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Segment Anything Model (SAM) Assisted Remote Sensing Supervision for Mariculture—Using Liaoning Province, China as an Example

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Abstract: Obtaining spatial distribution information on mariculture in a low-cost, fast, and efficient manner is crucial for the sustainable development and regulatory planning of coastal zones and mariculture industries. This study, based on the Segment Anything Model (SAM) and high-resolution remote sensing imagery, rapidly extracted mariculture areas in Liaoning Province, a typical northern province in China with significant mariculture activity. Additionally, it explored the actual marine ownership data to investigate the marine use status of Liaoning Province's mariculture. The total area of mariculture we extracted in Liaoning Province is 1052.89 km^2. Among this, the area of cage mariculture is 27.1 km^2, while raft mariculture covers 1025.79 km^2. Through field investigations, it was determined that in the western part of Liaodong Bay, cage mariculture predominantly involves sea cucumbers. In the southern end of Dalian, the raft mariculture focuses on cultivating kelp. On the other hand, around the islands in the eastern region, the primary crop in raft mariculture is scallops, showing a significant geographical differentiation pattern. In the planned mariculture areas within Liaoning Province's waters, the proportion of actual development and utilization is 11.2%, while the proportion approved for actual mariculture is 90.2%. This indicates a suspicion that 9.8% of mariculture is possibly in violation of sea occupation rights, which could be due to the untimely updating of marine ownership data. Based on SAM, efficient and accurate extraction of cage mariculture can be achieved. However, the extraction performance for raft mariculture is challenging and remains unsatisfactory. Manual interpretation is still required for satisfactory results in this context.

Keywords: remote sensing; mariculture; coastal management; spatial analysis

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1. Introduction

Mariculture is a crucial global source of food, nutrition, income, and livelihood for humans [1]. In recent years, the unregulated expansion of mariculture has posed a significant threat to the ecological environment, leading to issues such as water pollution and the outbreak of green algae blooms in coastal areas [2–4]. Effective management of mariculture by relevant government agencies is a critical foundation for the sustainable development of mariculture. However, the rapid expansion of mariculture and the high cost of on-site research pose challenges for governments in conducting timely monitoring and management of mariculture. Therefore, low-cost, rapid, and accurate monitoring of mariculture is particularly important for the sustainable development of coastal areas and for the harmonious coordination of human, terrestrial, and marine resources.

Remote sensing offers advantages such as long-term observation and complete coverage, and currently, remote sensing-based monitoring of mariculture has made significant progress. It is important to note that mariculture comprises a diverse range of types. Generally, research on remote sensing extraction of mariculture refers to the extraction of visible culture facilities on the sea surface, such as cages and rafts. In addition to these two methods, there is also bottom culture. Bottom culture is a relatively extensive farming model that involves releasing juvenile mariculture organisms into the seabed area, cultivating species like mollusks and sea cucumbers without the need for artificial feeding. This cultivation method leans more towards natural processes, covering a much larger area compared to cage and raft mariculture. However, due to its seabed location, it cannot be observed using remote sensing methods. Therefore, unless otherwise specified, the mariculture extracted in this paper generally includes raft and cage mariculture. Based on remote sensing imagery, the extraction of mariculture areas can be broadly categorized into methods such as visual interpretation [5,6], information enhancement [7], feature learning [8,9], object-oriented methods [10,11], and deep learning methods [12–14]. Initially, research related to remote sensing extraction of mariculture areas focused largely on relatively small experimental zones, such as key bays for mariculture. However, with the continuous development of technological methods, there is now research conducted at a large regional scale for the extraction of mariculture areas.

For example, in the case of China, which accounts for over 60% of global mariculture production, several scholars have successfully conducted studies on mariculture extraction at both national and regional scales [11,15–19]. However, many of these studies have primarily focused on the spatial distribution and patterns of mariculture itself, overlooking alignment and correlation analysis with government-allocated mariculture planning areas. They have not effectively monitored or discriminated against information related to illegal mariculture activities. This limitation hinders the further planning and management of mariculture.

In a few rare studies, following the extraction of mariculture using remote sensing, an assessment of the regional mariculture development has been conducted by overlaying it with government-defined marine functional zoning. For instance, Wang et al., using Landsat satellite imagery, performed a multi-temporal extraction of mariculture areas in Shandong Province from 1990 to 2018 [20]. By overlaying the mariculture area data with government marine functional zoning maps, they evaluated the implementation and effectiveness of marine functional zoning. Similarly, Kang et al., also based on Landsat imagery, extracted mariculture areas in Liaoning Province from 2000 to 2018 and evaluated the developmental changes in mariculture [21]. While the aforementioned studies conducted a correlation analysis between the spatial distribution of mariculture and planning maps, they were limited by the accuracy and timeliness of these planning maps, making it challenging to monitor mariculture areas in violation of sea occupation rights effectively. Additionally, in terms of mariculture target extraction, the extraction methods in these studies still required parameter adjustments for different regions, resulting in relatively lower efficiency in practical applications.

Deep learning methods, as advanced techniques in the field of image recognition, have achieved success in remote sensing-based mariculture extraction. For example, using convolutional neural network models, mariculture at the object level can be successfully extracted [22–25]. However, most of these studies have focused on method exploration and investigating the macro-level spatial distribution and change patterns of mariculture. They have lacked case studies oriented towards the specific management needs of coastal areas.

Furthermore, deep learning methods still face significant challenges in practical applications. Aside from hardware requirements, in order to achieve effective feature extraction with deep learning methods, it is essential to build a high-quality sample database. The nature of mariculture, with its high dynamics and the inherent difficulty of acquiring information underwater, coupled with the complexity of remote sensing imaging caused by environmental changes, results in substantial variations in the mariculture targets within remote sensing images from different mariculture modes, processes, regions, hydrological conditions, weather conditions, and data sources or resolutions. As a result, the comprehensive cost of building a high-quality mariculture sample database from scratch is relatively high. Therefore, in practical management tasks, in order to ensure interpretation accuracy, management departments predominantly rely on manual visual interpretation methods to extract mariculture objects, which is highly inefficient. Currently, practical methods that can simultaneously achieve a high degree of automation, strong adaptability, and high interpretation accuracy are essentially lacking.

With the continuous accumulation of vast amounts of data and the further development of deep learning and artificial intelligence technologies, the field of image recognition has seen the emergence of large models represented by SAM [26]. Compared to traditional deep learning models, SAM is trained on 1 billion masks from 11 million images and has the ability for zero-shot generalization. It eliminates the need to rebuild the sample database when performing object extraction, providing the possibility for efficient automatic extraction in the context of mariculture.

Based on the background described above, this research attempts to apply SAM for the automatic extraction of mariculture targets. The study focuses on Liaoning Province, the northernmost and most complex mariculture environment in China, to investigate the extraction performance of the SAM model. The targets extracted in our study include raft mariculture and cage mariculture at sea, excluding benthic mariculture that is not observable on the seabed. Building upon this, real maritime ownership data will be integrated to identify areas with unauthorized occupation and to analyze and discuss various issues in the existing mariculture practices in Liaoning.

2. Study Area and Data

2.1. Study Area

Liaoning Province is the northernmost coastal province in China, bordering the Bohai Sea and the Yellow Sea to the south. It experiences a temperate monsoon climate and is situated between 118°53′ to 125°46′E and 38°43′ to 43°26′N, as shown in Figure 1. The coastline of Liaoning Province stretches from the mouth of the Yalu River in the east to the boundary with Hebei Province in the west, spanning five different latitudes from north to south. The coastline is characterized by its winding and intricate nature, featuring diverse geological types. Numerous rivers flow into the sea along the coast, enriching the area with nutrients. This has given rise to two major marine ecosystems, the northern Yellow Sea and the Liaodong Bay, which are significant for fisheries production in the region [27]. In recent years, influenced by market demand and policies, the mariculture areas of various scales in Liaoning Province have shown a growing trend [21]. The growth rate of mariculture production and the expansion rate of mariculture ponds in Liaoning also rank among the highest in China's coastal provinces [28].

Liaoning Province ranks at the forefront among Chinese provinces in terms of the diversity of mariculture types and the total mariculture area [16]. However, most mariculture activities in Liaoning Province are conducted by mariculture companies or individuals. Due to the relatively shallow water depth in the Bohai Sea, mariculture is spatially dispersed, and there are also numerous mariculture activities around some offshore islands, increasing the complexity of mariculture monitoring. Remote sensing observations in Liaoning's mariculture primarily include cage mariculture and raft mariculture. Cage mariculture is mainly for cultivating fish and sea cucumbers, while raft mariculture focuses on shellfish and algae. Based on preliminary visual interpretation, we found that the majority of mariculture in Liaoning is distributed within 20 km of the mainland coastline. Some mariculture areas also appear around islands relatively far from the mainland but generally not exceeding 20 km from the islands. To ensure that mariculture areas are not overlooked, we used the coastlines of the mainland and islands as a reference, creating a 35 km buffer zone seaward as the experimental area for this study.

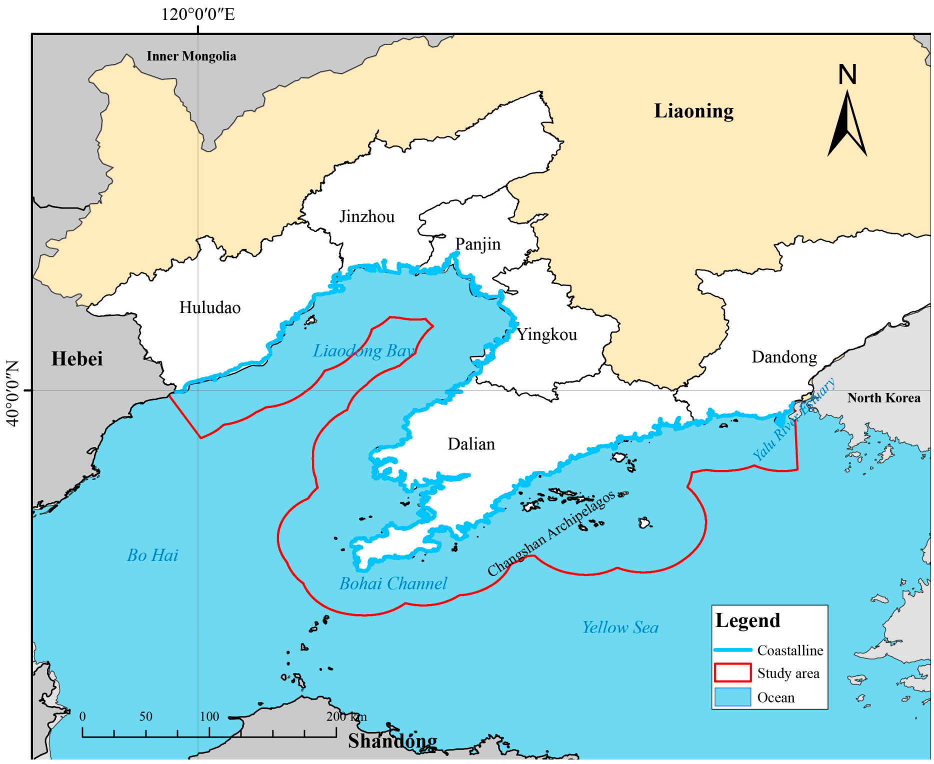

Figure 1. Study area—coastal zone of Liaoning.

2.2. Data

Due to frequent cloud cover and rainfall over the sea, which is unfavorable for satellite observations, various high-resolution optical remote sensing images were used in the study to ensure coverage of the research area. These images primarily include satellites such as GF-1, GF-2, GF-6, and ZY-3, with specific parameters detailed in Table 1. The data has undergone fusion processing, achieving a resolution equivalent to the panchromatic band, typically within the range of 1–2 m. We completed the pansharpening process for images in ArcGIS using the Gram–Schmidt method.

The coastal zone is often cloudy and rainy, which limits the availability of optical imagery. Furthermore, Liaoning is located in the northern part of China, and during the winter, nearshore seawater can freeze, making it challenging to observe mariculture activities and further reducing the available imagery within the temporal window. Additionally, strong winds can generate significant waves on the sea surface, hindering the recognition of mariculture and further reducing the available imagery. To ensure effective extraction of mariculture, it is necessary to carefully select remote sensing images.

In this study, we initially obtained images for the entire year of 2021 from the satellites listed in Table 1. We observed that the sea near Bohai Bay freezes in January and February, affecting the recognition of mariculture. Therefore, we first excluded images from these two months. Subsequently, most images with relatively poor quality were eliminated based on the condition of cloud cover being less than 15%. This is primarily because the main body of mariculture is located beneath the water surface, and a high cloud cover can obscure the mariculture area and alter the reflectance distribution of both main and ancillary images, making the already weak signals of mariculture even fainter. Following this, manual inspection was carried out to remove images with significant wind and waves, as turbulent waves can also impact the identification of mariculture. The final set of images used in our analysis was concentrated in the period from March to May when the image quality was relatively better. As a supplement, a small number of images from September and November were also included. On the other hand, to minimize the data processing workload, we prioritized images with relatively larger swath widths. GF-2 images, with a smaller swath width, were used only as a supplement to the 2 m resolution data, as they could not completely cover the study area. In conclusion, we utilized a total of 19 scenes of GF-1 images, 2 scenes of GF-2 images, 8 scenes of GF-6 images, and 8 scenes of ZY-3 images.

Table 1. High-resolution satellite parameters.

Satellite	Band	Spectral Range (μm)	Spatial Resolution (m)	Swath Width (km)	Revisit Period (Day) (Satellite Yaw)
GF-1 (PMS)	PAN	0.45~0.90	2	60	4
	B	0.45~0.52	8		
	G	0.52~0.59	8		
	R	0.63~0.69	8		
	NIR	0.77~0.89	8		
GF-2 (PMS)	PAN	0.45~0.90	1	45	5
	B	0.45~0.52	4		
	G	0.52~0.59	4		
	R	0.63~0.69	4		
	NIR	0.77~0.89	4		
GF-6 (PMS)	PAN	0.45~0.90	2	90	4
	B	0.45~0.52	8		
	G	0.52~0.60	8		
	R	0.63~0.69	8		
	NIR	0.76~0.90	8		
ZY-3 (TDI CCD)	PAN	0.45~0.80	2.1	51	5
	B	0.45~0.52	6		
	G	0.52~0.59	6		
	R	0.63~0.69	6		
	NIR	0.77~0.89	6		

3. Method

The overall methodology employed in this study is illustrated in Figure 2. High-resolution remote sensing images undergo preprocessing, including radiometric calibration, geometric correction, and image fusion. Land and water separation is achieved based on continental vector data and the Normalized Difference Water Index (NDWI) to remove land areas and reduce interference in the extraction of mariculture. For the ocean areas, the first step involves using SAM to extract the more prominent cage mariculture. Then, for the weaker information associated with raft mariculture, after further using NDWI to remove small islands, vessels, and cage mariculture in the sea, brightness stretching is applied to the raft mariculture areas to enhance the information. SAM is then employed for extraction. The results are subsequently visually inspected, modified, and supplemented to obtain the final spatial distribution data of mariculture. These results are overlaid with maritime ownership data, and an overall assessment of the distribution of mariculture is conducted.

3.1. Segment Anything Model

The SAM model is a large-scale model in the field of image segmentation based on the Transformer vision model. It is trained on a total of over 1.1 billion masks from more than 11 million images [26], showcasing remarkable image segmentation capabilities. SAM consists of three main components: an image encoder, a flexible prompt encoder, and a fast mask decoder. The image encoder is built upon a pre-trained Vision Transformer with a Masked Autoencoder (MAE), enabling it to handle high-resolution image inputs. The prompt encoder can support sparse types of prompts in the form of points, boxes, and text, as well as dense types of prompts in the form of masks. The mask decoder maps the image embedding, prompt embeddings, and an output token to a mask. SAM is designed as an interactive promptable model during training, allowing it to perform image segmentation tasks with zero-shot capability in practical applications, making it more efficient compared to traditional deep learning models.

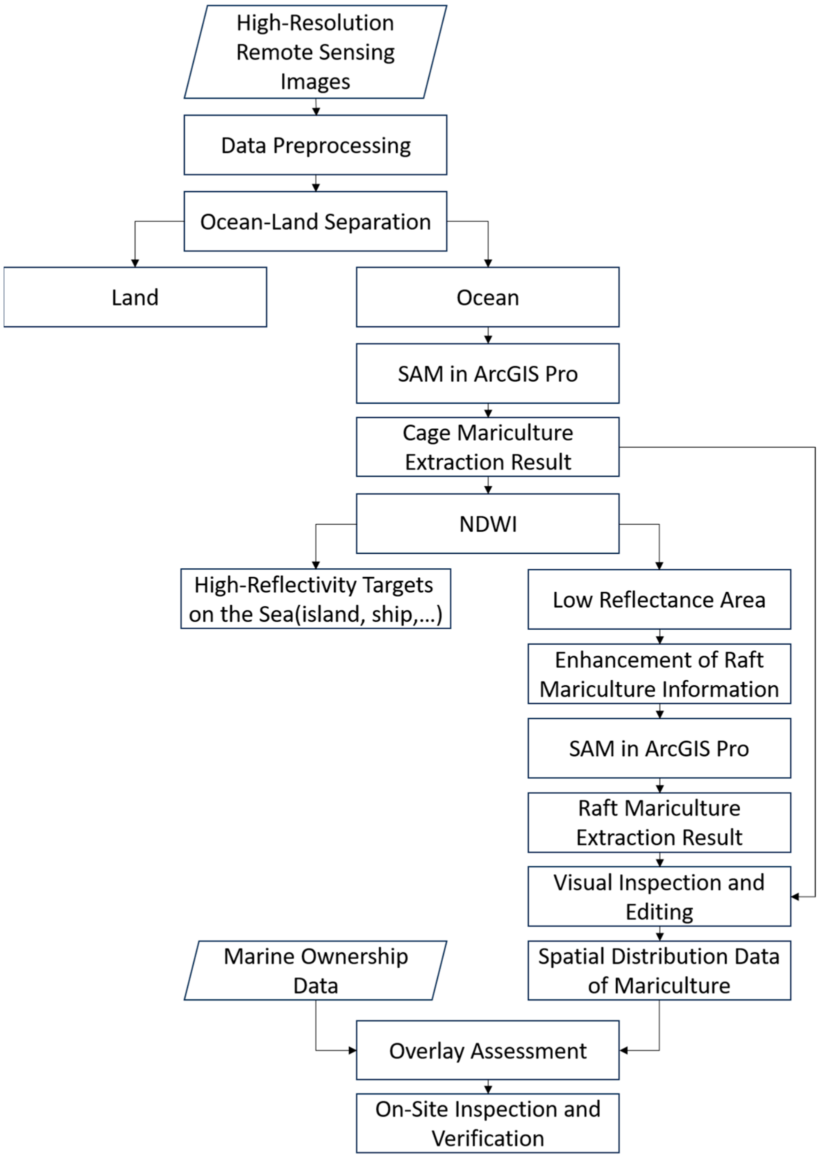

Figure 2. Extraction workflow diagram for mariculture in Liaoning.

In this study, we initially downloaded the SAM.dlpk file from the internet (https://www.arcgis.com/home/item.html?id=9b67b441f29f4ce6810979f5f0667ebe, accessed on 7 June 2023.) and configured the deep learning framework in ArcGIS Pro 3.1 software to invoke the SAM model. We extracted mariculture based on SAM by utilizing the deep learning object detection feature in ArcGIS. The specific parameter settings for SAM extraction of mariculture in ArcGIS are as follows: padding = 256; batch_size = 64; box_nms_thresh = 0.7; points_per_batch = 64; stability_score_thresh = 0.95; min_mask_region_area = 0.

3.2. The Extraction of Cage Mariculture Based on SAM

The contrast between the segmented target and its surrounding background has a direct impact on the segmentation results achieved with the SAM model. Cage mariculture is primarily composed of the framework, buoys above the water surface, and cages or nets beneath the water surface (See Figure 3a). Since the cages or nets are located below the framework and cannot be identified in remote sensing images, extracting cage mariculture essentially involves extracting the framework above the water surface.

(a) (b) (c)

Figure 3. Field inspection photos. (**a**) Cage mariculture; (**b**) alga raft mariculture (kelp); (**c**) bivalve raft mariculture (hanging cages).

The framework is typically made of plastic materials and has a higher reflectance compared to the background seawater, appearing as a gray-white tone in images. The framework is generally in a regular rectangular shape, and at high resolutions, it is possible to discern the fine mesh pattern of cage mariculture, which forms a distinctive texture feature. In an area, cage mariculture typically follows similar specifications, so their shapes and sizes are relatively regular. Additionally, because the cage mariculture framework floats on the water surface, it has a significant contrast with the background seawater. Therefore, the SAM model can be directly used for segmentation and extraction.

3.3. The Extraction of Raft Mariculture Based on SAM

Raft mariculture consists primarily of three components: floating rafts, hanging ropes or cages, and fixed cables. The floating rafts are composed of floats connected by ropes, keeping the rafts afloat on the sea surface. At even intervals along the floating raft ropes, hanging ropes, or cages are connected. Hanging ropes are primarily used for cultivating seaweed (See Figure 3b), while cages are used for rearing scallops and oysters (See Figure 3c), among other marine products. These hanging ropes and cages are submerged in the seawater. One end of the fixed cable is attached to the floating raft, while the other end is secured to weights, serving the purpose of anchoring.

Since the main components of raft mariculture are located mostly beneath the water surface, only individual floats are visible on the sea surface in remote sensing images. This results in very weak imaging information. Raft mariculture is often densely arranged, with several dozen ropes forming a group, leading to the appearance of rectangular bands in images. Raft mariculture for seaweed cultivation gradually exhibits vegetation features as the mariculture products mature. In remote sensing images, it appears as deep blue rectangular bands with relatively strong information in the near-infrared spectrum. However, information for shellfish cultivation is much weaker compared to seaweed cultivation, and direct extraction using the SAM model yields less satisfactory results.

To achieve this, information enhancement is required for raft mariculture. After extracting cage mariculture, the sea surface is divided into areas of high-brightness targets and low-brightness regions based on the Normalized Difference Water Index (NDWI). High-brightness targets generally include small islands, vessels, and other high-brightness objects like cages, while the low-brightness region contains the weak information associated with raft mariculture. After removing the high-brightness areas, brightness stretching is applied to the sea areas where raft mariculture is located to enhance the raft mariculture information. Subsequently, segmentation is carried out based on the SAM model.

3.4. Accuracy Assessment

In order to examine the extraction effectiveness of SAM on mariculture, an accuracy assessment was performed on the automatically extracted mariculture data. Within the study area, 1000 random sample points were generated for both cage mariculture and raft mariculture intensive areas. The categories of these sample points were determined through manual visual interpretation, and an accuracy assessment was conducted using the F1 score method.

The F1 score is a combination of precision and recall. Precision represents the proportion of correct identification in the extracted mariculture area, and recall represents the proportion of the actual mariculture area correctly extracted. In practice, precision and recall are often in conflict, so the F1 value is commonly used to comprehensively measure the two indicators [11]. The larger the F1 value, the better the accuracy of the extraction result.

$$\mathrm{F1} = 2 \times \frac{\mathrm{Recall} \times \mathrm{Precision}}{\mathrm{Recall} + \mathrm{Precision}} \tag{1}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{2}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{3}$$

where TP refers to the number of sample points when the type of mariculture area is correctly identified, FP refers to the number of sample points incorrectly identified as the mariculture area, and FN refers to the number of sample points in the actual mariculture area but not identified.

3.5. Overlay Assessment with Maritime Ownership Data

In order to assess the actual status of mariculture development and its consistency with government planning, the extraction results of mariculture are overlaid with maritime ownership data. Maritime ownership data is non-public government data, and therefore, the consistency between actual mariculture and planning is measured in the form of a spatial grid. Initially, a $0.01° \times 0.01°$ grid is created as the basic unit to cover the policy planning and actual mariculture areas. Subsequently, the mariculture data is overlaid with management data, and a comparison is made between the mariculture extraction results and the policy planning status within each grid. Each grid may fall into one of the following four categories:

Type 1: "Both approved and cultivated" means that within a specific grid, both the extracted mariculture area and management data are present. This indicates that mariculture activities in that grid are legitimate, meaning they have been approved by authorities and are actively taking place.

Type 2: "Approved but not cultivated" means that within a specific grid, only management data exists, and there is no extracted mariculture area. This indicates that there is currently no actual mariculture activity in that grid. However, based on the management data, the government has approved the use of that area for mariculture. Therefore, this grid is considered a potential mariculture development area, and it may be developed for mariculture in the future.

Type 3: "Cultivated but not approved" means that within a specific grid, only the extracted mariculture area exists, and there is no management data. This indicates that there is mariculture activity in that area, but there is no relevant government approval or regulatory data. As a result, this may be considered as unauthorized mariculture. Further investigations and legal measures may be necessary to either legalize or stop the mariculture activities, depending on local regulations and policies.

Type 4: "Neither approved nor cultivated" means that within a specific grid, there is neither an extracted mariculture area nor relevant management data. This indicates that there is no mariculture activity in that area, and it has not received government approval for mariculture. Therefore, this grid is considered unsuitable for developing mariculture, and other uses or conservation measures may need to be considered to maintain ecological balance and environmental sustainability.

Through overlay assessment, each grid in the study area is assigned a specific category, and the degree of consistency between the actual state of mariculture development and government planning is quantified based on the concept of a confusion matrix.

$$\begin{cases} R_{re} = \frac{T_1}{T_1+T_2} \\ R_{ra} = \frac{T_1}{T_1+T_3} \end{cases} \tag{4}$$

where T_1, T_2, T_3, T_4 represent the proportions of different types of grids; R_{re} stands for the retention rate, indicating the proportion of planned mariculture areas that have been actually developed and utilized; R_{ra} represents the rationality rate, indicating the proportion of extracted mariculture areas that have received legitimate approvals.

4. Results

4.1. Mariculture Extraction Results

Based on the technical process described in this article, the mariculture in Liaoning Province's coastal zone was extracted, and the extraction results are shown in Figure 4.

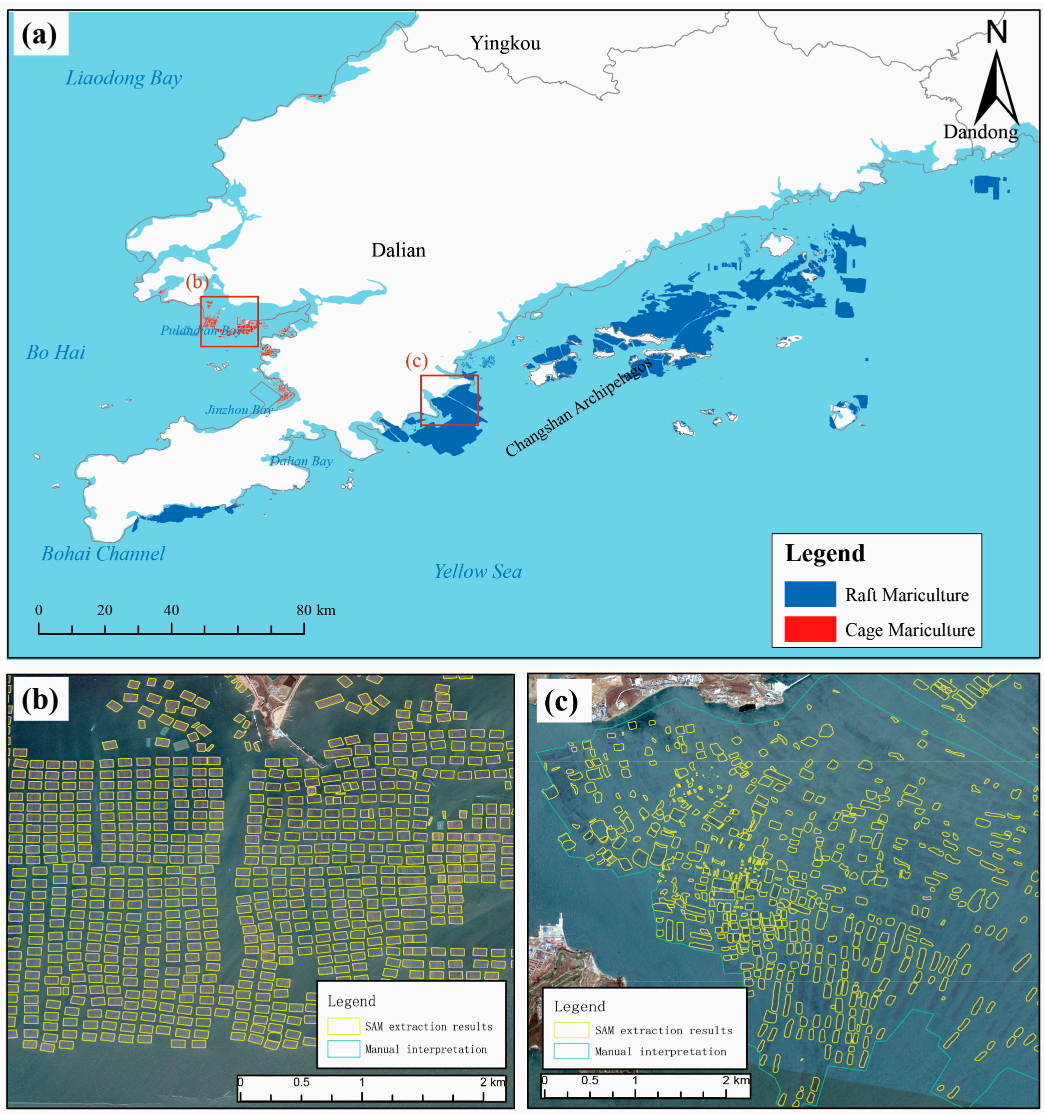

Figure 4. Presentation of the extracted mariculture results in Liaoning. (**a**) Liaoning mariculture extraction results; (**b**) The results of SAM extraction of cage mariculture and manual interpretation; (**c**) The results of SAM extraction of raft mariculture and manual interpretation.

The results of SAM's automatic extraction of cage aquaculture and raft aquaculture are shown in Figure 4b,c, respectively. After randomly generating 1000 samples, the accuracy of SAM's automatic extraction results was validated using the F1 score. For cage mariculture, SAM demonstrated excellent recognition performance with an F1 score of 96.1%, including a recall of 95.6% and precision of 96.6%. However, SAM's automatic identification of raft mariculture was not ideal, with an F1 score of only 63.8%, including a recall of 95.3% and precision of 47.9%. This indicates that SAM has outstanding extraction performance for cage mariculture, enabling fast and accurate extraction. However, it is not effectively applicable to the extraction of raft mariculture.

After automatic extraction, manual inspection and correction of the data were performed. For cage mariculture, due to the good performance of automatic extraction, only a small number of missed cages were added manually, and some objects incorrectly identified as ship or seawall were removed. In contrast, raft mariculture automatic extraction had more omissions, requiring more manual supplementation. Since the boundaries of many raft mariculture are blurry in remote sensing images, manual correction only involved outlining the outer contours of the raft mariculture areas. The manually corrected areas are indicated by blue boxes in Figure 4b,c. The final obtained data for Liaoning mariculture are shown in Figure 4a.

Mariculture in Liaoning is mainly concentrated in the southern-central part of Liaoning Province near Dalian, with Dalian serving as the dividing point. In the areas west of Dalian within Liaodong Bay, the primary mode of mariculture is cage mariculture, while in the areas east of Dalian, raft mariculture is the predominant mode. According to the statistics, the total area of extracted mariculture is 1052.89 km^2, with a cage mariculture area of 27.1 km^2 and a raft mariculture area of 1025.79 km^2. Cage mariculture areas are all located within 10 km of the coastline and have relatively smaller distribution areas. In contrast, the spatial distribution of raft mariculture is more extensive, with some located up to nearly 20 km offshore. Even on the eastern side, where raft mariculture is more distant from the mainland, the farthest distance can exceed 60 km, but they are all distributed around the offshore islands.

According to on-site inspections, cage mariculture in Liaodong Bay primarily involves the cultivation of sea cucumbers, while raft mariculture mainly includes the cultivation of kelp and scallops. Kelp cultivation is predominantly located at the southern end of Dalian, while raft mariculture in the vicinity of the Changshan Islands to the east focuses on the cultivation of scallops and oysters, among other shellfish.

Among the various types of mariculture, cage mariculture is the most effectively extracted because it primarily floats on the surface of the water, making both its spectral and geometric characteristics more prominent. Algae raft mariculture, when algae crops are mature, exhibits distinct dark brown stripes and relatively clear spectral features, resulting in good extraction during this period. However, when algae crops are not mature, the spectral information is weaker, making automatic extraction more challenging. On the other hand, scallop raft mariculture, which involves hanging cages in a submerged manner, lacks prominent spectral characteristics, making it the most challenging to identify. Automatic extraction is less effective for this method, often requiring manual visual interpretation for accurate identification.

4.2. The Overlap Statistics between Mariculture Extraction Results and Management Data

After establishing a grid with units of $0.01^\circ \times 0.01^\circ$, the mariculture extraction data are overlaid with the maritime ownership data, as shown in Figure 5.

According to the statistics, in the marine area of Liaoning Province, there are 2036 grids classified as "Both approved and cultivated", covering an area of approximately 2508 km^2 (converted grid area, not actual area, the same applies to the following). There are 16,168 grids classified as "Approved but not cultivated," covering an area of approximately 19,920 km^2. And there are 222 grids classified as "Cultivated but not approved," covering an area of approximately 273 km^2. Based on the calculation method in Section 3.4, the retention rate of planned mariculture areas that are actually developed is 11.2%, while the rationality rate of those actually approved for mariculture is 90.2%.

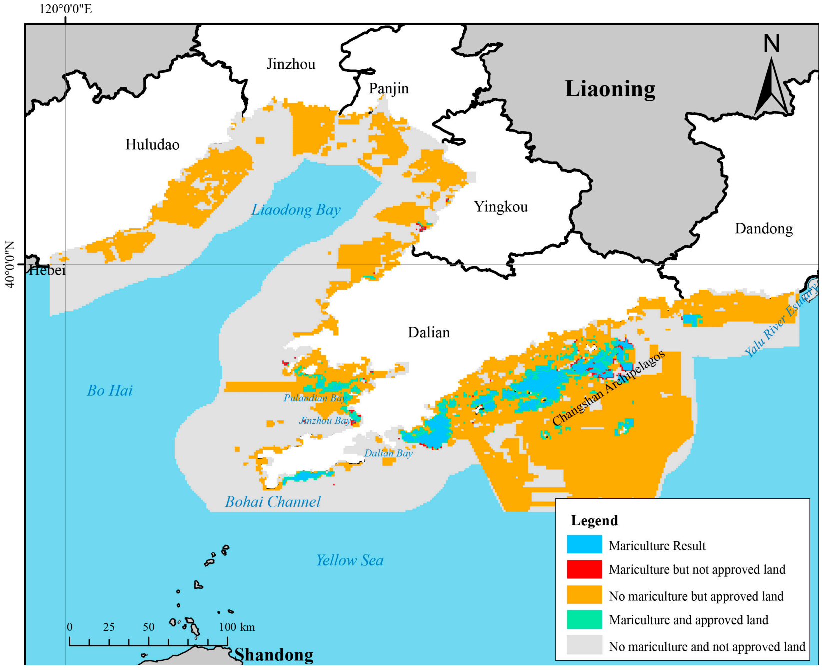

Figure 5. The overlap situation between the mariculture extraction data and marine ownership data.

The relatively low retention rate of planned mariculture areas that are actually developed may have two main reasons. First, remote sensing can only observe and extract surface mariculture activities, while bottom cultivation practices in mariculture are widespread but cannot be detected through remote sensing. As a result, there may be a significant portion of the planned areas where bottom cultivation occurs, but this is not reflected in the remote sensing extraction results, leading to the low rate. Second, in this study, data was selected to ensure image quality, and the available dataset is concentrated in the months of April and May. This means that some mariculture areas might not be captured, resulting in a lower proportion of actual mariculture compared to planned areas. The fact that 90.2% of mariculture activities are conducted with official approval suggests that mariculture activities are generally effectively regulated. However, the presence of 9.8% of mariculture activities that are not within the planned range could be attributed to two main reasons. First, there may be instances of unauthorized or unreported mariculture activities conducted in areas where they have not been approved. Second, it is possible that the marine ownership data used in this study is not up-to-date or does not cover some areas where mariculture activities are conducted in compliance with regulations.

Furthermore, we observed that areas suspected of illegal activities consistently occur at the edges of existing mariculture zones, with rare instances of independently occurring illegal mariculture zones. Since, during data overlay, we have standardized both the marine ownership data and the mariculture data we extracted to the WGS-84 coordinate system, spatial positioning discrepancies between the data can be ruled out. In most cases, these expansions occur in the direction away from the shore in existing mariculture zones, aligning with the expansion pattern of mariculture. However, this suspected illegal expansion could also be a result of farmers or mariculture companies being unaware of their actual legal boundaries at sea. The determination of the nature of the suspected illegal area still needs to be combined with actual visits and investigations.

5. Discussion

5.1. Comparison with Other Studies

This study is based on high-resolution remote sensing imagery and utilizes the deep learning SAM model to extract the mariculture areas in Liaoning Province, China. In addition to this study, there have been several other studies that have also extracted mariculture areas in Liaoning using remote sensing imagery (See Figure 6). For example, Kang et al. used 15 m Landsat imagery and the OBVS-NDVI method to extract multi-year mariculture data from 2000 to 2018 [21]. Fu et al. used 16 m wide GF-1 WFV imagery and the deep learning HCHNet model to extract mariculture areas in China [22]. Liu et al. (2022) used dense time series 10 m Sentinel-2 and Sentinel-1 imagery to extract mariculture areas in China in 2020 [16]. We have conducted a comparative analysis of these studies with respect to extraction results, data characteristics, and the methods employed.

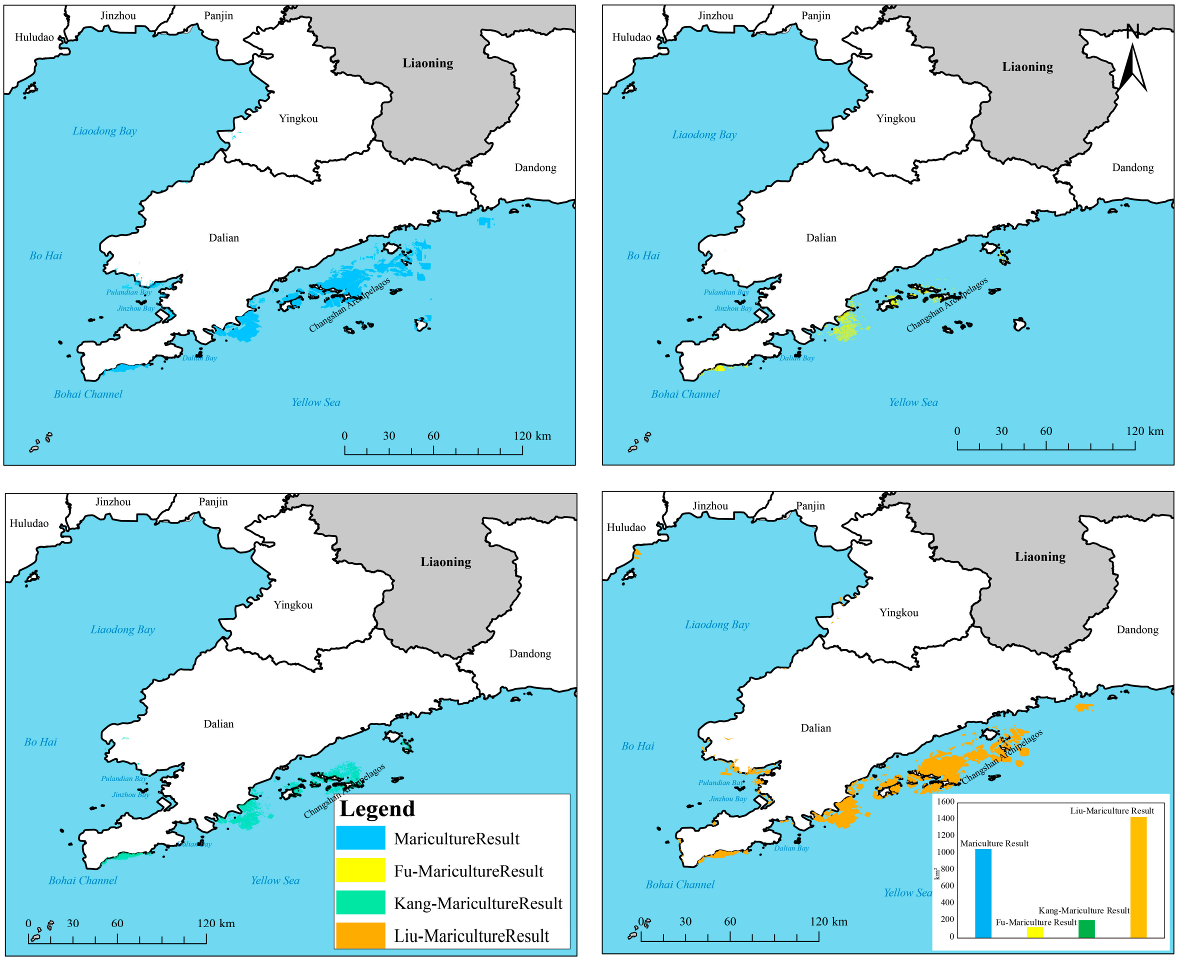

Figure 6. Comparative analysis of extraction results from various studies.

5.1.1. Comparison of Mariculture Extraction Results

In the above-mentioned studies, Kang's extraction resulted in a mariculture area of 204.28 km^2 (data year 2018), Fu's extraction covered 116.01 km^2 (data year 2016–2019), and Liu's extraction encompassed 1432.24 km^2 (data year 2020). These figures significantly differ from the mariculture area extracted in this study, which is 1052.89 km^2. The main reason for these disparities is that Kang and Fu's studies focused on extracting individual mariculture targets, leading to smaller area statistics. On the other hand, Liu's results encompassed the spatial regions of mariculture areas, including the mariculture targets and the surrounding background water. As a result, it produced the largest area. In this study, SAM was used to extract both cage mariculture and raft mariculture as separate targets. However, due to the poor extraction performance of SAM for raft mariculture, a large number of artificially interpreted mariculture areas have been added in a regional form. This delineation method is consistent with the data form in Liu's study. As a result, our mariculture area is lower than Liu's but far exceeds the studies of Kang and Fu. Furthermore, the temporal differences in remote sensing imagery used in these studies also lead to differences in the area between different studies to some extent. However, in comparison, the primary factor influencing the variation in area is still the differences in mariculture targets and regions.

From a spatial distribution standpoint, we have conducted a comparative analysis of our extraction results with those of other studies. Our extraction results largely coincide with Kang's findings, where Kang's results exhibit noticeable omissions in cage mariculture within the Bohai Bay and raft mariculture on the easternmost side. However, in comparison to Kang's results, our findings also show minor omissions in raft mariculture in the central part of Dalian. Fu's extraction results are slightly smaller in comparison to Kang's, with the primary difference being a higher rate of omission in raft mariculture around the Changshan Islands. Liu's extraction results are the most comprehensive, covering the mariculture areas extracted in other studies for the most part. There are only isolated instances where our results include mariculture areas not captured in Liu's results. Conversely, our results have some omissions in raft mariculture areas in the eastern and central parts of the study area compared to Liu's results. The primary reason for this could be Liu's utilization of year-long time-series data from two types of imagery, namely the 2020 Sentinel-2 multispectral and Sentinel-1 SAR, which minimizes omissions. In contrast, our study employed imagery primarily concentrated in April and May, failing to cover the entire year's time series, potentially leading to some omissions.

5.1.2. Comparison of Remote Sensing Images Used

Figure 7 displays a detailed comparison of the research results within a specific area. The mariculture type depicted in the figure is cage mariculture. Our study employed optical imagery with a spatial resolution of 2 m, which offers superior spatial detail representation compared to optical imagery with a resolution of 10 m or greater. Therefore, our results have effectively extracted individual cage mariculture objects. Kang's research, on the other hand, utilized Landsat 8 imagery with a spatial resolution of 15 m. Consequently, it was unable to effectively capture individual mariculture cages and shellfish rafts with less distinctive spectral characteristics, leading to omissions in the extraction results. Fu's imagery had a spatial resolution of 16 m and thus faced similar challenges. In contrast, Liu's study utilized optical Sentinel-2 imagery with a 10-m spatial resolution, covering the entire year of 2020, in addition to Sentinel-1 SAR imagery. Due to Liu's study using temporal images, their extraction of mariculture areas is the most comprehensive. However, the final results present the outer boundaries of mariculture areas without individual mariculture objects, mainly constrained by the spatial resolution of the images.

5.1.3. Comparison of Extraction Methods

Kang's study, based on an object-oriented approach, required an initial object-based segmentation of the study area. Following segmentation, a combination of edge and spectral features was employed, with threshold values set to perform the final mariculture extraction. Notably, both the size of segmentation units and the threshold values required iterative adjustments for each scene, resulting in relatively low efficiency.

Fu's research was based on deep learning models, which, once trained, allowed for the direct extraction of mariculture targets from new remote sensing imagery. However, in the initial stages of the study, there was a need to create a specialized mariculture sample library, incurring relatively high time costs. Additionally, the extraction performance was poorer for mariculture objects not well represented in the sample library, particularly those in different watercolor environments or imaging conditions. To improve performance, additional samples needed to be incorporated into the training process, and the challenge of incorporating expert knowledge for decision support proved complex.

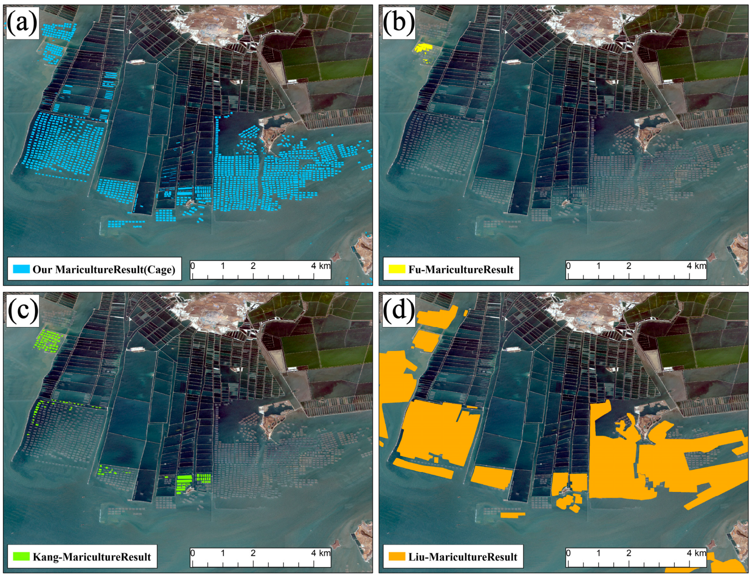

Figure 7. Detailed comparison of mariculture extraction results from various studies. (**a**) Our results; (**b**) Fu's results; (**c**) Kang's results; (**d**) Liu's results.

Liu's approach relied on the Google Earth Engine (GEE) platform for synthesizing time-series remote sensing imagery and enhancing mariculture target extraction. While effective for capturing the overall distribution of sea-based mariculture within a certain time frame, it yielded relatively poor results in the extraction of changing mariculture objects within single-scene imagery. This method is suitable for obtaining the overall distribution range of offshore mariculture within a certain time frame, but it is not suitable for mariculture regulation with high timeliness requirements.

This study interprets mariculture areas based on the SAM model. The SAM model is developed using a large dataset and does not require the construction of additional training samples. It can directly interpret mariculture from high-resolution imagery. Moreover, it does not necessitate setting extraction thresholds repeatedly for different scenes or images, making it the most efficient method. However, since the SAM model is still trained on natural images, its performance in recognizing features in remote sensing imagery is relatively poor. Real-world mariculture monitoring still heavily relies on manual inspection and correction. However, if deep learning models are developed using remote sensing imagery as training data in the future, it will further enhance the extraction accuracy of mariculture targets and reduce the need for human intervention.

Additionally, most of the current extraction methods still primarily rely on the features of remote sensing imagery for extraction. To truly achieve automatic extraction and intelligent monitoring of mariculture, further exploration is required in the direction of incorporating knowledge into the process [29].

5.2. Analysis and Recommendations for the Inconsistent Areas in the Mariculture Planning of Liaoning Province

From a spatial distribution and mariculture-type perspective, the areas inconsistent with the plan are mainly concentrated on the eastern side of the study area. The primary mariculture mode is raft-based farming, with shellfish such as scallops and oysters as the main cultured species. In contrast, there are relatively fewer areas inconsistent with the plan for sea cucumber cage mariculture within Bohai Bay, and these areas are sporadically distributed. The likely reason for this difference is closely related to the mariculture mode used for the cultured species. In the case of sea cucumber mariculture in Bohai Bay, while it involves using sea cages at sea to a certain extent, large-scale sea cucumber farming is primarily conducted in onshore pond facilities. Sea cucumber cage mariculture, due to reasons related to cost and farming efficiency, typically remains at a relatively small scale. Consequently, it is not likely to undergo significant expansion, and there will not be substantial spatial changes associated with it. On the other hand, in the eastern side of the study area, particularly around Haiwang Jiudao, the primary mariculture mode is raft-based farming of shellfish. This region exhibits characteristics of being "large-scale" and "rapidly expanding". The development trend is characterized by radiating expansion outward from the mariculture islands as its central point. Therefore, it is more likely for mariculture areas to exceed the originally planned areas. In addition, sea cucumber mariculture in Liaoning is mostly located in the mainland coastal areas, while shellfish raft mariculture is mainly concentrated in the vicinity of islands at a certain distance from the mainland, which is relatively inconvenient for timely supervision and may lead to the occurrence of illegal mariculture practices.

In Figure 5, there is still a significant area within the planned mariculture zone where mariculture activities have not been observed. It is highly likely that this portion of the area is used for bottom culture mariculture. The spatial distribution of bottom culture mariculture cannot be accurately determined through remote sensing methods. However, according to the Fisheries Statistical Yearbook [30], bottom culture mariculture accounts for approximately 70% of the mariculture in Liaoning Province. In this study, the "approved but not cultivated" areas make up 87.7% of the overall approved mariculture zones, indicating that a significant portion of these areas are indeed designated for bottom culture mariculture.

Based on the above analysis, we have formulated the following recommendations for the regulation of mariculture in Liaoning:

(1) Establish varying levels of regulatory oversight for different types of mariculture

Liaoning's sea cucumber cage mariculture is scattered, but shellfish and seaweed raft mariculture are more widely distributed, with rapid expansion in shellfish mariculture. Therefore, different types of mariculture should have varying levels of regulatory oversight. There should be a particular focus on strengthening the regulation of shellfish raft culture.

(2) Enhance offshore island-based mariculture monitoring using remote sensing techniques

With the advancement of mariculture technology and regional economic development, mariculture around offshore islands is growing rapidly. In comparison to coastal mariculture near the mainland, monitoring mariculture around offshore islands is relatively more challenging, and illegal encroachment on marine areas is more likely to occur. Therefore, remote sensing methods can be employed to promptly assess the development status of mariculture around offshore islands, preventing the occurrence of illegal encroachment for mariculture.

(3) Integrate underwater detection technology to enhance the investigation and regulation of bottom culture mariculture

In Liaoning, bottom culture mariculture is widely distributed, and it represents a significant portion of the industry. However, it is difficult to accurately determine its spatial distribution using remote sensing satellites or drones. Therefore, for bottom culture mariculture, advanced underwater detection technologies such as underwater robots and submersible instruments can be utilized to strengthen the investigation and regulation of bottom culture mariculture.

(4) Refine and timely update the types of marine data

The marine ownership data contains information about culture types. However, due to different marine usage patterns, cultivation methods such as cage and raft mariculture, as well as bottom culture, can coexist. This results in areas registered as bottom culture showing the presence of raft and cage mariculture. However, the actual extent of raft and cage mariculture cannot be accurately displayed in marine ownership data. What management authorities may require is a further refinement of marine ownership data, clearly defining the actual extent of bottom culture and the areas within it where raft and cage mariculture occur. In addition, timely verification and updating of marine information, along with the establishment of a real-time, shared marine property registration system, should help reduce inconsistencies between mariculture distribution and marine ownership data. This would contribute to better scientific management and development of marine aquaculture.

6. Conclusions

This study utilized high-resolution remote sensing imagery and the SAM model to extract and analyze mariculture in Liaoning Province, China. It also incorporated marine ownership data to assess the marine usage situation in Liaoning's mariculture. Based on the findings and identified issues, the study has provided recommendations for addressing these concerns.

This study attempts to acquire mariculture objects automatically based on the SAM model. We found that SAM demonstrates outstanding extraction performance for cage mariculture, with an F1 score reaching 96.1%. However, SAM's performance is less satisfactory for raft aquaculture, and the F1 score can only reach 63.8%. Manual interpretation is still required to obtain more comprehensive raft mariculture data.

The study extracted a total mariculture area of 1052.89 km^2. Within this, cage mariculture covered an area of 27.1 km^2, and raft mariculture occupied 1025.79 km^2. Cage mariculture was evenly distributed within 10 km of the mainland coastline, while raft mariculture extended as far as offshore islands, distributed in sea areas located 60 km or more away from the mainland coastline.

Through field surveys, it was observed that cage mariculture in Liaodong Bay on the western side of Liaoning primarily involved sea cucumber as the cultivated species, while raft mariculture at the southern tip of Dalian was focused on kelp cultivation. On the eastern side of the islands, raft mariculture primarily cultivated scallops, demonstrating a distinct geographical differentiation pattern in the choice of mariculture species.

When overlaying the results of the mariculture extraction with marine ownership data, it was found that in the marine areas of Liaoning Province, the ratio of planned mariculture areas that are actually developed and utilized is 11.2%, while the ratio of approved mariculture areas in actual cultivation is 90.2%. This suggests that there is a suspicion that 9.8% of mariculture potentially involves illegal encroachment, which might be attributed to delays in updating the marine ownership data. The relatively low ratio of actual development and utilization of mariculture areas may be due to the significant presence of bottom culture mariculture, which cannot be effectively monitored through remote sensing techniques.

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References

1. FAO. *Fisheries and Aquaculture Topics. The State of World Fisheries and Aquaculture (SOFIA)*; FAO Fisheries and Aquaculture Department: Rome, Italy, 2022.
2. Keesing, J.K.; Liu, D.; Fearns, P.; Garcia, R. Inter-and intra-annual patterns of Ulva prolifera green tides in the Yellow Sea during 2007–2009, their origin and relationship to the expansion of coastal seaweed aquaculture in China. *Mar. Pollut. Bull.* **2011**, *62*, 1169–1182. [CrossRef] [PubMed]
3. Liu, D.; Keesing, J.K.; He, P.; Wang, Z.; Shi, Y.; Wang, Y. The world's largest macroalgal bloom in the Yellow Sea, China: Formation and implications. *Estuar. Coast. Shelf Sci.* **2013**, *129*, 2–10. [CrossRef]
4. Wartenberg, R.; Feng, L.; Wu, J.J.; Mak, Y.L.; Chan, L.L.; Telfer, T.C.; Lam, P.K. The impacts of suspended mariculture on coastal zones in China and the scope for integrated multi-trophic aquaculture. *Ecosyst. Health Sustain.* **2017**, *3*, 1340268. [CrossRef]
5. Xu, Y.; Zhang, Z.; Wang, X.; Wen, Q.; Liu, F.; Li, N. Remote Sensing Monitoring and Temporal Variation Analysis of Coastal Aquaculture in Shandong Province in the Recent Three Decades. *J. Geo-Inf. Sci.* **2014**, *16*, 482–489.
6. Wei, Z.; Xing, Q.; Guo, R.; Li, L. Study on the Spatial Distribution Variation of Porphyra Aquaculture in the Southern Yellow Sea During the Period 2000-2015 Retrieved by Satellite Remote Sensing. *J. Ocean. Technol.* **2018**, *37*, 17–22.
7. Wu, J.; Marín Del Valle, T.; Ruckelshaus, M.; He, G.; Fu, Y.; Deng, J.; Liu, J.; Yang, W. Dramatic mariculture expansion and associated driving factors in Southeastern China. *Landsc. Urban Plan.* **2021**, *214*, 104190. [CrossRef]
8. Xu, Y.; Wu, W.; Lu, L. Remote Sensing Mapping of Cage and Floating-raft Aquaculture in China's Offshore Waters Using Machine Learning Methods and Google Earth Engine. In Proceedings of the 2021 9th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), Shenzhen, China, 26–29 July 2021. [CrossRef]
9. Xue, M.; Chen, Y.; Tian, X.; Yan, M.; Zhang, Z. Detection the Expansion of Marine Aquaculture in Sansha Bay by Remote Sensing. In Proceedings of the IGARSS 2018—2018 IEEE International Geoscience and Remote Sensing Symposium, Valencia, Spain, 22–27 July 2018. [CrossRef]
10. Zheng, Y.; Wu, J.; Wang, A.; Chen, J. Object- and pixel-based classifications of macroalgae farming area with high spatial resolution imagery. *Geocarto Int.* **2017**, *33*, 1048–1063. [CrossRef]
11. Wang, M.; Cui, Q.; Wang, J.; Ming, D.; Lv, G. Raft cultivation area extraction from high resolution remote sensing imagery by fusing multi-scale region-line primitive association features. *ISPRS J. Photogramm. Remote Sens.* **2017**, *123*, 104–113. [CrossRef]
12. Shi, T.; Xu, Q.; Zou, Z.; Shi, Z. Automatic Raft Labeling for Remote Sensing Images via Dual-Scale Homogeneous Convolutional Neural Network. *Remote Sens.* **2018**, *10*, 1130. [CrossRef]
13. Lu, Y.; Shao, W.; Sun, J. Extraction of Offshore Aquaculture Areas from Medium-Resolution Remote Sensing Images Based on Deep Learning. *Remote Sens.* **2021**, *13*, 3854. [CrossRef]
14. Cui, B.-G.; Zhong, Y.; Fei, D.; Zhang, Y.-H.; Liu, R.-J.; Chu, J.-L.; Zhao, J.-H. Floating Raft Aquaculture Area Automatic Extraction Based on Fully Convolutional Network. *J. Coast. Res.* **2019**, *90*, 86–94. [CrossRef]
15. Fu, Y.; Deng, J.; Wang, H.; Comber, A.; Yang, W.; Wu, W.; You, S.; Lin, Y.; Wang, K. A new satellite-derived dataset for marine aquaculture areas in China's coastal region. *Earth Syst. Sci. Data* **2021**, *13*, 1829–1842. [CrossRef]
16. Liu, X.; Wang, Z.; Yang, X.; Liu, Y.; Liu, B.; Zhang, J.; Gao, K.; Meng, D.; Ding, Y. Mapping China's offshore mariculture based on dense time-series optical and radar data. *Int. J. Digit. Earth* **2022**, *15*, 1326–1349. [CrossRef]
17. Wang, Z.; Yang, X.; Liu, Y.; Lu, C. Extraction of coastal raft cultivation area with heterogeneous water background by thresholding object-based visually salient NDVI from high spatial resolution imagery. *Remote Sens. Lett.* **2018**, *9*, 839–846. [CrossRef]
18. Wang, Z.; Zhang, J.; Yang, X.; Huang, C.; Su, F.; Liu, X.; Liu, Y.; Zhang, Y. Global mapping of the landside clustering of aquaculture ponds from dense time-series 10 m Sentinel-2 images on Google Earth Engine. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *115*, 103100. [CrossRef]
19. Liu, Y.; Wang, Z.; Yang, X.; Zhang, Y.; Yang, F.; Liu, B.; Cai, P. Satellite-based monitoring and statistics for raft and cage aquaculture in China's offshore waters. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *91*, 102118. [CrossRef]
20. Wang, J.; Sui, L.; Yang, X.; Wang, Z.; Liu, Y.; Kang, J.; Lu, C.; Yang, F.; Liu, B. Extracting Coastal Raft Aquaculture Data from Landsat 8 OLI Imagery. *Sensors* **2019**, *19*, 1221. [CrossRef]
21. Kang, J.; Sui, L.; Yang, X.; Liu, Y.; Wang, Z.; Wang, J.; Yang, F.; Liu, B.; Ma, Y. Sea Surface-Visible Aquaculture Spatial-Temporal Distribution Remote Sensing: A Case Study in Liaoning Province, China from 2000 to 2018. *Sustainability* **2019**, *11*, 7186. [CrossRef]
22. Fu, Y.; Ye, Z.; Deng, J.; Zheng, X.; Huang, Y.; Yang, W.; Wang, Y.; Wang, K. Finer Resolution Mapping of Marine Aquaculture Areas Using WorldView-2 Imagery and a Hierarchical Cascade Convolutional Neural Network. *Remote Sens.* **2019**, *11*, 1678. [CrossRef]
23. Hu, Y.; Fan, J.; Wang, J. Classification of PolSAR Images Based on Adaptive Nonlocal Stacked Sparse Autoencoder. *IEEE Geosci. Remote Sens. Lett.* **2018**, *15*, 1050–1054. [CrossRef]
24. Fan, J.; Zhao, J.; An, W.; Hu, Y. Marine Floating Raft Aquaculture Detection of GF-3 PolSAR Images Based on Collective Multikernel Fuzzy Clustering. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2019**, *12*, 2741–2754. [CrossRef]
25. Liu, Y.; Yang, X.; Wang, Z.; Lu, C.; Li, Z.; Yang, F. Aquaculture area extraction and vulnerability assessment in Sanduao based on richer convolutional features network model. *J. Oceanol. Limnol.* **2019**, *37*, 1941–1954. [CrossRef]
26. Kirillov, A.; Mintun, E.; Ravi, N.; Mao, H.; Rolland, C.; Gustafson, L.; Xiao, T.; Whitehead, S.; Berg, A.C.; Lo, W.-Y. Segment anything. *arXiv* **2023**, arXiv:2304.02643. [CrossRef]
27. Li, H.; Man, W.; Li, X.; Ren, C.; Wang, Z.; Li, L.; Jia, M.; Mao, D. Remote sensing investigation of anthropogenic land cover expansion in the low-elevation coastal zone of Liaoning Province, China. *Ocean Coast. Manag.* **2017**, *148*, 245–259. [CrossRef]

28. Duan, Y.; Tian, B.; Li, X.; Liu, D.; Sengupta, D.; Wang, Y.; Peng, Y. Tracking changes in aquaculture ponds on the China coast using 30 years of Landsat images. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102383. [CrossRef]
29. Wang, Z.; Yang, X.; Zhou, C. Geographic knowledge graph for remote sensing big data. *J. Geo-Inf. Sci.* **2021**, *23*, 16–28.
30. Ministry of Agriculture and Rural Affairs of the People's Republic of China; China Society of Fisheries. *2020 China Fishery Statistical Yearbook*; China Agriculture Press: Beijing, China, 2020.