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Quadrennial Series Dataset of Coastal Aquaculture Distribution of China Based on Landsat Images (1990–2022)

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Abstract: Coastal aquaculture is a significant part of the economy in China's coastal regions; however, it raises ecological and environmental concerns. In this study, the Google Earth Engine (GEE) cloud computing platform was utilized to apply a multi-feature method to extract coastal aquaculture areas using a long time series of dense remote sensing images from 1990 to 2022. A spatial distribution dataset of coastal aquaculture areas was acquired. The dataset covered the coastal region of China from 1990 to 2022, providing a spatial resolution of 30 m and a temporal resolution of four years. The collection consisted of 99 files, totaling 43.4 GB of data. The entire dataset was compressed into a single file of only 75.6 MB.

Keywords: China; aquaculture area; Landsat images; long time series

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Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: https://doi.org/10.3974/geodb.2023.09.01.V1 or https://cstr.escience.org.cn/CSTR:20146.11.2023.09.01.V1.

1 Introduction

Coastal aquaculture, including land aquaculture ponds and marine aquaculture zones, is an

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[2] Yin, Y. M., Zhang, Y. H., Hu, Z. W., *et al*. Quadrennial series dataset of coastal aquaculture distribution of China based on Landsat images (1990–2022) [J/DB/OL]. *Digital Journal of Global Change Data Repository*, 2023. https://doi.org/10.3974/geodb.2023.09.01.V1. https://cstr.escience.org.cn/CSTR:20146.11.2023.09.01.V1.

economic pillar in China's coastal regions. In addition, it provides a significant amount of food and is essential for improving human nutrition. The Food and Agriculture Organization of the United Nations reported that the contribution of aquaculture to fish production worldwide significantly increased from 25.7% in 2000 to 46.0% in 2018[1,2]. However, the rapid expansion of aquaculture has led to various challenges that threaten sustainable development. These issues include the occurrence of red tides, eutrophication of seawater, degradation of wetland resources, and excessive and unjustifiable utilization of water resources[3,4]. Timely access to dependable information regarding the spatial distribution and patterns of aquaculture is of paramount importance to ensure the scientific management of coastal zones and promote sustainable growth of the aquaculture industry. Remote sensing technology offers several advantages over conventional field surveys and statistical approaches. For example, it provides a wide detection range, allowing for the observation of large areas. Additionally, it has a rapid acquisition period, enabling data collection within a short timeframe. Furthermore, remote sensing allows for continuous and dynamic observations, thereby facilitating the monitoring of changes over time. Hence, remote sensing technology is an efficient approach for dynamic monitoring of aquaculture regions[5,6]. Optical imagery offers rich spectral information and broad spatial coverage and has been widely employed to map coastal aquaculture activities[7]. Moreover, remote sensing data provide a long-term historical perspective, allowing the analysis of dynamic changes in aquaculture[8]. Landsat data, which have provided optical remote sensing data since 1984, are particularly valuable for observing dynamic changes in coastal aquaculture. To facilitate the processing of massive and intensive long time-series data, the Google Earth Engine (GEE) platform offers a wealth of remote sensing data along with powerful algorithms and computational capabilities. This study aims to generate a long-term series dataset of land aquaculture ponds and marine aquaculture zones in China from 1990 to 2022 using the GEE platform. This dataset will not only serve as a fundamental resource for policy development and implementation but will also provide a theoretical framework for assessing sustainable development in the aquaculture sector.

2 Metadata of the Dataset

The dataset of the Quadrennial series dataset of coastal aquaculture distribution of China based on Landsat images (1990–2022)[9] is summarized in Table 1.

Table 1 Metadata summary of the Quadrennial series dataset of coastal aquaculture distribution of China based on Landsat images (1990–2022)

Items	Description
Dataset full name	Quadrennial series dataset of coastal aquaculture distribution of China based on Landsat images (1990–2022)
Dataset short name	CAP_MA_China_1990_2022
Authors	Yin, Y. M. AAC-1460-2022, MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, yinyumeng2021@email.szu.edu.cn Zhang, Y. H. GYR-3820-2022, MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, zyhui@szu.edu.cn Hu, Z. W. AAX-7567-2021, MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, zwhoo@szu.edu.cn

(*To be continued on the next page*)

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Items	Description
Authors	Xu, Y. AAX-7694-2021, College of Urban and Environmental Sciences, Central China Normal University, xuyue2022010474@mails.ccnu.edu.cn Wang, J. Z. Q-4555-2019, School of Artificial Intelligence, Shenzhen Polytechnic, jzwang@szpt.edu.cn Wang, C. AAX-7615-2021, Satellite Application Center for Ecology and Environment, Ministry of Ecology and Environment of P. R. China, wangchen_ch@163.com Shi, T. Z. GBX-5637-2022, MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, tiezhushi@szu.edu.cn Wu, G. F. B-8735-2018, MNR Key Laboratory for Geo-Environmental Monitoring of Great Bay Area, Shenzhen University, guofeng.wu@szu.edu.cn
Geographical region	Coastal zones of China
Year	1990–2022
Temporal resolution	4 years
Spatial resolution	30 m
Data format	.tif
Data size	75.6 MB (compressed)
Data files	Four-yearly coastal aquaculture maps 1990–2022 (18 in total), including coastal land aquaculture ponds (9) and marine aquaculture zones (9). The naming convention for coastal land aquaculture ponds is CAP_China_year and for marine aquaculture zones is MA_China_year, where the last four digits are the year
Foundations	Science, Technology and Innovation Commission of Shenzhen Municipality (JCYJ20220818101617037); National Natural Science Foundation of China (42201347)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	***Data*** from the Global Change Research Data Publishing & Repository includes metadata, datasets (in the *Digital Journal of Global Change Data Repository*), and publications (in the *Journal of Global Change Data & Discovery*). ***Data*** sharing policy includes: (1) ***Data*** are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use ***Data*** subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute ***Data*** subject to written permission from the GCdataPR Editorial Office and the issuance of a ***Data*** redistribution license; and (4) If ***Data*** are used to compile new datasets, the 'ten percent principal' should be followed such that ***Data*** records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset[10]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS/ISC, GEOSS

3 Data Processing

The dataset was produced based on Landsat 5 and Landsat 8 imagery provided by the GEE from 1990 to 2022. The coastal aquaculture sample sites were manually collected using Google image data.

The spectral, textural, and solar geometric features of land aquaculture ponds and marine aquaculture zones were analyzed, and key features were selected for classification. Supervised classification based on the random forest algorithm was implemented using the GEE platform. Finally, yearly data were obtained by synthesizing each classification result in a year using multiple algorithms.

3.1 Study Area

Coastal aquaculture is extensively distributed across coastal zones. The coastal zone of China between the estuary of the Yalu River in the north and the estuary of the Beilun River in the south (18.2°N–40.5°N) was selected as the study area. The study area covers 14 provinces, from north to south: Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Taiwan, Guangdong, Hong Kong, Macao, Guangxi, and Hainan.

Offshore and onshore areas are defined as the zone between a 20-km buffer line landward and seaward from the coastline, which can cover all coastal aquaculture areas, based on a series of field surveys and visual interpretation of the latest Google Earth images.

3.2 Algorithms

(1) Otsu method

The Otsu method[11] was employed to automatically distinguish between waterbodies and non-water areas. This method sets the threshold value as the maximum ratio of the interclass variance to the intraclass variance. Subsequently, the pixels with water body index values lower or higher than the determined threshold were classified as non-water or water, respectively. This process ultimately enables the extraction of water bodies.

(2) Random forest algorithm

Features were first selected based on a random forest algorithm according to their importance. Each feature value was transformed into a random number that was used to calculate the impact of the parameter on the accuracy of the model. Multiple calculations were performed, resulting in an average decrease in the accuracy value, which was used to rank features based on their importance. Subsequently, the aquaculture extraction model was trained using a random forest algorithm. In this classification algorithm, decision trees serve as the fundamental building blocks. For each input sample, N trees were used to generate N classification results. The random forest classifier analyses all classification voting results to determine the category with the highest number of votes, which becomes the final output category for the sample data[12]. The output of the random forest method is affected by two crucial factors: the number of decision trees that constitute the random forest algorithm and the number of features employed in each decision tree.

(3) Plural synthesis

The concept of plurality is used in the classification process because of its association with the most frequent data values in the dataset[13]. This approach reduces the risk of misclassifying a diverse range of extractions. Plurality is advantageous because it is a straightforward method that is not affected by extreme data values[14].

3.3 Technical Routes

Figure 1 illustrates the technological process employed to generate the long-term coastal aquaculture dataset using the GEE platform for 1990 to 2022. Aquaculture was first extracted based on each clear image in the year and the extraction results were synthesized using the plural method to generate the annual results. For each image, the following four steps were followed: (1) each image was pre-processed and spectral, texture, topographic, and solar geometry features were extracted; (2) the Modified Normalized Difference Waterbody Index (MNDWI) was used to automatically extract water body areas, including coastal aquaculture; (3) samples were chosen from high-resolution Google Earth images; and (4) feature selection was performed on the extracted features and the top features were selected for random forest classification to obtain the classification results of each image.

An accuracy evaluation was conducted using high-resolution Google Earth images to verify the accuracy of the data.

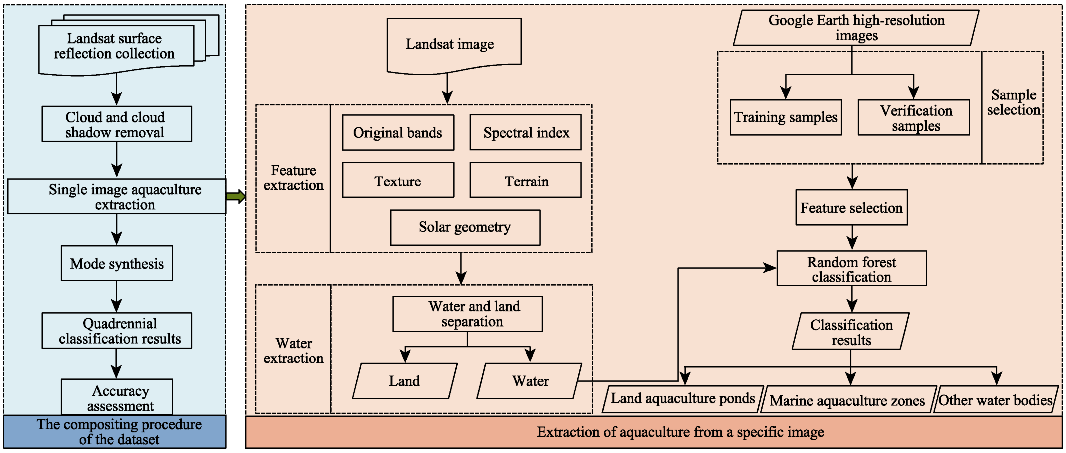


Figure 1 Datasets development flowchart of classification algorithm.

(1) Data pre-processing and feature extraction

This study employed Landsat surface reflectance data obtained from the GEE. Landsat 5 images from 1990 to 2010 and Landsat 8 images from 2014 to 2022 were used. Landsat surface reflectance data contained the QA_Pixel band generated using the mask function (CFMask) algorithm. This band obtains quality information for each pixel, including land, water bodies, clouds, and cloud shadows and retains high-quality observations[15]. Various features such as the vegetation index, water body index, building index, soil index, texture features, and solar geometry features were computed, as elaborated in the Appendix.

(2) Water body area extraction

To enhance the accuracy of the aquaculture extraction, an aquatic land separation technique was employed to reduce the influence of other feature classes. The water body index approach is particularly effective for highlighting spectral distinctions between water and non-water surfaces, making it widely used for water body extraction[16,17]. Several water body indices facilitate the discrimination between water and land to extract water body regions, such as the normalized difference water body index (NDWI), modified normalized difference water body index (MNDWI), two automatically matched water body extraction indices (AWEInsh and AWEIsh), the water index (WI2015), and the multi-band water index (MBWI). A comparative analysis of these indices[18] revealed that MNDWI demonstrates the highest stability. Therefore, MNDWI was used to accentuate the water bodies that were subsequently extracted through a thresholding process using the Otsu method.

(3) Sample selection

Previous research on the classification of aquaculture areas[19, 20] and other pertinent information were considered to develop a classification system consisting of two main categories: water bodies and aquaculture areas. The aquaculture areas were further divided into land aquaculture ponds and marine aquaculture zones and the specific discriminatory signs are shown in Table 2.

To train the classifier, sample points were selected from both the onshore and offshore study areas based on Landsat 5 and Landsat 8 data. The number of sample points for each category is listed in Tables 3 and 4.

Table 2 Visual interpretation of discriminatory signs

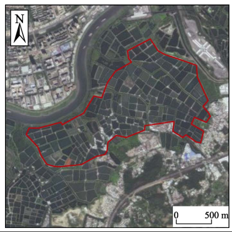
Feature class	Description	Image
Water	Water bodies include rivers, lakes, mudflat wetlands, and offshore waters	
Marine aquaculture zone	Marine aquaculture zones are usually located in bays and near-shore marine waters and include both net-pen aquaculture and raft aquaculture. Net-pen aquaculture areas in shallow marine areas consist of aquatic plastic frames and suspended net-boxes, which are concentrated and regularly rectangular in distribution. The net tank aquaculture facilities are brighter in color in the images compared to the water column. Raft aquaculture facilities consist of aquatic bamboo rafts (for floating) and submerged thick ropes (for securing aquatic products). The raft aquaculture area is characterized by dark grey stripes	
Land aquaculture pond	Land aquaculture ponds are formed by reclaiming coastal wetlands or inland lakes, usually separated by dykes and varying in size. They are regular and compact in shape, with clear boundaries, displaying a regular texture, and the color of the pond is consistent with the surrounding seawater	

Table 3 Number of training samples for aquaculture pond classification

Feature class	Number of samples of Landsat 5	Number of samples of Landsat 8
Water	14,000	14,000
Land aquaculture pond	20,372	20,000

Table 4 Number of training samples for the classification of maritime aquaculture areas

Feature class	Number of samples of Landsat 5	Number of samples of Landsat 8
Water	21,967	26,913
Marine aquaculture zone	8,687	77,25

(4) Feature selection and aquaculture area extraction

In classification tasks, the presence of correlated features can lead to inefficiencies in processing, as well as information redundancy, which ultimately decreases accuracy[21]. To address these challenges, this study employs a random forest feature importance ranking method to reduce the dimensionality of the data.

By leveraging the random forest algorithm, a subset of key features of high importance was selected, enabling the extraction of aquaculture areas based on these selected features. The random forest model was constructed with 100 trees without imposing a maximum depth constraint and with a minimum requirement of one sample per tree node. The number of features per tree was set as the square root of the total number of variables.

(5) Plural syntheses of the classification results

The aquaculture zones were extracted from each image for a year using a random forest classifier (Figure 2a). To determine the final category, the frequency of occurrence of each category was calculated by counting the pixels for each class (Figure 2b). Subsequently, the category with the highest frequency was selected as the final classification result for the year. This process is summarized in Figure 2.

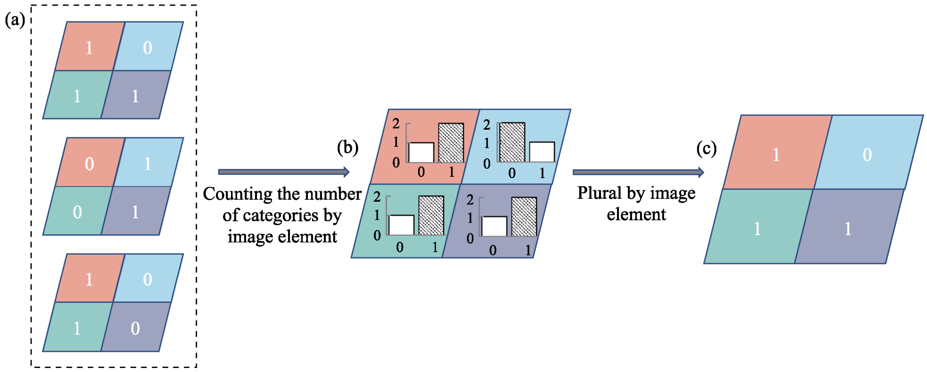


Figure 2 Schematic map of the synthesis of multiple classification results: (a) classification results of dense time series images, (b) number of category statistics results, and (c) final classification results

(6) Accuracy evaluation

In this study, validation sample points were randomly generated and interpreted using Google Earth images. The confusion matrix was calculated by comparing the classification results of the validation sample points with the visual interpretation results, and the overall accuracy and kappa coefficient were used to evaluate the accuracy of the aquaculture area extraction.

4 Data Results and Validation

4.1 Data Composition

The dataset consists of national coastal aquaculture area data from 1990 to 2022 at 4-year intervals, containing land aquaculture ponds and marine aquaculture zones. It has a spatial resolution of 30 m and is in .tif format.

4.2 Data Products

Over the past 32 years, the area of China's coastal aquaculture initially increased and then decreased. As shown in Figure 3a, from 1990 to 2014, the area of land aquaculture ponds showed an overall increase from 13,140.19 to 16,650.04 km^2, with a net increase of 3,509.85 km^2 (146.24 km^2/year). The largest increase occurred between 1994 and 1998 (2,892.07 km^2, 723.02 km^2/year). From 2014 to 2022, the total area of coastal land aquaculture ponds in China continually declined from 16,650.04 to 13,763.29 km^2, with a net loss of 2,886.75 km^2 (360.84 km^2/year). The largest decline occurred between 2018 and 2022 (1,862.24 km^2, 465.56 km^2/year).

As shown in Figure 3b, marine aquaculture zones showed a continuously increasing trend from 1990 to 2022, increasing from 4,577.21 to 10,769.00 km^2, a net increase of 6,191.78 km^2 (193.49 km^2/year), with the largest increase occurring between 1990 and 1994 (1,660.58 km^2, 415.14 km^2/year)

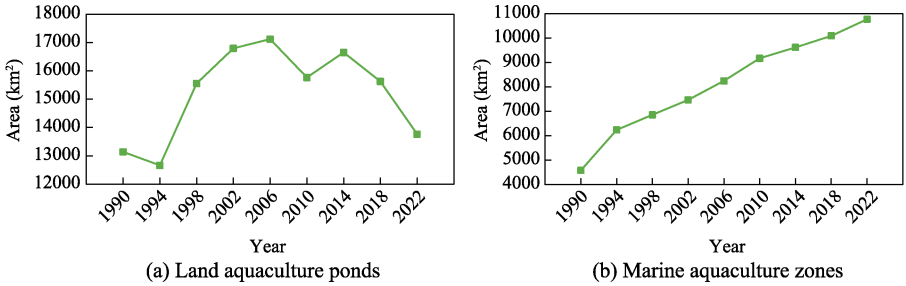


Figure 3 Changes in coastal aquaculture areas of China from 1990–2022

As shown in Figure 4a, Shandong had the largest area of land aquaculture ponds in 2022 (22.95% of the total land aquaculture pond area), followed by Liaoning (accounting for 15.55%), Guangdong (accounting for 14.80%), Hebei (accounting for 10.83%), and Jiangsu (accounting for 10.36%). Together, these five provinces account for 74.49% of the total area of aquaculture ponds along the Chinese coast. While Hainan, Guangxi, Shanghai, Hong Kong, and Macao only accounted for 4.78%.

As shown in Figure 4b, Fujian province had the largest area of marine aquaculture zones in 2022 (accounting for 37.98%), followed by Zhejiang (accounting for 21.43%), Shandong (accounting for 15.05%), and Guangdong (accounting for 10.50%). Together, these four provinces accounted for 84.96% of the total area of marine aquaculture zones. Hong Kong, Shanghai, Hebei, Tianjin, and Macao only accounted for 0.99%.

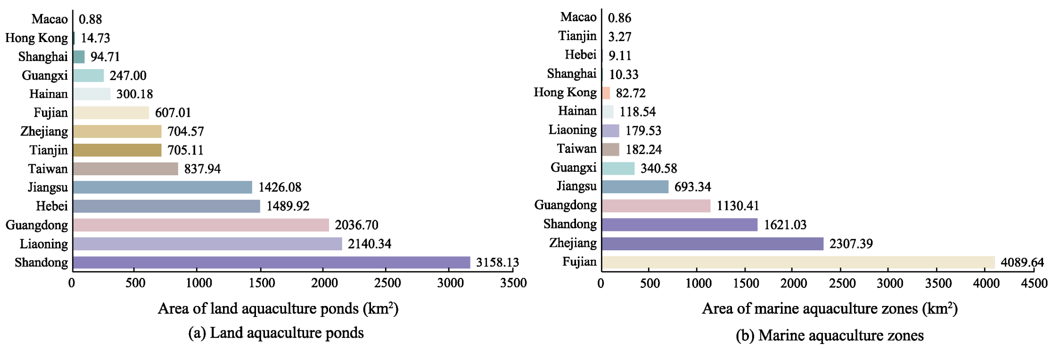


Figure 4 Aquaculture zone areas in China by province in 2022

4.3 Data Validation

In total, 6,000 random points (1,000 land aquaculture ponds, 1,000 marine aquaculture zones, and 4,000 others) were generated and evenly distributed in the study area. Google Earth imagery for each year from 1990 to 2022 was used as a base map for visual interpretation to identify land aquaculture ponds, maritime aquaculture areas, and other areas. A confusion matrix was generated from the visual interpretation and classification results to derive kappa coefficients and overall accuracy. The results of the accuracy evaluation for each year are shown in Figure 5. The average overall accuracy of the remote sensing mapping results was 96.25% and the average kappa coefficient was 0.92. The overall accuracy for all years was not less than 95.00% and the kappa coefficient was not less than 0.90, indicating that the set of remote-sensing mapping products had high classification accuracy.

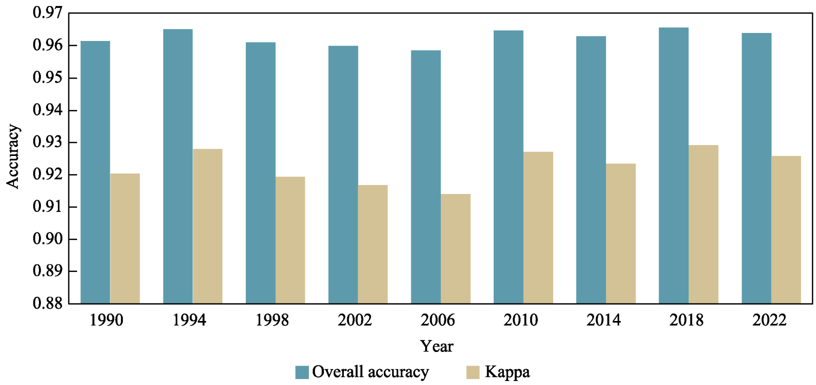


Figure 5 Statistics of the overall accuracy and kappa coefficients of the dataset

5 Discussion and Conclusion

This study determined the distribution of coastal aquaculture areas in China from 1990 to 2022 using long time series Landsat imagery based on the GEE platform. The dataset covers the entire coastal zone of China with a spatial resolution of 30 m and temporal resolution of four years. The validation results showed that the dataset has high accuracy, with an overall accuracy of 96.25%. The dataset can be applied to analyze the evolution of coastal aquaculture areas in China, providing important support for policy formulation and implementation, as well as a scientific basis for assessing sustainable development.

Author Contributions

Hu, Z. W., Wang, C., and Wu, G. F. designed the algorithms for the dataset. Yin, Y. M. and Xu, Y. collected and processed the samples and remote-sensing image data. Zhang, Y. H. and Shi, T. Z. designed the model and algorithm. Yin, Y. M. and Xu, Y. performed data validation. Yin, Y. M., Zhang, Y. H., and Hu, Z. W. wrote the paper.

Conflicts of Interest

The authors declare no conflicts of interest.

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