km^2, comprising 85.04% raft mariculture and 14.96% cage mariculture. 95.33% of the OSSM was concentrated in Asia. (2) The interpreted national OSSM areas align well with the FAO production statistics trends. Obtaining these areas using remote sensing offers greater timeliness compared to production statistics, which is advantageous for dynamic monitoring and production estimation. (3) Through analysis of global pond aquaculture data, it was found that most coastal areas worldwide had a single-type of aquaculture. However, in parts of Asia, regions with both OSSM and pond aquaculture coexisted. The data acquired in this study, characterized by detailed spatial information, provide significant insights for constructing spatial models of mariculture, researching resource-environment effects, and informing management practices.

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1. Introduction

The escalating global population growth, coupled with increasing societal affluence, has precipitated a surge in human food demand. However, this surge has sparked competition between land-based

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food production and human developmental needs for land and resources, progressively constricting development space and presenting formidable challenges to global sustainable development. Against this backdrop, the significance of mariculture conducted in the oceans, which constitute 71% of the Earth's surface, in global food production has steadily increased (Free et al. 2022). According to statistical data from the Food and Agriculture Organization of the United Nations (FAO), since 2014, global aquaculture yields have surpassed those of wild-caught fisheries (FAO 2022), underscoring the substantial potential of mariculture in global food provisioning (Costello et al. 2020). Beyond its fundamental role as a blue food basket, mariculture serves as a pivotal component of oceanic blue carbon and thus plays an indispensable role in climate change mitigation (Zhang et al. 2017). Moreover, the mariculture industry serves as a significant source of employment and contributes to poverty alleviation in developing countries (Ottinger, Clauss, and Kuenzer 2016), thereby providing multifaceted support to global efforts toward sustainable development. However, despite its manifold advantages, the unchecked and indiscriminate expansion of mariculture may engender severe ecological environmental issues (Wartenberg et al. 2017), precipitating phenomena such as algal blooms (Liu et al. 2013), biological invasions (Wang et al. 2014), and navigational hindrances (Zeng et al. 2015). Furthermore, the mariculture industry is inherently susceptible to elevated risks, including climate change and extreme marine hydrodynamic disasters, which may inflict substantial losses upon the mariculture sector (Callaway et al. 2012; Froehlich, Gentry, and Halpern 2018; Zhang et al. 2021). Hence, fine spatial delineation of mariculture areas is imperative for scientifically gauging its environmental impacts and risks, thereby realizing the imperative of sustainable mariculture development.

At present, spatially explicit global mariculture data can primarily be obtained through several means. First, mariculture statistical data are a common source. A notable example is the FishStat dataset[1] provided by the FAO. This dataset encompasses global fishery production and trade data for 1950–2022, which can be filtered based on regions, countries, and mariculture types. Additionally, individual countries engaged in mariculture typically maintain fishery statistical yearbooks and corresponding databases, documenting information such as production, area, and employment, including mariculture-related data. The advantages of such data lie in their accessibility, high reliability, and detailed information (often containing species-specific details). However, one limitation is that these data are typically aggregated at the administrative unit scale and lack fine spatial location information. Consequently, the spatial heterogeneity within statistical units is not reflected and cannot be integrated with other geographic data for more refined spatial analysis, hindering the effective management and adjustment of the mariculture industry.

Due to the lack of fine location information in statistical data, some studies have attempted to integrate big data with statistical information to achieve relatively fine-scale mapping of mariculture spatial locations through allocation methods. For instance, Clawson et al. compiled global publicly available mariculture farm locations and simulated the allocation of unknown mariculture sites based on mariculture production data for 2017, thereby creating a spatial dataset covering mariculture farms worldwide(Clawson et al. 2022). In other food systems, such research endeavors have been undertaken earlier, such as research on marine industrial fisheries (Kroodsma et al. 2018; Watson and Tidd 2018), grains (Theobald et al. 2020), and livestock (Gilbert et al. 2018). The advantage of such spatial mapping data lies in their finer spatial location information compared to statistical data. Additionally, it can be corroborated using production statistical data, enabling comprehensive research that combines statistically reliable data with relatively fine-scale spatial location information. However, the spatial location information in this type of data is based on model allocation and is not inherently real. Hence, it can only provide a relatively rough spatial reference, so further efforts are needed to improve the spatial accuracy and objectivity.

The third method involves acquiring mariculture data based on remote sensing imagery (Liu et al. 2022; Ottinger, Clauss, and Kuenzer 2016; 2018). Compared to the previous two methods, data obtained from remote sensing imagery are objectively real, have a high global consistency, and can reduce human errors in data collection while narrowing down global statistical standards and temporal differences. Remote sensing satellites typically revisit locations within 10–20 days, significantly enhancing the speed and efficiency of data acquisition compared to annual statistical data. Moreover, the diversity of remote sensing sensors such as optical and synthetic aperture radar (SAR) enables image acquisition in regions with diverse and complex climatic conditions globally. Therefore, remote sensing-based data are more suitable for large-scale global research. Additionally, remote sensing data have an extremely high spatial accuracy, and high-resolution remote sensing and unmanned aerial vehicle (UAV) imagery is capable of capturing sub-meter spatial location information. Consequently, this type of data, characterized by real and fine-grained spatial information and a high acquisition efficiency, offers significant advantages over statistical data in terms of achieving scientifically managed mariculture and conducting interactive interdisciplinary research based on spatial information. It should be noted that there are various types of mariculture, primarily including bottom sowing mariculture, pond mariculture, raft mariculture, and cage mariculture. Remote sensing images cannot effectively observe bottom sowing mariculture; therefore, the mariculture referred to in this paper is limited to the types of mariculture that can be observed via remote sensing, excluding bottom sowing mariculture. Based on the location, pond mariculture is situated on land, while raft mariculture and cage mariculture primarily float on the sea surface, and there are significant differences between them. We have previously interpreted global pond aquaculture (including freshwater and seawater ponds) based on remote sensing images. Therefore, in this study, we focused on raft mariculture and cage mariculture. Given that these two types generally float on the sea surface, we collectively refer to them as offshore surface seawater mariculture (OSSM).

Currently, numerous studies have utilized remote sensing imagery to extract OSSM information, employing diverse extraction algorithms such as visual interpretation methods, feature enhancement methods (Wu et al. 2021; Yu et al. 2020), feature learning methods (Xue et al. 2018), object-oriented methods (Wang, Cao, et al. 2018; Wang, Yang, et al. 2018; Zheng et al. 2017), and deep learning methods (Chen et al. 2024; Fu et al. 2022; Geng, Fan, and Wang 2017; Liu, Yang, et al. 2019; Ma et al. 2022; Zhang et al. 2020). However, most studies have focused on implementing extraction algorithms in small-scale regions, and only a few studies have extracted OSSM data at the national scale. For instance, Liu et al., Fu et al., and Yin et al. extracted mariculture data for China, which accounts for over half of global mariculture production (Fu et al. 2021; Liu et al. 2020; 2022; Yin et al. 2023). In contrast, more studies have focused on the extraction of land-based aquaculture ponds (Duan et al. 2020; 2021; Jia et al. 2021; Luo et al. 2022; Peng et al. 2022; Sun et al. 2024; Wang et al. 2022; Xia, Guo, and Chen 2020; Zhang et al. 2023). This is primarily due to the inherent challenges associated with extracting OSSM information from remote sensing imagery, such as its relative microscopic nature, strong dynamics, and weak information content compared to terrestrial features (Fan et al. 2015; Fan et al. 2019). Moreover, the diverse types of OSSM globally, complex and varied marine backgrounds, dynamic changes, and lack of high-precision reference data for OSSM areas further exacerbate the difficulties in large-scale OSSM extraction. Consequently, to date, continental and global-scale OSSM data based on remote sensing remain largely unexplored. Nevertheless, owing to the continuous observations provided by remote sensing satellites and the open-access Google Earth Engine (GEE) (Tamiminia et al. 2020), the foundation for extracting global OSSM data has been established at the data level.

In this study, we utilized the GEE platform to integrate time-series Sentinel-2 and Sentinel-1 satellite imagery from the entire year of 2020 to generate enhanced feature maps of OSSM. Additionally, historical imagery with a sub-meter resolution from Google Earth was incorporated to extract fine-scale spatial distribution data on global OSSM. To ensure the accuracy of the data, we employed multiple sources of information, including statistical data, textual materials, electronic maps, and image videos, to cross-validate and refine the dataset. Through this comprehensive approach, we obtained the first global scaled spatially refined dataset of the OSSM distribution. Subsequently, we analyzed the global distribution of OSSM based on this dataset.

2. Data and methods

Figure 1 illustrates the interpretation workflow of OSSM utilized in this study. First, we defined the study area. Based on our team's previous experience interpreting OSSM data for China, the distribution generally did not exceed 100 km from the mainland and island coastlines. Therefore, based on global coastal data products, a buffer zone was constructed extending 10 km inland and 100 km seaward as the study area for this research. The purpose of constructing a 10 km buffer zone inland was to account for the presence of lagoons connected to the ocean in some coastal areas where OSSM activities may also occur. Additionally, OSSM may also occur in some estuaries, so it was necessary to ensure that the study area included these areas. Due to the highly uneven global distribution of OSSM, we divided the study area by continent to improve work efficiency. The regions included Asia, Europe, Africa, North America, South America, and Oceania. Specifically, for Asia, where OSSM is extensively distributed, we further subdivided this region in more detail. China, due to its large-scale OSSM, was defined as its own separate subdivision. The region north of China, including North Korea, South Korea, and Russia, was defined as one subdivision. The area south of China and to the boundary of the Eurasian continent was defined as another subdivision. Japan and island nations in Southeast Asia were subdivided by country.

After defining the study area, image selection was conducted using the GEE platform based on the study area and time period. Sentinel-2 and Sentinel-1 satellite images were chosen as the primary data sources, and we selected images acquired in 2020 with a cloud coverage less than 80% and covering the study area for the entire year.

We used Liu's method (Liu et al. 2022) for preliminary detection and extraction of OSSM. Due to the relatively weak information about OSSM targets and their intermittent appearance throughout the year, a time-series data synthesis approach was employed to highlight the OSSM targets. After segmenting the OSSM targets using the edge features, we performed a preliminary extraction of the OSSM targets by combining spectral features, texture features, and patch area features. Liu's method is suitable for interpreting high-density OSSM regions in Asia, represented by China. However, there are many regions with scattered OSSM occurrences worldwide. To ensure the quality of the final interpretation, we performed visual interpretation using enhanced feature maps and submeter resolution historical Google imagery after the preliminary interpretation of the OSSM using Liu's method. After the initial interpretation, a quality check was conducted via multiple rounds of regional cross-validation and comparison with network electronic map data, statistical data, and information from online news reports. The data were iteratively verified via the collaborative use of multiple information sources.

In this study, the types of OSSM included raft mariculture and cage mariculture. These two types of mariculture are described separately below.

Raft mariculture primarily involves cultivating algae and mollusks such as shellfish. It typically includes three main components: floating rafts, hanging ropes or cages, and fixed cables. The floating rafts, connected by floats and ropes, are kept afloat on the sea surface by the floats. Hanging ropes or cages, evenly spaced along the raft ropes, are mainly used for cultivating seaweed such as kelp, while cages are employed for cultivating shellfish such as scallops and sea cucumbers, the cages of both hang in the seawater. Fixed cables connect one end of the raft to a float and the other end to a sinker, serving a stabilizing function. Since the main body of raft mariculture is located mostly beneath the water surface, and only individual floats visible on the water surface, the imaging information in remote sensing images is very weak. Raft mariculture setups are often densely arranged, with several ropes forming a group, and appear as rectangular bands in images. As the cultivation of algae matures, it gradually exhibits spectral characteristics similar to vegetation, appearing as dark rectangular bands in remote sensing images, and these images contain relatively strong information in the near-infrared band. However, the information related to shellfish cultivation is weaker compared to that of algae cultivation, which typically manifests as bright-toned cultivation ropes that only appears in high-resolution images.

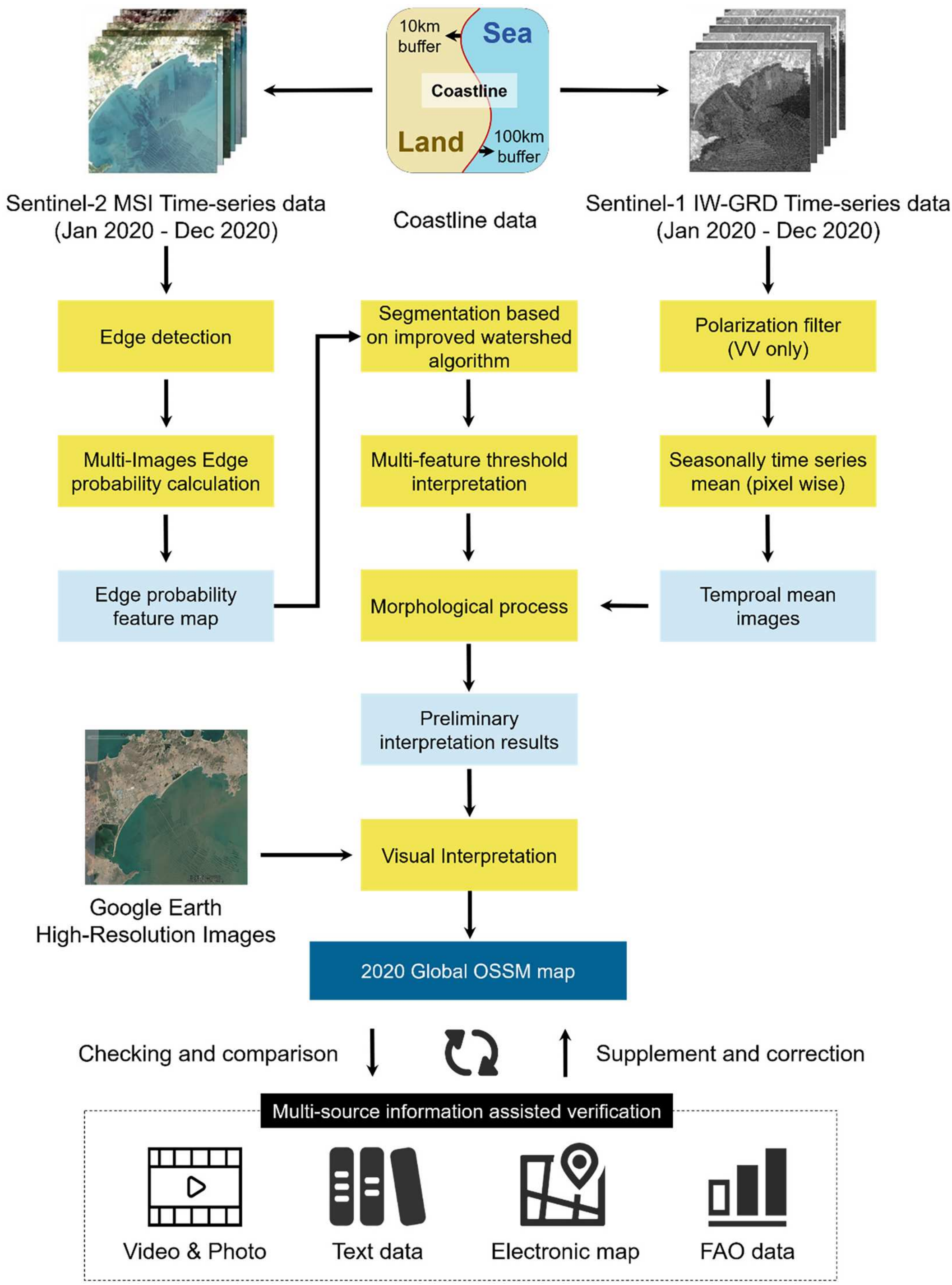

Figure 1. Flowchart of interpretation of global OSSM data for 2020.

Cage mariculture can generally be divided into two forms: deep-water cages, typically used for salmon and other fish cultivation, and shallow-water cages, referred to as common cages in this study. Common cages are usually located in relatively shallow water areas and are used for fish cultivation, as well as for cultivating sea urchins, sea cucumbers, and other marine products. Both types of cages consist of structures such as frames, netting, and anchors. In remote sensing images, cage mariculture exhibits strong geometric features. The majority of deep-water cages are circular and have diameters of 20–50 m, but square deep-water cages also exist. The most significant characteristics of deep-water cages are their regular shapes and the absence of texture inside the cages. Common cages are widely distributed in regions such as China and Asia, are often rectangular in shape, and typically exhibit distinct texture structures inside the cages. Unlike raft culture, the appearance of cage mariculture in remote sensing images remains unchanged with the growth of the cultured organisms. Furthermore, due to the long-term exposure of the frame part of the cage above the water surface and its distinct geometric characteristics, cage mariculture is more easily identifiable in remote sensing images compared to raft mariculture.

2.1. Data use

Three types of remote sensing images were used in the OSSM interpretation in this study: Sentinel-2 images, Sentinel-1 images, and historical images from Google Earth. Among these, Sentinel-2 images have a resolution of 10 m and cover visible light bands, making OSSM targets relatively easy to distinguish. Additionally, the Sentinel-2 single satellite revisit period is 10 days, providing multiple image coverages per year to meet the monitoring needs of highly dynamic OSSM activities. Sentinel-1, as an SAR satellite, is well-suited for monitoring regions with frequent cloud cover and rainfall, such as Southeast Asia, and coastal areas prone to climate change. Moreover, it provides good imaging results for targets on the sea surface and raft mariculture, which may not be clearly visible in optical images. The Sentinel-1 single satellite revisit period is 12 days, ensuring multiple image coverages per year.

From the GEE platform, which has a cloud coverage threshold of 80%, we ultimately selected 937,764 Sentinel-2 optical images and 140,263 Sentinel-1 SAR images covering the study area. Historical images from Google Earth, although fewer in terms of imaging dates throughout the year, have the highest sub-meter resolution. This enabled a more detailed inspection and verification of OSSM areas that could not be conclusively identified in the Sentinel-2 and Sentinel-1 images.

In addition to remote sensing images, we also utilized global coastline data to generate the boundaries of the regions comprising the study area, as well as for image selection. Furthermore, exclusive economic zone data were integrated to assert ownership and conduct area statistics for OSSM in various countries.

2.1.1. Sentinel-1 multi-temporal images

Sentinel-1 (including Sentinel-1A and Sentinel-1B) is a C-band synthetic aperture radar that operates at a frequency of 5.405 GHz. It supports both single polarization (vertical-vertical (VV) and horizontal-horizontal (HH)) and multi-polarization (VV + VH and HH + HV) modes. The single satellite revisit cycle is 12 days (6 days for dual satellites). Images acquired in the default interference wide (IW) mode have a swath width of 250 km and a spatial resolution of 5 × 20 m (Torres et al. 2012). However, due to the limited penetration capability of the cross-polarization VH data compared to the single-polarization HH data, mariculture areas are challenging to discern in VH data (Zhang et al. 2020). Therefore, only the single-polarization VV data were utilized to extract the mariculture areas.

From the GEE platform, we selected all of the available VV Sentinel-1 images covering the study area acquired from 1 January 2020, to 31 December 2020, in IW mode in ground range detected (GRD) format. These Sentinel-1 images in the GEE platform have undergone preprocessing using the European Space Agency's (ESA) Sentinel-1 toolbox, which includes thermal noise removal, radial calibration, and terrain correction.

2.1.2. Sentinel-2 multi-temporal images

The Sentinel-2 satellites (including Sentinel-2A and Sentinel-2B) are equipped with a Multispectral Instrument (MSI) capable of capturing optical images with a high spatial resolution of 10 m. The MSI comprises 13 spectral bands, including of four bands with a 10-meter resolution, six bands with a 20-meter resolution, and three bands with a 60-meter resolution. After the launch of Sentinel-2B, the revisit time of the Sentinel-2 satellites decreased from 10 to 5 days. We gathered all of the available Level-2A Sentinel-2 data for the study area acquired from January 2020 to December 2021 from the GEE platform, specifically focusing on the 10-meter resolution bands. Images with cloud cover of less than 80% were chosen and were subsequently masked using the quality assessment band (QA60) to mitigate the influence of clouds.

2.1.3. Coastline data

We employed coastline data to delineate the scope of our study area. The 2015 global sea land (and islands) coastline data, which has a meter-level spatial resolution, was utilized (Liu, Shi, et al. 2019). This dataset provides global coverage and was generated using human–computer interaction methods, Google Earth images, digital elevation model (DEM) data, and multi-source maps and publications of various scales. Rigorous inspection procedures were conducted to ensure the high reliability of the data. Drawing from previous experience in interpreting OSSM in China, we generated a 100 km buffer zone seaward and a 10 km buffer zone landward based on these data to define our study area. The 10 km buffer zone landward was established to ensure the inclusion of OSSM facilities extending inland along riverbanks and those potentially located within estuaries along coastal zones.

2.1.4. Exclusive economic zone data

Exclusive economic zone (EEZ) data were utilized to determine the country to which the extracted OSSM belonged, facilitating the completion of OSSM area statistics on a national basis. The data we utilized were obtained from the World EEZ v12 dataset.[2]

2.2. Methods

2.2.1. Preliminary interpretation of OSSM enhanced by temporal features

We used a method based on enhanced temporal features for the preliminary interpretation of the OSSM. Due to the relatively weak information about the mariculture in the satellite imagery and its dynamic nature, a single remote sensing image may fail to accurately interpret mariculture if the imaging time is not appropriate. Therefore, a temporal synthesis approach was adopted to enhance the mariculture information in the Sentinel-1 and Sentinel-2 images.

For the temporal synthesis of the Sentinel-1 images, VV polarization images that were more indicative of mariculture were selected. Then, median composites of these images were generated for the entire year within the study area (Liu et al. 2022). Although the signals of mariculture are weak and dynamically variable, temporal synthesis via the accumulation of multiple images enhances the signal difference between mariculture and the seawater background, thereby highlighting the mariculture targets.

In the case of Sentinel-2 imagery, the diverse and complex nature of global-scale seawater backgrounds often leads to variations in the spectral characteristics of mariculture under different seawater conditions. Artificial mariculture facilities typically exhibit regular and relatively distinct geometric edges, which serve as significant features for mariculture identification. Therefore, temporal enhancement of the edge features of mariculture was pursued. The specific procedure was as follows: first, the images were grouped into intervals of 15 days, resulting in a total of 24 image sets over the course of a year. Within each of these 24 sets, the Canny operator was employed to extract the edge features from the water areas in the images, thus generating edge feature maps. Simultaneously, the edge feature maps within each set were composited to obtain 24 composite edge feature images. These 24 composite edge feature images were then ranked based on the feature intensity, and the top eight images in terms of the feature intensity were selected for further feature image synthesis so as to maximize the enhancement of the mariculture edges throughout the year.

After enhancing the edge feature map of the image, the image was segmented using an improved watershed algorithm. For each segmented patch, the OSSM patches were identified by comprehensively selecting spectral features (mean gray value), texture features (Gray-level Co-occurrence Matrix (GLCM) variance), and geometric features (area). The threshold of the mean gray value was dynamically determined using the moment-preserving algorithm, the segmentation threshold for the GLCM variance feature was set to 10.2, and the threshold range for the area feature was the number of pixels comprising a single patch, which was between 60 and 290,000. The specific parameter settings have been described by Liu (Liu et al. 2022).

2.2.2. Cross-validation by subregion and data quality assessment guided by multi-source information

The preliminary extraction of global OSSM was achieved based on enhanced features. However, due to factors such as the small size and scattered distribution of OSSM targets, significant differences in the styles across global regions, the susceptibility to weather and sea conditions, and the presence of non-mariculture targets that are easily confused, achieving high-precision automated extraction of the OSSM at the global scale remains challenging. To ensure the reliability of the data, we conducted visual interpretation of the global OSSM based on the preliminary automated extraction results, integrating temporally enhanced Sentinel-1 and Sentinel-2 imagery and submeter high spatial resolution historical imagery from Google Earth.

After interpretation of the global remote sensing imagery, we performed cross-validation of the extracted OSSM data by integrating various sources. These sources included FAO statistical data, electronic map data, online news reports, and multimedia content such as images and videos.

First, we cross-verified the extracted OSSM data with global production data from the FAO FishStat database to avoid significant omissions. Given the diversity and regional variations in the OSSM, we used Google Map's geospatial data to assist in identifying uncertain OSSM targets. For instance, if the surrounding area of a suspected OSSM site included names indicating seafood restaurants, marine farms, or fishery companies, it was likely that the target was indeed related to mariculture.

In cases where no indicative names were included, we conducted online searches to examine whether there were textual descriptions, news reports, and/or multimedia content such as photos and videos related to mariculture in the vicinity of the suspected site. This comprehensive approach allowed us to make informed judgments on whether the target was associated with mariculture.

Additionally, mariculture is an interactive human activity, so the absence of signs of other human activities, such as buildings, roads, and traces of boats in historical imagery within the vicinity of a suspected site, suggests that it is likely not a mariculture site.

Finally, we conducted field surveys in China and several countries in Southeast Asia to analyze and verify certain OSSM targets.

During the verification process, we identified several targets that could easily be confused with OSSM (Figure 2), for example, loosely arranged boats docked outside ports and maritime timber transport activities in Canada. These types of targets appeared very similar to mariculture in time-series composite imagery, and we excluded a substantial number of such targets after multiple rounds of inspection.

Additionally, in the bays in Southeast Asia, we observed numerous V-shaped and T-shaped structures, which we suspect were related to fishing operations rather than mariculture. Consequently, these structures were not included in the mariculture interpretations in this study.

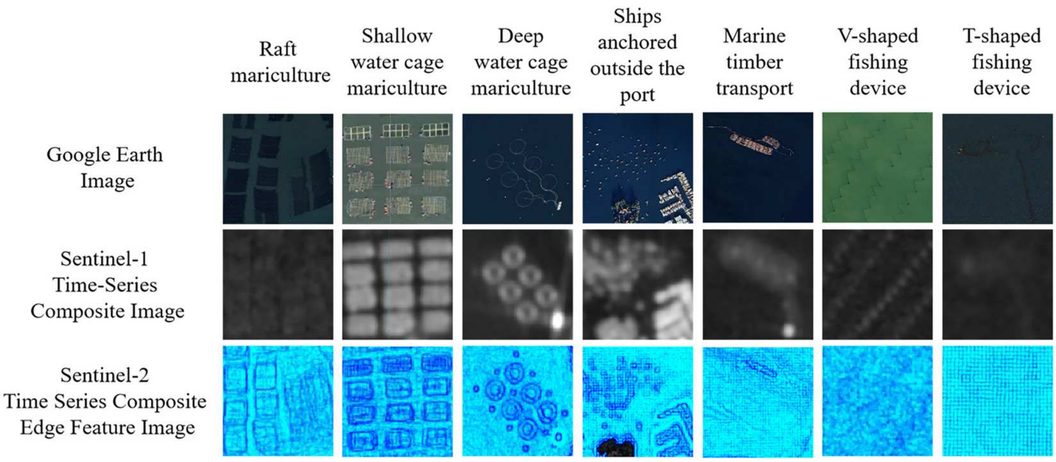

Figure 2. Performance of OSSM and confusable targets in different images.

3. Results

3.1. Spatial distribution of global OSSM

Figure 3 illustrates the global distribution of the OSSM in 2020. To optimize the visual representation, this map was created using the Plate Carrée projection, and the actual area calculations were performed using the equal-area Eckert IV projection.

The calculation of the OSSM area was completed in ArcGIS using the area statistics based on the final interpreted patches. It is important to note that in some statistical yearbooks, the measurement unit for cage mariculture is volume. However, in this study, based on remote sensing imagery, we could not obtain specific box volumes or depths for the interpreted cage objects. Additionally, the volume differences in cage mariculture are quite large, making it unsuitable to convert between area

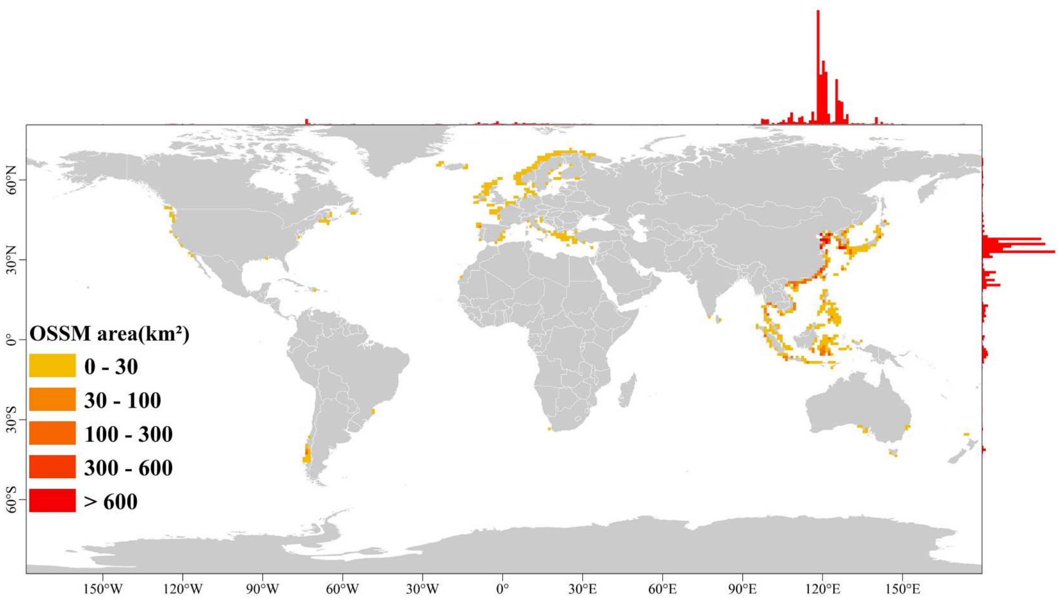

Figure 3. Global distribution of OSSM in 2020.

and volume using rough values. Therefore, in this study, we uniformly used area for the statistics and analysis of both the raft mariculture and cage mariculture.

Given the small scale of the OSSM targets globally, a 1 × 1° grid was constructed to enhance the visibility of the global OSSM distribution.

The grid cells in the map were categorized into five levels based on the OSSM area within each cell. The classification standard was simplified to integers based on the natural breaks method. A higher level indicates a greater OSSM area and a higher density within the grid cell.

From the global perspective, the total area of OSSM reached 20,079.97 km^2, and 91.5% was located in the Northern Hemisphere, while only 8.5% was located in the Southern Hemisphere. The northernmost OSSM site was located at a latitude of 71°N on Maug Island, Norway, while the southernmost site was located at a latitude of 45°S in Aysén, Chile. The OSSM extended from the equator to the northernmost latitude of 71°N, and OSSM occurred at every latitude. However, there was a gap in OSSM between the equator and the northernmost distribution point, that is, no OSSM activity was observed between latitudes of 10°S and 25°S.

The global distribution of the OSSM was highly uneven. On the continental scale, Asia had the largest area dedicated to OSSM, covering 19,142.88 km^2 and accounting for 95.33% of the total area, followed by Europe (560.77 km^2m 2.79%), South America (216.96 km^2, 1.08%), Oceania (90.67 km^2, 0.45%), North America (54.33 km^2, 0.27%), and Africa (14.35 km^2, 0.07%). The dominance of Asia in OSSM was overwhelming. However, within Asia, the distribution was also uneven. The OSSM was primarily concentrated in East and Southeast Asia and was scarce in South and West Asia.

Based on the EEZ data, the OSSM areas in the various countries were systematically compiled. Among the top 20 countries, China stood out as the world's largest OSSM nation, contributing to over half of the global total and accounting for 57.88%. In addition to China, the prominent OSSM countries in Asia included South Korea (15.49%), Indonesia (8.02%), Japan (4.38%), Thailand (2.40%), Vietnam (2.32%), North Korea (2.13%), the Philippines (1.97%), and Myanmar (0.65%). The combined OSSM area of these Asian countries alone exceeded 90% of the global total. Additionally, several European countries engaged in OSSM, including Norway (0.89%), France (0.59%), Spain (0.41%), the United Kingdom (0.26%), Ireland (0.12%), Italy (0.09%), Russia (0.08%), and Denmark (0.08%). Other countries involved in OSSM included Chile (1.04%), Australia (0.43%), and the United States (0.09%).

Approximately 94% of the global OSSM was located within bays, while other OSSM activities primarily occurred around islands, shoals, and similar areas. This distribution can be attributed to the relatively calmer conditions in bays and around islands and shoals, which facilitate the setup and management of OSSM facilities. Additionally, the reduced wave activity in these areas lowers the energy expenditure of the cultured organisms, promoting faster growth. Bays and islands also provide natural harbors that offer protection against marine disasters such as typhoons and storm surges.

This phenomenon indicates that the number of bays and the complexity of the coastline are natural assets for the development of OSSM. Regions with numerous bays and intricate coastlines have a significant potential for OSSM development, whereas those with fewer bays and smoother coastlines have less potential. Our data support this conclusion, that is, major OSSM nations such as China, Indonesia, Norway, and Chile possess complex coastlines containing numerous bays and islands and contained abundant OSSM. In contrast, regions such as India in South Asia, Yemen and Oman in West Asia, and the southern coast of the African continent, which are characterized by relatively straight coastlines and few bays, exhibited minimal development of OSSM.

It is important to note that while bays provide a potential advantage for OSSM, the actual development of OSSM depends on various factors. Not all bays are suitable for OSSM, nor are all non-bay areas unsuitable. Our data merely indicate that compared to other areas, bays generally offer a more favorable environment for the development of OSSM.

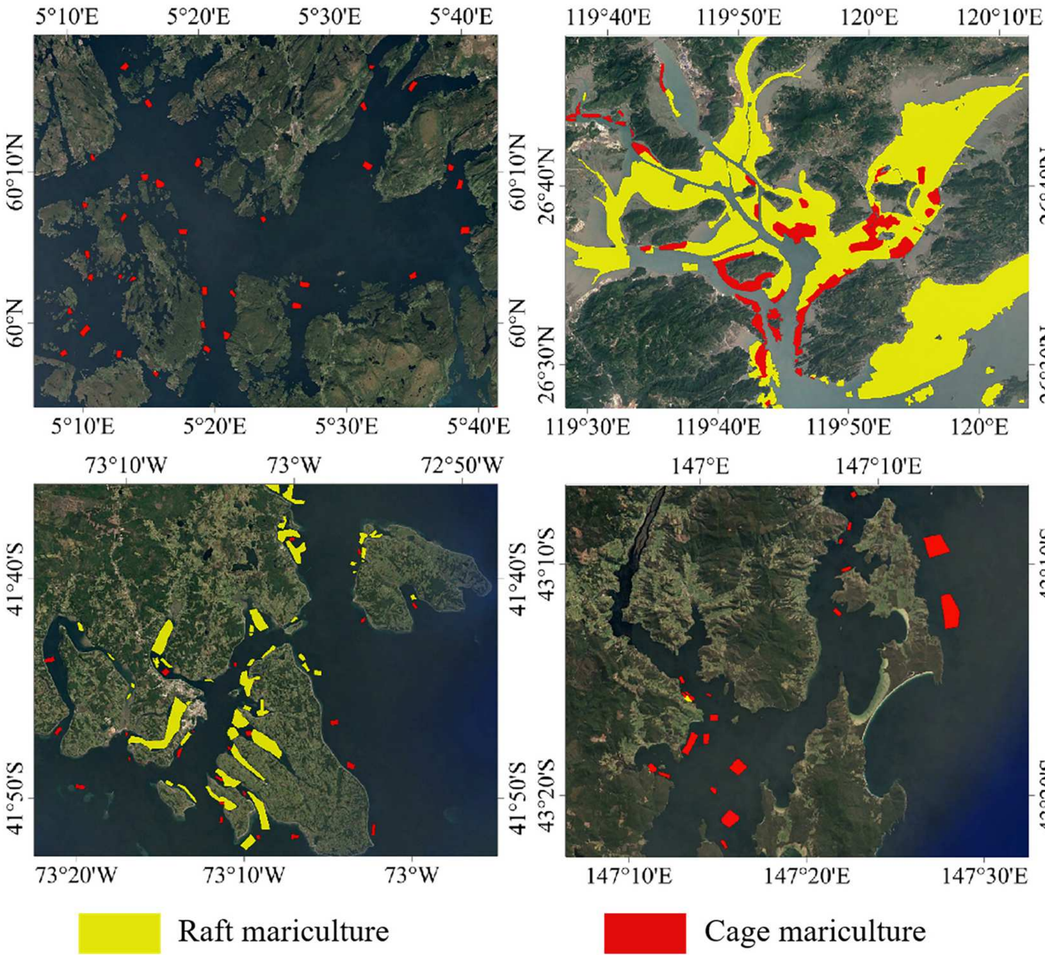

Figure 4. Detailed presentation of global OSSM data.

Figure 4 illustrates the details of the marine aquaculture extraction, showcasing regions in Norway (Europe), China (Asia), Chile (South America), and Australia (Oceania). It is evident that the OSSM in countries in East Asia, exemplified by China, differed significantly from that in other regions worldwide. China's OSSM was exceptionally extensive, and some areas contained OSSM operations that cover entire bays. In contrast, the OSSM in other regions tended to be more sporadically distributed within bays.

Currently, China is the largest country in terms of OSSM area and production. However, this extensive development may have reached, or even exceeded, the saturation point. Our data indicate that the OSSM in China is continuously distributed along the coastline, and most of the bays support substantial OSSM operations. The bays without OSSM are primarily located in urban coastal zones, tourism areas, commercial ports, and shipping channels. As a result, there are virtually no unused bays in China. This situation is similar to that in Japan and South Korea.

Therefore, from the perspective of the development potential of traditional OSSM, countries such as China, Japan, and South Korea have limited space for further expansion. In contrast, Southeast Asian countries that contain significant OSSM industries, such as Indonesia and the Philippines, still possess considerable development potential due to their extensive coastlines and numerous bays and islands, many of which remain undeveloped. Similarly, other countries with

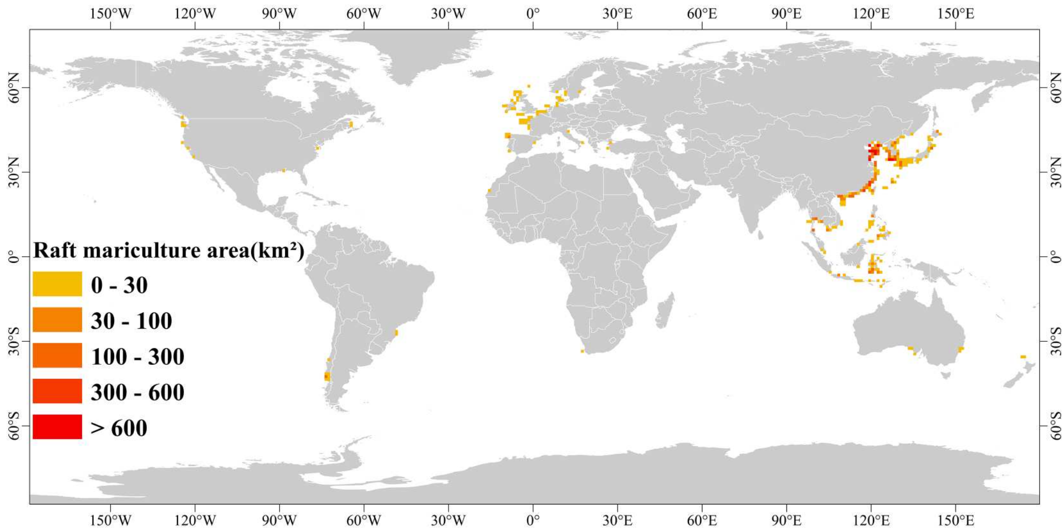

Figure 5. Global spatial distribution of raft mariculture in 2020.

substantial OSSM, such as Russia, the United States, Canada, and Australia, have relatively low OSSM densities, indicating significant potential for future growth.

3.2. Global spatial distribution of raft and cage mariculture

In this study, we categorized OSSM into raft mariculture and cage mariculture. Figures 5 and 6 illustrate the global spatial distributions of these two types of OSSM, respectively. It should be noted that due to the relatively small area occupied by cage mariculture, we applied separate classification criteria to highlight the spatial distribution differences. Raft mariculture covered larger areas, thus maintaining classification criteria consistent with the overall OSSM distribution.

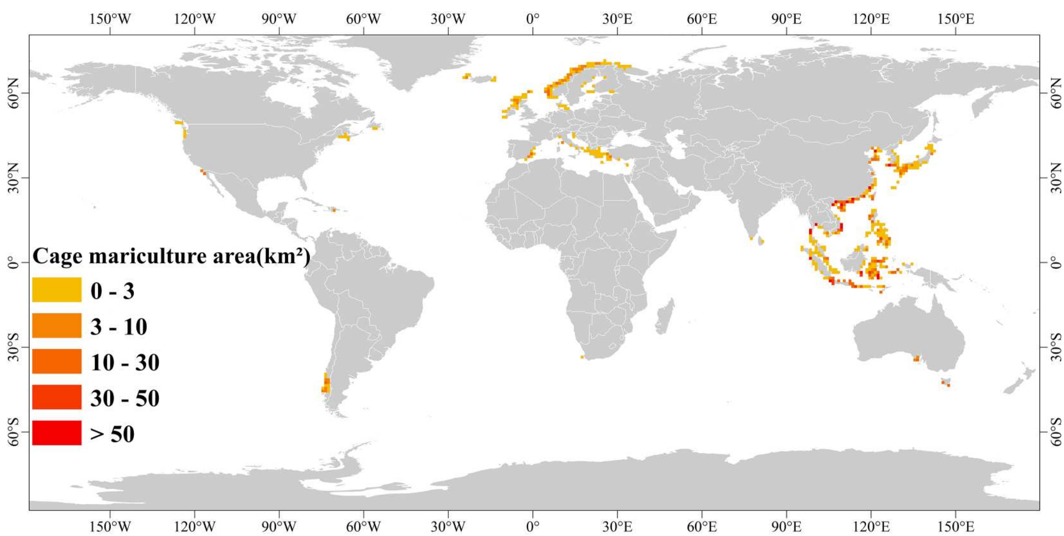

Figure 6. Global spatial distribution of cage mariculture in 2020.

First, in terms of volume comparison, the area of the raft OSSM was significantly larger than that of the cage OSSM. The global area of the raft OSSM extracted in this study was 17,075.85 km^2, accounting for 85.04% of the total, while the area of the cage OSSM was 3,004.13 km^2, accounting for only 14.96%. This difference was primarily determined by the type of OSSM and the corresponding species being cultured. The raft OSSM primarily involved cultivating seaweeds (e.g. kelp and nori) and bivalves (e.g. Ostreidae and Mollusca), which typically require large cultivation spaces arranged on the sea surface. In contrast, the cage OSSM primarily focused on cultivating fish and high-value marine delicacies. The unit cost of culturing these species is relatively high, leading to the requirement of significantly less space compared to raft OSSM.

In addition to the significant difference in the areas of these two types of OSSM, there were also notable differences in the spatial distributions of the raft OSSM and cage OSSM. Although the cage OSSM occupied a smaller area, its spatial distribution generally aligned with the overall pattern of the OSSM. The cage OSSM was widely distributed in East Asia and Southeast Asia. Furthermore, significant areas of cage OSSM were located in Europe, particularly in Norway and around the Aegean Sea in Turkey and Greece. Extensive cage OSSM was also prevalent in Chile in South America. The high-density cage OSSM areas were concentrated in China, Indonesia, Thailand, Norway, and Australia.

Although the raft OSSM occupied nearly six times the area of the cage OSSM, its spatial distribution was not as extensive as that of the cage OSSM. The raft OSSM was notably more concentrated in East Asia and Southeast Asia. In the European region, the distribution of the raft OSSM was less extensive compared to that of the cage OSSM and was primarily concentrated in the United Kingdom, France, and Spain. Additionally, in Chile in South America, scale of the raft OSSM was significant. The high-density raft OSSM areas were located in China, South Korea, North Korea, Japan, Vietnam, the Philippines, Spain, and Chile.

Table 1 presents the overall OSSM area extracted in this study, as well as the top 20 countries in terms of the raft OSSM and cage OSSM areas. China ranked first in terms of the overall OSSM area, accounting for 57.88% of the total area and exceeding the combined OSSM areas of all of the other countries globally. The top seven countries were all located in Asia, and their combined OSSM area exceed 90% of the global total. Chile contained the largest OSSM area among the South American countries, accounting for 1.04% of the total; while Norway contained the largest area among the

Table 1. Rankings of countries according to the proportion of the OSSM area (top 20).

	Total		Raft mariculture		Cage mariculture	
Rank	Country	Percentage of area (%)	Country	Percentage of area (%)	Country	Percentage of area (%)
1	China	57.88	China	64.43	Indonesia	35.20
2	South Korea	15.49	South Korea	17.59	China	20.66
3	Indonesia	8.02	Japan	4.61	Vietnam	10.74
4	Japan	4.38	Indonesia	3.24	Norway	5.93
5	Thailand	2.40	North Korea	2.49	Philippines	5.13
6	Vietnam	2.32	Thailand	2.38	Myanmar	4.09
7	North Korea	2.13	Philippines	1.41	South Korea	3.60
8	Philippines	1.97	Chile	0.95	Japan	3.08
9	Chile	1.04	Vietnam	0.84	Thailand	2.53
10	Norway	0.89	France	0.69	Australia	2.15
11	Myanmar	0.65	Spain	0.37	Chile	1.55
12	France	0.59	Australia	0.13	UK	1.20
13	Australia	0.43	Ireland	0.12	Spain	0.64
14	Spain	0.41	United States	0.10	Mexico	0.58
15	UK	0.26	UK	0.09	Turkey	0.42
16	Ireland	0.12	Russia	0.07	Malaysia	0.39
17	United States	0.09	Italy	0.06	Iceland	0.29
18	Italy	0.09	Canada	0.04	Denmark	0.29
19	Mexico	0.09	Myanmar	0.04	Greece	0.28
20	Denmark	0.08	New Zealand	0.02	Italy	0.26

European countries, accounting for 0.89%. Among the top 20 countries, nine, three, seven, and one were located in Asia, Europe, North and South America, and Oceania.

When considering raft OSSM separately, China maintained the top position, with the raft OSSM area accounting for an increased proportion of 64.43%. The top seven countries were still located in Asia, and their combined raft OSSM area exceeded 90% of the global total. Chile in South America ranked eighth in terms of the raft OSSM area, accounting for 0.95% of the total. France ranked first in terms of the raft OSSM area among the European countries, accounting for 0.69%, and it ranked tenth overall. Among the top 20 countries in terms of the raft OSSM, 17 were the same as those in the global top 20. Norway, Mexico, and Denmark dropped out of the top 20 in the raft OSSM ranking. The new entries were Russia, Canada, and New Zealand, ranking 16th, 18th, and 20th, respectively.

The ranking according to the cage OSSM was significantly different. Indonesia ranked first, accounting for 35.20% of the total cage OSSM area, and China ranked second, accounting for 20.66%. Vietnam ranked third largest globally, accounting for 10.74%, and Norway ranked fourth, accounting for 5.93%. Among the top 20 countries in terms of cage OSSM, nine were located in Asia, and North Korea was replaced by Malaysia. The number of European countries increased to eight (including Turkey, as its OSSM was mainly located in the Aegean Sea), but there were significant changes in the specific countries. France and Ireland dropped out of the top 20 and were replaced by Turkey and Greece. In the Americas, Chile remained the largest country in terms of the cage OSSM area, and Mexico occupied the 14th position (0.58%).

4. Discussion

4.1. Comparison with FAO OSSM production statistics data

Based on global OSSM production quantity data from the FishStat database published by the FAO, we conducted a comprehensive comparison with our data. Since the FishStat data do not include the area of the OSSM but only the production quantity, these data did not perfectly match our data. However, these data can reflect certain correlation trends to some extent. Table 2 presents the top 20 countries in terms of the OSSM production quantity in 2020, as well as their respective areas and percentages.

Table 2. Comparison with FAO OSSM production statistics data.

Country (Top 20 based on FAO data)	Proportion of production (%, from FAO)	Proportion of area (%, based on our research)
China	65.24	57.88
Indonesia	14.36	8.02
South Korea	3.93	15.49
Philippines	2.95	1.96
Chile	2.62	1.04
Norway	2.60	0.89
Japan	1.69	4.38
North Korea	1.16	2.13
Vietnam	0.64	2.32
Turkey	0.51	0.07
Spain	0.43	0.41
Malaysia	0.40	0.07
United Kingdom	0.36	0.26
United States	0.35	0.09
Canada	0.28	0.07
France	0.26	0.59
Greece	0.22	0.04
Thailand	0.21	2.40
New Zealand	0.20	0.02
Russia	0.18	0.08
other	1.57	0.27

By analyzing the differences between the proportions of the area and production quantity, we found that countries in which the proportion of the OSSM area exceeded the proportion of the production quantity included South Korea, Japan, North Korea, Vietnam, France, and Thailand. The majority of these countries were located in Asia, and France was the only European country. In contrast, the countries in which the proportion of the OSSM area was lower than the proportion of the production quantity were located in Asia, Europe, the Americas, and Oceania. However, the number of Asian countries in which the proportion of the OSSM area was lower than that of the production quantity was notably smaller, including China, Indonesia, the Philippines, and Malaysia.

The observed disparities were likely correlated with the type of OSSM practiced. Raft mariculture primarily cultivates algae and shellfish, while cage mariculture focuses on fish. Raft systems are deployed on the sea surface and typically require larger areas than cage systems. However, the unit area yield of algae cultivation is significantly lower than that of fish cultivation. Therefore, in countries in which the raft mariculture area far exceeded the cage mariculture area, the proportion of the OSSM area to the global production quantity tended to be higher than the proportion of the production quantity. This analysis is consistent with the findings for South Korea, Japan, North Korea, France, and Thailand, in which the area of the raft mariculture greatly exceeded that of the cage mariculture.

Raft mariculture was predominantly practiced in Asian countries, explaining why most countries with a higher proportion of OSSM area compared to the production quantity were located in Asia. France was the only European country in which the raft mariculture area substantially exceeded the cage mariculture area, which is consistent with this analysis. Vietnam was an exception, that is, the cage mariculture area exceeded the raft mariculture area, yet the production quantity proportion was smaller than the proportion of the area. This anomaly may be due to the specific species cultivated, stocking densities within OSSM facilities, and differences in OSSM techniques. This requires further in-depth investigation to achieve an accurate interpretation.

Furthermore, the interpretational differences between the raft and cage mariculture in this study exacerbate the phenomenon in which the proportion of the raft mariculture area is higher than the proportion of the production quantity when the raft mariculture area significantly exceeds the cage mariculture area. Raft mariculture is typically distributed over large marine areas, and individual OSSM facilities are located relatively close to each other. To ensure efficiency during interpretation, the high-density raft mariculture areas were delineated along with the marine areas between the OSSM facilities. This practice led to overestimation of the raft mariculture area compared to the actual area. In contrast, cage mariculture is usually more dispersed and is often delineated based on individual cages or groups of cages, resulting in relatively less marine area beyond the cages. The conversion rate from the raft OSSM area to the production quantity was already lower than that for the cage OSSM. Moreover, the raft mariculture areas interpreted in this study tended to be more inflated compared to the cage mariculture areas, further contributing to the discrepancy that the countries with a higher proportion of raft mariculture area typically had a lower proportion of production quantity.

It is also important to note that the statistics from the FAO data encompass the production quantity of all of the mariculture products. In contrast, in this study, we focused solely on the mariculture observable on the ocean surface in satellite remote sensing imagery (OSSM). In addition to OSSM, mariculture includes industrialized mariculture and bottom culture, which cannot be extracted based on satellite observations. This disparity is a significant reason for the differences between the proportions of the OSSM areas extracted in this study and the mariculture production quantity proportions reported by the FAO for each country.

The uniqueness of China may be attributed to the presence of a substantial amount of industrialized and bottom mariculture, which was not accounted for in this study. Moreover, as the world's leading country in terms of mariculture, China has experienced rapid technological advancements and has established numerous large-scale mariculture platforms and vessels, further enhancing the production quantity per unit area (Zhang and Gui 2023). Consequently, China contributed a higher proportion of the production quantity despite its relatively smaller proportion of the mariculture area.

Despite some discrepancies between the mariculture production and area obtained from remote sensing imagery, their overall distribution trends were largely consistent. In most countries, the difference between the OSSM area and mariculture production did not exceed 3%. Therefore, leveraging the correlation between the OSSM area and mariculture production across different countries offers significant advantages. Our research enables the dynamic assessment of OSSM production using highly timely remote sensing imagery, significantly enhancing the efficiency of traditional methods that rely on statistical surveys. Furthermore, in the future, it will be possible to achieve precise spatial representation of production data through spatialized OSSM data. This is crucial for constructing quantitative spatial models of OSSM and for researching the resource and environmental impacts of OSSM activities.

4.2. Comparison with global spatial modeling and allocation research on OSSM

Our research findings are the first instance of obtaining global spatial distribution data on OSSM based on remote sensing satellite imagery. Prior to this, Clawson et al. aimed to achieve detailed mapping of the OSSM spatial distribution(Clawson et al. 2022) and constructed the most comprehensive database of OSSM farm locations worldwide using massive big data and recorded the location information of each accessible OSSM farm in point format. Then, for OSSM farms with limited data availability, a model based on key factors such as the distance of OSSM farms for the coastline or ports was designed and the average productivity of OSSM farms was obtained from statistical data. It was inferred that the quantity and location of OSSM farms with missing data, completed relatively detailed spatial mapping of OSSM farms in 73 countries globally in 2017, and presented the results in point format. The types of OSSM they studied included fish, mollusks, crustaceans, and non-crustacean shellfish (algae OSSM, which accounts for half of global OSSM production, was not included in their study due to data limitations).

Since Clawson et al.'s data consisted of point location information for OSSM farms, direct comparison with our OSSM patch data was not feasible. Therefore, we only conducted a simple comparison between the overall distribution trends of the global OSSM in both datasets. The results revealed a high level of consistency between the OSSM data we obtained and Clawson et al.'s results. It should be noted that Clawson et al.'s data not only included offshore OSSM, which was also extracted in our study, but also encompassed brackish water OSSM, represented by OSSM ponds along the coast. Although our study did not cover land-based OSSM ponds, our team has previously conducted remote sensing extraction of global land-based pond OSSM in 2020 (Wang et al. 2022). Therefore, we were able to conduct a comprehensive comparison (Figure 7).

Our findings demonstrate consistency in several aspects. First, globally, OSSM is predominantly concentrated in Asia, particularly in Southeast Asia. China alone accounts for over half of the world's OSSM, with continuous stretches of coastal OSSM in East and Southeast Asian countries. Additionally, significant volumes of OSSM are located in European countries, notably Norway, France, the United Kingdom, Ireland, Greece, and Turkey. Chile in South America also hosts a considerable amount of OSSM, and there are notable OSSM activities in the western regions of Canada and Mexico in the Americas. In Africa, the OSSM is relatively limited. In the northern region, Egypt hosts a modest amount, but the majority of the continent lacks significant OSSM operations.

The most significant disparity between the results of our study and those of Clawson et al. is in the results for the southern region of Alaska in the United States and along the southwestern coast of Canada. According to Clawson et al.'s research, there were specific and well-defined OSSM facilities in these areas. However, during our interpretation process, we did not identify large-scale OSSM distributions in these region. One possible explanation for this is that while there may have been some OSSM facilities in this area, they were not large-scale operations, which is also suggested by Clawson et al.'s research results. Therefore, we may have overlooked a small number

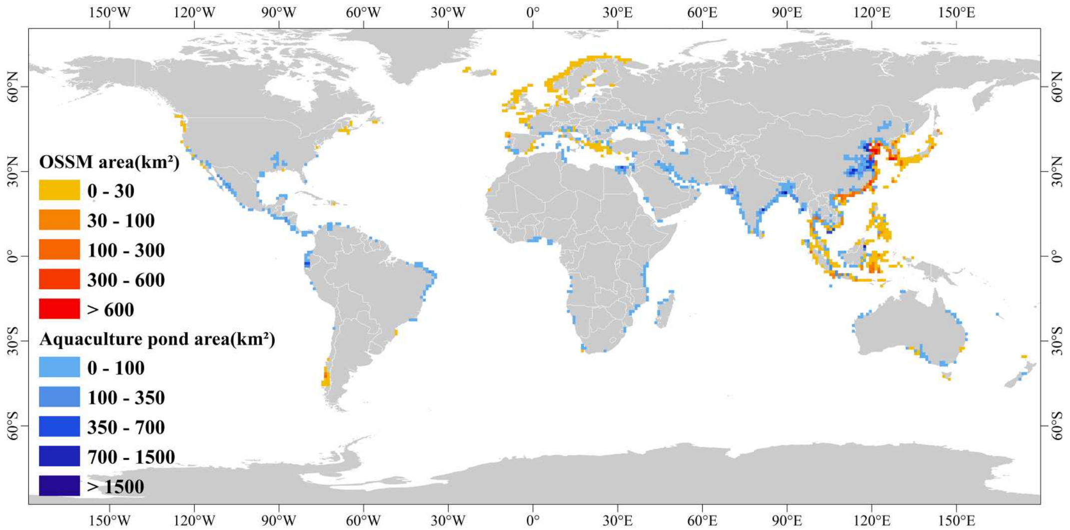

Figure 7. Global spatial distribution of aquaculture in 2020.

of OSSM areas in this region. Furthermore, Clawson et al.'s results also indicate the presence of a significant volume of OSSM in New Zealand. Although we identified OSSM and pond OSSM areas in New Zealand, the scale was not substantial. One reason for these discrepancies could be that Clawson et al.'s data included factory-style OSSM, whereas we could only identify open-sea OSSM and OSSM ponds from satellite imagery, making it difficult to recognize OSSM operations within closed facilities.

Compared to Clawson et al.'s data, our data, derived from remote sensing satellite imagery, provide fine and reliable spatial location information. Additionally, our data can intuitively reflect the volume and distribution density of the OSSM. Furthermore, our study also included algae OSSM, which was not included in Clawson et al.'s research.

However, Clawson et al.'s study also possesses advantages that our study lacks. First, Clawsonet al.'s OSSM facility data can be associated with specific types of OSSM, such as Salmonidae fish, unfed or algae-fed bivalve mollusks, shrimp, and prawns. In contrast, in our study, based on remote sensing imagery, we could only discern the type of OSSM facility, and we could not directly identify the specific types of OSSM species being cultivated within the facility. Second, due to limitations of the imaging principles of OSSM, our results captured floating OSSM facilities on the sea surface, and underwater bottom-culture OSSM and OSSM within factory facilities were not captured. In contrast, Clawson et al.'s research, based on statistical data and actual location information about OSSM facilities, covered all sources of OSSM, except algae OSSM. Third, our data only enabled statistical assessment of the OSSM areas did not provide accurate evaluations of the OSSM quantity and production output. Clawson et al.'s results can better correlate and match with existing statistical data.

Therefore, it is difficult to unilaterally determine the superiority or inferiority of our study compared to Clawson et al.'s research. Instead, these two studies should be seen as complementary, reflecting the global distribution patterns of OSSM from different perspectives.

4.3. Comprehensive global spatial pattern of OSSM and onshore aquaculture ponds

In our previous work, we extracted aquaculture ponds on land on the global scale based on dense time-series Sentinel-2 satellite images covering a total of 4,015,054 slices throughout 2020 (Wang et al. 2022). By combining our previous dataset with the OSSM data obtained in this study, we assembled a comprehensive dataset of aquaculture covering the entire globe, complete with fine geospatial information (Figure 7). It is important to note that the OSSM interpreted in this study does not spatially overlap with the land-based pond aquaculture. However, for visual representation purposes, both types of aquaculture are highlighted using a 1 × 1° grid. In the coastal zone, there are instances where both types of aquaculture coexist within a single grid. To emphasize the findings of this study, only the OSSM is displayed in such cases.

The total global area of aquaculture was 75,417.00 km^2, of which OSSM comprised 20,079.97 km^2, accounting for 26.63%, and pond aquaculture comprised 55,337.03 km^2, accounting for 73.37%. Asia remained the global center for aquaculture, with an area of 68,482.42 km^2, accounting for 90.80% of the total, followed by South America (2,245.45 km^2, 2.98%), North America (1,833.06 km^2,2.43%), Africa (1,505.39 km^2, 2.00%), Europe (1,146.67 km^2, 1.52%), and Oceania (205.98 km^2, 0.27%).

Among the continents, the proportion of OSSM to pond aquaculture varies significantly, yet for all of the continents, the area of pond aquaculture exceeded that of OSSM. In South America, North America, and Africa, the pond aquaculture areas were substantially larger, with OSSM comprising only 9.66, 2.96, and 0.95% of their total aquaculture areas, respectively. In contrast, Asia had a higher proportion of OSSM, accounting for 27.95% of its total aquaculture area. Europe and Oceania had nearly equal distributions of marine and pond aquaculture, with OSSM accounting for 48.90 and 44.02% of their total aquaculture areas, respectively.

Table 3 lists the top 20 countries according to their total aquaculture areas. Among these, 13 are Asian countries (China, Indonesia, Vietnam, India, South Korea, Bangladesh, Thailand, the Philippines, Myanmar, Japan, North Korea, Iraq, and Iran), three are North American countries (Mexico, the United States, and Honduras), two are South American countries (Ecuador and Brazil), one is a European country (France), and one is an African country (Egypt). China leads in terms of both marine and pond aquaculture areas. Indonesia ranks second in terms of the total aquaculture area, with significant areas of both marine and pond aquaculture; however, its pond aquaculture area is smaller than that of Vietnam, which ranks third overall. Vietnam has a substantial pond aquaculture area but a relatively small OSSM area.

Table 3. Top 20 countries in terms of global aquaculture area.

		Total		OSSM		Pond Aquaculture	
Rank	Country	Area (km^2)	Percentage of area (%)	Area (km^2)	Percentage of area within the country (%)	Area (km^2)	Percentage of area within the country (%)
1	China	33337.90	44.20	11622.00	34.86	21715.90	65.14
2	Indonesia	7887.62	10.46	1611.37	20.43	6276.25	79.57
3	Vietnam	7528.36	9.98	465.46	6.18	7062.90	93.82
4	India	4747.49	6.29	0	0.00	4747.49	100.00
5	South Korea	3155.90	4.18	3111.01	98.58	44.89	1.42
6	Bangladesh	3058.12	4.05	0	0.00	3058.12	100.00
7	Thailand	2251.47	2.99	482.47	21.43	1769.00	78.57
8	Philippines	1731.83	2.30	394.60	22.79	1337.23	77.21
9	Myanmar	1652.15	2.19	129.97	7.87	1522.18	92.13
10	Ecuador	1518.79	2.01	0	0.00	1518.79	100.00
11	Egypt	1276.72	1.69	0	0.00	1276.72	100.00
12	Mexico	959.67	1.27	17.54	1.83	942.13	98.17
13	Japan	880.16	1.17	880.16	100.00	0	0.00
14	North Korea	526.34	0.70	427.27	81.18	99.07	18.82
15	Iraq	506.41	0.67	0	0.00	506.41	100.00
16	United States	379.99	0.50	18.57	4.89	361.42	95.11
17	Brazil	364.52	0.48	8.32	2.28	356.20	97.72
18	Iran	310.46	0.41	0	0.00	310.46	100.00
19	France	273.46	0.36	118.22	43.23	155.24	56.77
20	Honduras	206.79	0.27	0	0.00	206.79	100.00

Among the top 20 countries, the development of marine and pond aquaculture is highly uneven. In 18 of these countries, the ratio of the areas dedicated to the two types of aquaculture exceeds 3:1. Seven countries, namely, India, Bangladesh, Ecuador, Egypt, Iraq, Iran, and Honduras, do not engage in OSSM at all. These countries commonly have their pond aquaculture, predominantly located in coastal areas, indicating that pond aquaculture development may be prioritized in these regions and thereby limiting the space available for OSSM. In most countries, the pond aquaculture area significantly exceeds the OSSM area. The exceptions are South Korea, Japan, and North Korea. Japan does not have pond aquaculture, while South Korea and North Korea have very limited pond aquaculture areas. Given the geographic proximity of these three countries, it is plausible to suggest that this phenomenon may be influenced by dietary and cultural factors.

In light of the above, does the fact that many countries have only one aquaculture mode in their coastal zones suggest that OSSM and pond aquaculture are mutually exclusive at the regional level? The answer should be no. Evidence from many Asian regions reveals that abundant pond aquaculture in coastal areas coexist with significant OSSM areas nearby. This at least indicates that marine and coastal pond aquaculture are not mutually exclusive, that is, they can coexist. The term 'coexist' here does not refer to the spatial overlap of raft or cage mariculture within pond culture, but rather to the spatial adjacency where pond culture exists on the landward side of the coast, while OSSM exists on the seaward side. As for why this coexistence primarily occurs only in some Asian regions, several conjectures can be made.

First, Asian countries have higher population densities and consequently greater food demands compared to other regions worldwide. Therefore, more land and sea space is allocated for food production in Asia, which is a significant factor contributing to the vast expanse of aquaculture in this region.

Second, coastal areas in Asia, like in many other parts of the world, are rich in marine and terrestrial resources and are often densely populated (Small and Nicholls 2003). Coastal zones, which support large populations, are increasingly being encroached upon by aquaculture ponds. This expansion even extends into areas less suitable for aquaculture, such as mangroves and tidal wetlands (Jayanthi et al. 2022; Jia et al. 2018; Richards and Friess 2016), leading to oversaturated aquaculture zones where both pond and marine aquaculture occur simultaneously.

Third, there are more developing countries in Asia compared to Europe and the Americas, and many of these countries have relatively underdeveloped economies. Fishing communities in coastal areas often serve as the primary economic centers in these regions. Conversely, in more developed countries such as those in Europe and the Americas, urban centers and ports tend to dominate coastal areas. This may lead to fewer instances of the coexistence of pond and marine aquaculture in Europe and the Americas.

Fourth, aquaculture operates as an industry system, and large-scale aquaculture areas are characterized by comprehensive industrial chains, including breeding, processing, storage, transportation, and sales facilities, creating cluster effects (Ahmad et al. 2021). Moreover, the accumulation of aquaculture culture, technology, equipment, and professional personnel in areas with existing aquaculture foundations facilitates the emergence of new aquaculture ventures in the vicinity. Given that Asia has a larger aquaculture volume and workforce compared to other regions, this phenomenon of coexisting pond and marine aquaculture is more likely to occur in Asia.

The uneven development of marine and coastal pond aquaculture across Asian countries may be significantly influenced by cost considerations associated with pond and marine aquaculture. Both types of aquaculture entail a diverse array of methods, ranging from land-based pond aquaculture with well-established wastewater treatment and hatchery facilities to large-scale deep-sea cage systems or other platform structures for OSSM, all of which require substantial financial investment (Turcios and Papenbrock 2014). However, based on the data extracted via our interpretation, the majority of the aquaculture in Asia consists of relatively low-cost traditional pond systems and standard cage or raft systems. Typically, the development and maintenance costs of land-based pond aquaculture are lower than those of OSSM. Therefore, in regions with limited technological and financial resources, prioritizing the development of land-based pond aquaculture may be more feasible. Due to the requirement of corresponding onshore facilities for OSSM, when a region develops a dominant industry in pond aquaculture and the coastal zone is densely populated with ponds, the development of OSSM will be limited. However, this is just one factor among many. Other potential influencing factors include climate, the geographic conditions of coastal and inland areas, historical and cultural factors, and policy disparities. These factors warrant further exploration in subsequent studies.

4.4. Limitations and future work

In this study, we interpreted global OSSM targets via the integration of remote sensing and multi-source big data. However, our research has some limitations. Due to the small and scattered nature of OSSM on a global scale, its diverse forms, complex seawater backgrounds, and numerous confounding targets, achieving automated, high-precision extraction of OSSM is challenging. To prioritize extraction accuracy, we utilized time-series imagery to automatically synthesize and enhance OSSM targets and then combined multiple sources of information to extract OSSM areas. While this approach maximizes the reliability of the extracted OSSM targets, it is less efficient overall, i.e. it required substantial manual involvement in the data production and relatively long processing times.

Furthermore, in areas with a dense OSSM distribution, our interpretation yields the range of the OSSM areas encompassing both the OSSM targets and the surrounding seawater, rather than individual OSSM targets. As a result, when conducting area statistics, there may be fluctuations in the statistics of densely distributed OSSM areas compared to sparsely distributed areas, which may not accurately represent the true OSSM area.

Despite these limitations, utilizing our global interpretation process, we gained a strong understanding of the spatial distribution of global OSSM and the OSSM characteristics of different regions. Additionally, we collected a large number of samples of OSSM and confounding targets. We found that although there is significant differentiation in OSSM on the global scale, at smaller local scales, such as within a country or a portion of a country's maritime territory, OSSM can still exhibit a certain degree of consistency. Therefore, a potential avenue for future research is to partition the globe based on the distribution characteristics of OSSM. In regions where the features are relatively consistent, combining remote sensing with intelligent interpretation methods could enable efficient and intelligent dynamic interpretation of OSSM.

Furthermore, this study is the first acquisition of globally fine spatial data on OSSM. Analysis of these data can facilitate more refined development of research related to mariculture, which previously relied solely on statistical data. Such research includes global assessments of the suitability and development potential of mariculture (Gentry et al. 2017), precise estimates of mariculture production (Ju et al. 2020; Tacon 2020), evaluations of the ecological and environmental benefits of mariculture (Chen et al. 2022; Liu, Xia, et al. 2019; Tang et al. 2023), global mariculture trade (Wei et al. 2023), disaster prevention and management in mariculture (Chang et al. 2013; Wang et al. 2023), coastal zone management (Yu and Yu 2021), and sustainable development research (Merino et al. 2012; Wu, Yang, and Yang 2021).

5. Conclusions

In this study, we utilized the GEE platform and dense time-series data from Sentinel-1 and Sentinel-2 images, as well as historical imagery from Google Earth, to interpret global OSSM data for 2020. The results indicate that the global OSSM area was 20,079.97 km^2, with a raft mariculture area of 17,075.84 km^2 (85.04%) and a cage mariculture area of 2,995.13 km^2 (14.96%). The global distribution of OSSM was highly uneven, and that in Asia accounted for 95.33% of the total. In this region, the OSSM was primarily concentrated in East and Southeast Asia. Over 90% of the global OSSM was located within bays, which provide natural advantages for its development. Although East Asian countries such as China, Japan, and South Korea had large OSSM operations, their high farming densities may limit future growth in traditional mariculture practices. In contrast, other countries around the world that had relatively low OSSM densities may have substantial potential for expansion.

The trend of the area data extracted from remote sensing images is generally consistent with the FAO's production statistics. This consistency allows for estimation and spatial analysis of production based on area data, providing a new dimension of information for OSSM. By combining our data with terrestrial pond aquaculture data, we analyzed the spatial distribution of global aquaculture. The total global aquaculture area was 75,417.00 km^2, with an OSSM area of 20,079.97 km (26.63%) and a pond aquaculture area of 55,337.03 km (73.37%). Asia remained the global center for aquaculture, with an area of 68,482.42 km^2, accounting for 90.80% of the total. In most countries, the development of pond aquaculture and OSSM was imbalanced, and the ratio between the two exceeded 3:1. In the majority of coastal regions worldwide, only a single mode of aquaculture was prevalent. However, in some Asian countries, both OSSM and pond aquaculture coexisted within the same regions.

In this study, based on precise and spatially detailed global OSSM data obtained through remote sensing, our data and analysis method overcame the limitations of traditional statistical and modeling data, which lack accurate spatial information. Our results provide essential foundational data for mariculture research, facilitating spatially quantitative studies when combined with spatiotemporal big data. This approach is significant for researching mariculture resources, understanding environmental impacts, and enabling scientific management.

Notes

1. https://www.fao.org/fishery/en/fishstat (accessed on 6 April 2024).
2. https://www.marineregions.org/downloads.php#marbound (accessed on 17 March 2024).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability

The data will be made available upon request.

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