A Review of Model Training and Development in Satellite Remote Sensing Imagery

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Abstract

Satellite remote sensing imagery is a technology that captures images of the Earth's surface using sensors mounted on satellites in Earth's orbit. It plays a vital role in numerous fields, including geographic information systems, environmental monitoring and protection, urban planning and management, disaster response, and climate change research. The versatility and efficiency of satellite remote sensing imagery make it indispensable in modern technology, providing both macroscopic and microscopic insights into Earth observation. With advancements in remote sensing technology, its applications continue to expand. However, in practice, there are discrepancies between the quality of sample data derived from satellite remote sensing imagery and real-world conditions. These discrepancies may arise from cloud cover, sensor noise, low resolution, seasonal variations, or environmental changes. For example, cloud occlusion often leads to invalid pixel regions, while time-phase mismatches and poor raw image quality severely impact downstream processing. In water environment monitoring, limitations such as rapid temporal changes in water bodies further complicate data acquisition and analysis. To address these challenges, researchers have proposed robust solutions to enhance the quality and reliability of remote sensing image processing.

Keywords Remote Sensing Technology and Application; Artificial Intelligence; Remote Sensing; Remote Sensing Detection; Process Quality Control

1 Data Cleaning and Data Fusion Technology

During remote sensing image acquisition, external and technical limitations often degrade image accuracy. In order to solve these effects, experts began to study some major influencing sources and take measures to improve image accuracy.

Cloud cover, in particular, poses a significant challenge by attenuating or even obliterating ground information. Cloud detection and removal for medium-resolution imagery are critical for automated applications. Various methods, including threshold-based approaches, machine learning algorithms, multi-temporal image interpolation, and spatiotemporal interpolation, have been developed to address cloud occlusion [1].

Wavelet transform decomposes images into multi-resolution components, enabling the removal of cloud noise while preserving details. Data fusion techniques integrate multi-temporal or multi-sensor data to replace cloud-covered regions. Spatial statistical methods leverage spatial autocorrelation to estimate and interpolate obscured areas.

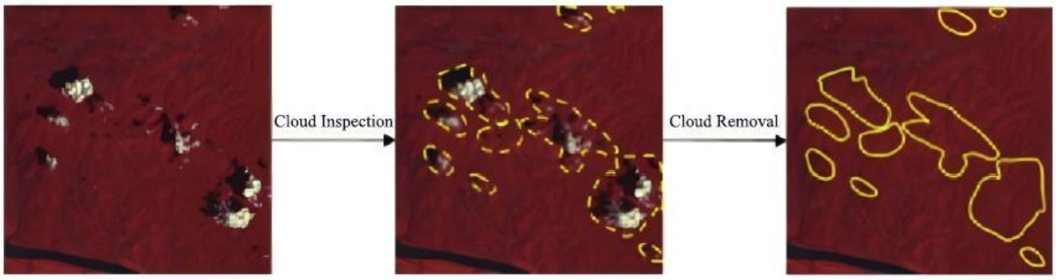

Fig. 1. Flow Chart of Thick Cloud Removal

Chen Yao, Wang Jinliang, and Li Shihua also studied and analyzed various cloud elimination methods. Homomorphic filtering is a frequency-domain-based image processing method that enhances high-frequency components to improve image contrast while removing low-frequency noise, such as cloud cover. Wavelet transform can use multi-resolution analysis to decompose the image into different frequency components, select low-frequency components from them and remove cloud cover noise, and can simultaneously save image details. Data fusion technology combines data from multiple time phases or multiple sensors to replace areas covered by clouds to eliminate the influence of clouds. Spatial statistical methods are based on spatial autocorrelation and use information from known regions to estimate and interpolate cloud-covered regions.

In view of the problem of cloud occlusion, a proposed method combines histogram specification to reduce grayscale differences between original and replacement images, alongside feature point extraction, global relaxation matching, and small-facet triangulation correction. The grayscale difference algorithm is defined as follows:

Let the probability density function of the original image be p(y), and that of the replacement image be q(x). Then,

$$Z_x = f_1(x) = \int_0^x p(v)dv\,, \quad z_y = f_2(y) = \int_0^y q(v)dv \qquad (1)$$

Under the condition Zy=Zx, the mapping $f_2^{-1}[f_1(x)]$ is determined to adjust the grayscale values of the replacement image pixel-wise.

Feature Point Extraction:

Within a3×3 window centered at an initial point (c,r), the covariance matrix N and the circularity qc,r, of the error ellipse are calculated using the Forstner operator:

$$N = \begin{vmatrix} \sum g_x^2 & \sum g_x g_y \\ \sum g_x g_y & \sum g_y^2 \end{vmatrix}, \quad q_{c,r} = \frac{4Det\ N}{(tr\ N)^2} \qquad (2)$$

where gx and gy represent gradients along the x and y directions, respectively.

Let P=[Pij] be an m×n matrix, where Pij denotes the matching probability between (Ai,Bj).

Initialize p_{ij}^0 using the correlation coefficient within the registration window.

During the l-th iteration, the support probability $S^l(i,j;h,r)$ from a homologous point pair (Ah,Br) to (Ai,Bj) is defined as:

$$S^l(i,j;h,r) = p_{hr}^l \min\left(\frac{d_{ih}}{d_{jr}}, \frac{d_{jr}}{d_{ih}}\right) \qquad (3)$$

where dih and djr are distances between points.

Update the matching probability:

$$p_{ij}^{l+1} = p_{ij}^l . S_{ij}^l \qquad (4)$$

$$S_{ij}^l = \sum_{\substack{h=l \\ h\neq i}}^{m} W_h \begin{bmatrix} maxS^l(i,j;h,r) \\ l \leq r \leq n \\ r \neq j \end{bmatrix} \qquad (5)$$

Points with p_{ij}^l>T (threshold T≈1) are identified as homologous pairs.

This method resolves registration and correction issues between original and replacement images, ensuring smooth grayscale transitions near seams through feathering techniques [2].

In some cases, dehazing methods have shown superior performance in thick cloud removal compared to homomorphic filtering and Fourier transforms [3].

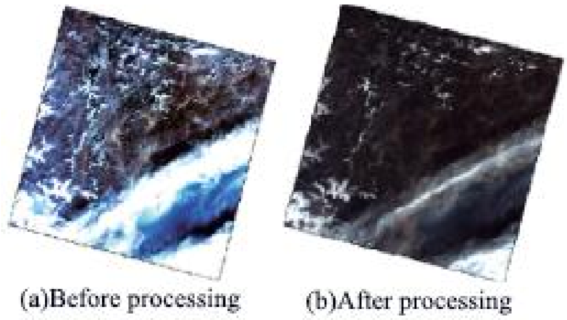

Fig. 2. Haze Removal

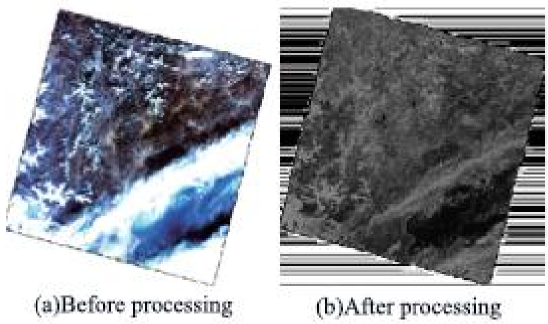

Fig. 3. Fourier Transform

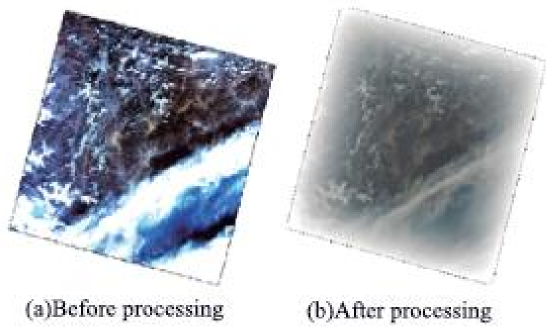

Fig. 4. Homomorphic Filtering

Cloud cover is not the only obstacle. To improve the clarity and accuracy of images, image denoising technology is indispensable in satellite remote sensing. The system can use image denoising technology to remove noise from images, so as to achieve the purpose of making the images clearer and more accurate. Deep learning-based denoising models such as CNN and GAN can also be used for model training and image denoising, or traditional image processing methods can be used to train denoising models to denoise the images projected by the images, thereby improving the quality of satellite remote sensing images.

Using remote sensing image data from different sensors or different times for integration and fusion to improve higher multi-faceted resolution, thereby enhancing the analysis and application capabilities of remote sensing data. In order to improve the accuracy of remote sensing monitoring, operations such as increasing contrast, noise reduction, sharpening, and color correction can be performed on the images to improve the clarity and visualization effect of the images. The processed images can clearly distinguish the types of ground objects, the image tones are uniform, the textures are clear, the contrast is moderate, and the colors are close to natural true colors [4].

2 Process Quality Control

Samples should build a comprehensive quality management system to implement whole-process quality control, with a focus on monitoring important content, key nodes and weak links in the project, including checking the overlap, noise, spots, bad lines and cloud and snow cover of the images, and ensuring that the side view angle meets the requirements of the regulations. Carry out a systematic quality standard processing process, including atmospheric correction, radiation calibration, image fusion, uniform color processing and DOM (Digital Orthophoto Map) generation and other key links. Through these processes, image distortion and distortion caused by sensors and atmospheric conditions can be eliminated, and the comparability and interpretability of data can be improved. At the same time, continuous inspection of the process quality can grasp the production unit's control of the production process quality, timely find serious or common problems affecting the quality of finished products, strengthen quality management in the production link, and eliminate quality hidden dangers to the greatest extent in the production link.

To test whether the production unit has mastered the technical requirements of the technical design book and the production process flow, and whether it can carry out mass production, an appraisal and inspection of the quality of the first piece of finished product must be conducted. Process quality checks are carried out for multiple key processes of the entire process in turn, and the technical capabilities and characteristics of the production unit are analyzed, and the relatively weak production links are summarized and focused on and investigated at the end point. Through long-term attention and inspection of the production progress, problems are found and hidden dangers are eliminated in time [5].

Table 1. Quality Inspection Content of Achievements

Quality Elements	Inspection Content
Spatial Reference System	Verify compliance of the geodetic datum and projection parameters with specifications.
Positional Accuracy	Check if the errors in the planimetric location of images, thegeometric registration errors between multispectral and panchromaticimages of the whole scene, and the edge matching accuracy meetthe required level of precision. Confirm documentation of exceptional cases in metadata or technical reports.
Logical Consistency	Verify file storage structure, organization, naming conventions, and formats. Ensure there are no missing, extra, orunreadable files.
Temporal Accuracy	Check timeliness and relevance of imagery data.
Image Quality	Inspect coverage, ground resolution, color mode, and chromatic characteristics. Ensure there is no unreasonable image noise or information loss.
Attachment Quality	Validate completeness and accuracy of metadata. Ensure deliverables are complete and standardized.

Regarding the quality problems of images, Zhang Yongjun et al. proposed the following solutions that can improve the clarity, authenticity and integrity of images. In multi-temporal images, the cloud area is regarded as an invalid pixel area, and the matrix low-rank information of multi-temporal images can be used for repair, and the original information of the non-cloud area should be preserved as much as possible. For the production method of large-scale remote sensing images, it is necessary to mosaic multiple images. When the colors of images taken in different regions are different, the color consistency processing method can be used to eliminate the color difference between images to improve the quality of splicing and make the images easier to distinguish. At the same time, if you want to improve the positioning accuracy of the image, you can use the area network adjustment technology that combines and integrates geometric and semantic information for joint constraint, especially when there are ground objects such as high-rise buildings and trees that affect the DEM elevation accuracy [6].

3 Temporal Analysis Methods

Due to the complex natural phenomena on the surface, remote sensing image technology is difficult to deal with natural diversity. Many experts have studied the different characteristics formed by seasonal changes and environmental changes and given effective solutions.

After studying the sea surface temperature inversion model based on deep neural network, and using deep learning for land cover and land use classification research, Wang Qiao proposed the application of deep learning and machine learning algorithms, such as joint deep learning, adaptive neural network, etc. to train AI, classify and feature process and extract according to images acquired at different times, automatically extract key feature information from high-resolution images, and integrate deep information and shallow ground objects by introducing attention mechanism. Information such as shape, structure, texture and hue to achieve the purpose of improving the analysis accuracy and efficiency of remote sensing data [18].

According to a study using change detection technology based on remote sensing images to analyze the changes in multi-temporal remote sensing images, Liu Sicong et al. proposed to identify the differences between images at different times through change detection technology, revealing the impact of environmental or seasonal changes on surface features [19].

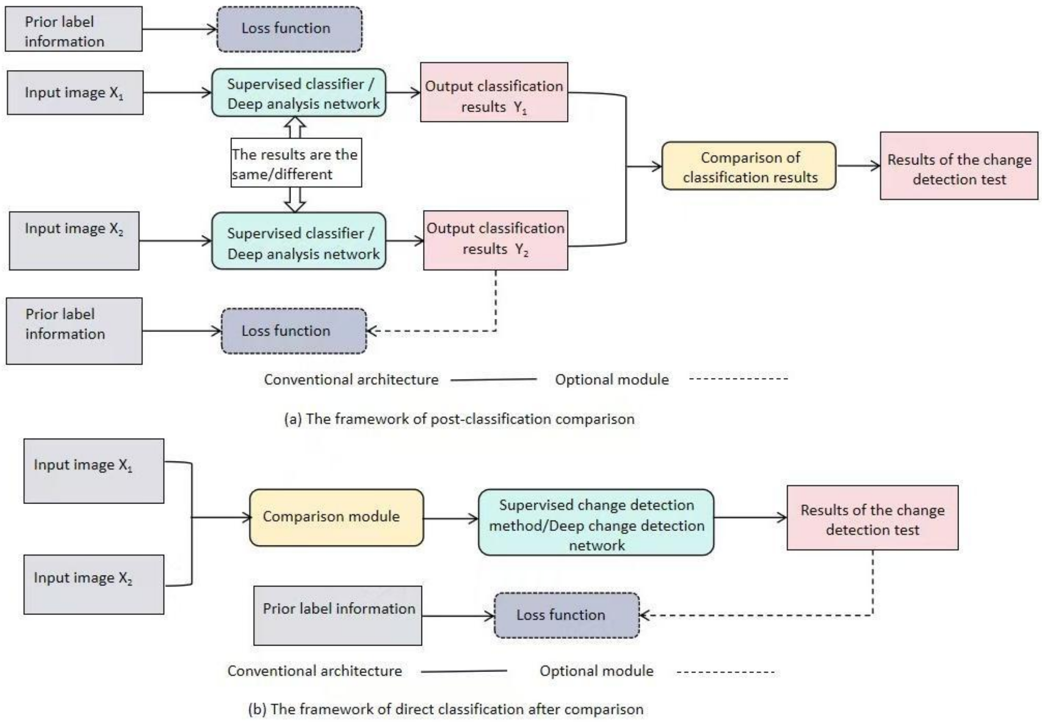

Fig. 5. Framework of Two Supervised Change Detection Techniques

Kuang Wenhui et al. used data from satellite remote sensing such as Landsat 8 OLI and GF-2 to develop vector data of land use change in China and a database of land use status, and analyzed the spatiotemporal characteristics of land use change in China from 2015 to 2020. Therefore, it is proposed to establish a spatiotemporal database of land use or cover change through continuous monitoring, and analyze and understand the overall law and regional characteristics of land use change remote sensing [20].

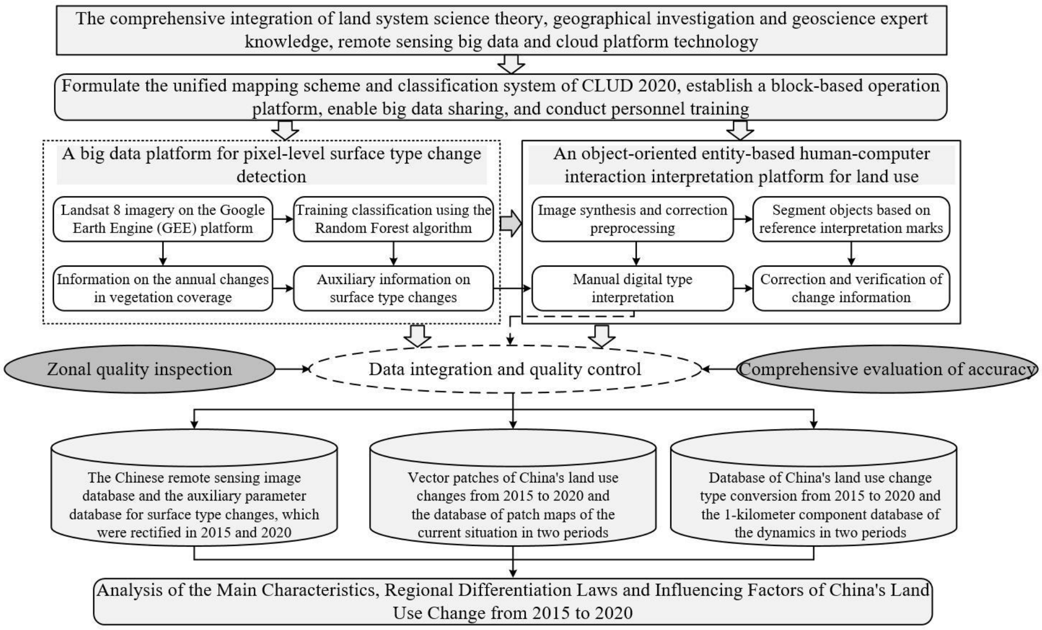

Fig. 6. Technical Process for Updating Land Use Change in China from 2015 to 2020

After long-term analysis of changes in some geographic areas, Yao Jiepeng, Yang Leiku, Chen Tan, and Song Chunqiao proposed that by fusing remote sensing data acquired at different times, the image feature differences caused by environmental or seasonal changes can be reduced. For example, combined with the random forest classification algorithm, using time-series images of multi-source remote sensing data such as Sentinel-1, 2 and Landsat 8, with the support of the cloud platform, large-scale multi-temporal wetland information extraction can be realized. The seasonal index method is used to analyze the seasonal changes of wetlands.

Among them, the seasonal index uses the arithmetic average method to calculate the relative number of monthly or quarterly changes of a certain index time series within a year:

$$S_k = \frac{\overline{x_k}}{\bar{x}}, \qquad \overline{x_k} = \frac{\sum_{i=1}^{n} x_i k}{n}, \qquad \bar{x} = \frac{\sum_{i=1}^{n} \sum_{i=1}^{m} x_i k}{nm} \tag{6}$$

where xk denotes the average value for month k in year i, m is the number of months, and n is the number of years.

At the same time, using cloud platforms such as Google Earth Engine's large-scale computing and storage capabilities, multi-temporal remote sensing data can be efficiently analyzed and processed to obtain and detect surface conditions and environmental change information. In order to better solve the spectral confusion and mixed pixel problems in pixel classification and improve the accuracy of classification, object-oriented classification methods can be used to deal with similar problems [21].

4 Challenges Faced by Remote Sensing Images in Water Body Analysis

Satellite remote sensing technology can provide key information in sudden natural disasters, provide detailed data support for the deployment of rescue forces, and help understand the scope and severity of disaster impact. Because of the rapid and continuous nature of water bodies, the state of water areas is even more difficult to predict than clouds. In order to solve the difficult problem of large-scale dynamic monitoring of surface water bodies with rapid, continuous, and high-resolution remote sensing, it is necessary to integrate remote sensing data of different resolutions to achieve high spatiotemporal resolution dynamic monitoring of surface water bodies, which can solve the problem of effective data loss. At the same time, to ensure data accuracy, the original data needs to go through pre-processing steps such as radiation correction, geometric correction and atmospheric correction. Users can further analyze through remote sensing image processing software, such as image classification, target detection, etc [28].

The insufficient coverage of monitoring station networks is also a major problem for monitoring water areas. Due to incomplete monitoring elements, the monitoring accuracy, density and real-time performance of the ground cannot meet the needs of business applications. To solve this problem, the combination of high-resolution space, aerial remote sensing technology and ground hydrological monitoring technology can be used to promote the establishment of a "space-air-ground" collaborative monitoring and perception system for the watershed, which will provide great help for remote sensing monitoring capabilities [29].

The spatiotemporal distribution characteristics of water bodies are of great significance for water resource monitoring and application. Satellite remote sensing data is used to extract parameters such as water body location, area, shape and river width, especially for the quantitative analysis of water bodies in high mountain uninhabited areas, which has the advantages of saving manpower and improving work efficiency. At the same time, optical images and SAR images are also used in water body recognition. The two have their own advantages and limitations. Optical remote sensing data is greatly affected by clouds and shadows, while SAR data can provide all-weather and all-time data. However, in complex mountainous areas, the impact of shadows on data is huge. In order to make up for their respective shortcomings, it is necessary to combine SAR and optical remote sensing images, or auxiliary information such as DEM, to establish corresponding models to realize the extraction of water bodies. Combining the two can improve the accuracy of water body extraction. Specific usage methods include, for example, using unsupervised classification methods to extract water bodies from optical images, and then using SAR data for mask refinement [30].

Table 2. Detailed Classification of Water Body Information Extraction Methods

Method	Sub - category Classification		Working Principle
Threshold Method	Single - band Method		Utilize the strong absorption characteristics of water bodies in the near - or mid - infrared bands to extract water body information
	Multi-band Method	Spectral Relationship Method	Based on the spectral characteristic curves of water bodies in different bands, select appropriate bands to construct a model for extracting water body information
		Ratio Method	
		Difference Method	
		Water Index Method	
		......	
Classification Method	Support Vector Machine Method		Based on the selected algorithm rules, in the high - dimensional feature space, use machine learning algorithms for optimal classification and extract water body information
	Decision Tree Method		Based on spatial data mining and knowledge discovery methods, extract water body information by determining classification attributes
	Object - Oriented Method		Extract water body information by segmenting images to keep the maximum homogeneity within objects and the maximum heterogeneity between objects
	......		

Deep learning plays an important role in monitoring water bodies. Deep learning methods can effectively remove the influence of shadows and buildings, which were the main problems restricting the accuracy of water body extraction. For example, convolutional neural networks and Deeplabv3 methods have achieved accuracies of 95.09% and 92.14% respectively, which are higher than the traditional water body index method, object-oriented method and support vector machine method [31].

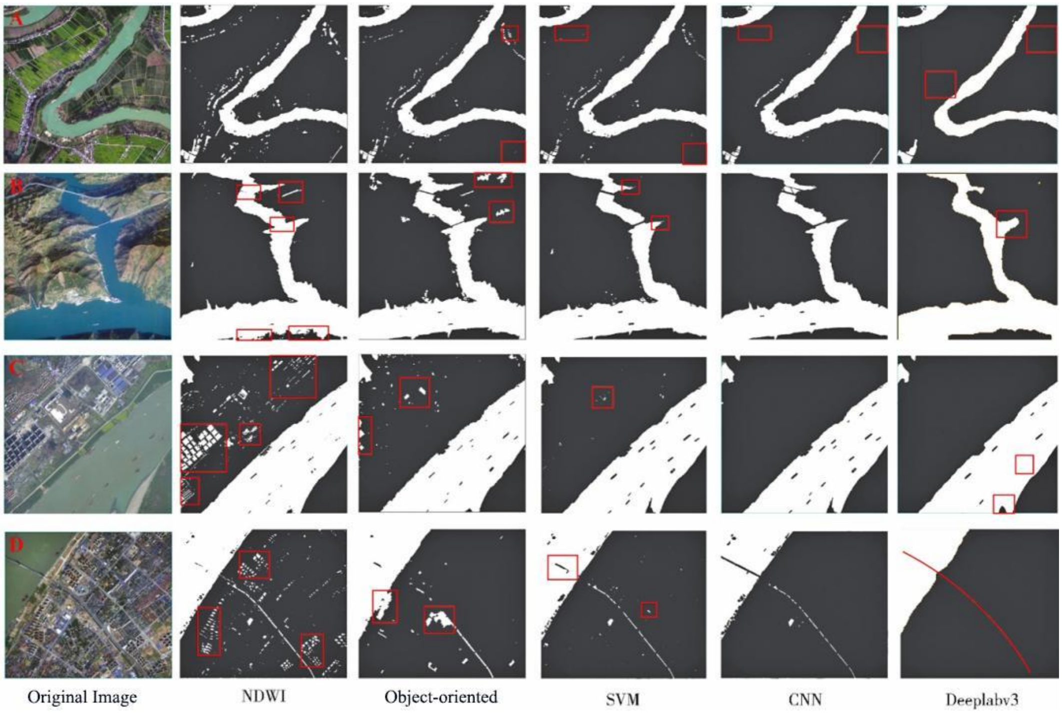

Fig. 7. Water Body Extraction Results of Different Methods

Some use deep learning semantic segmentation models to achieve higher accuracy than existing methods, and also improve the prediction speed. The algorithm parameter settings are relatively simple and less subject to manual intervention [32]. Some studies have optimized the structure of the U-Net network and used a combined loss function to solve the problem of data shallow feature loss or data imbalance, and also enhance the network's ability to extract image features, and improve the sensitivity to detailed water bodies [33].

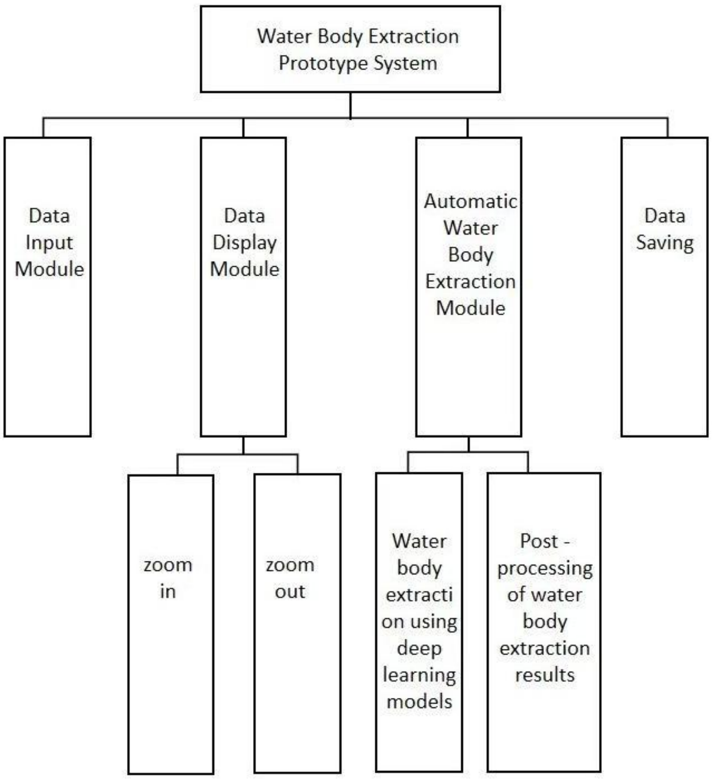

Fig. 8. Automatic Water Body Extraction Module

5 Current Issues and Challenges

Satellite the threshold method in cloud detection is fast and is easy to implement, but it requires more prior knowledge and manual settings, and it is subjective and limited in applicability. Spatial change detection methods rely on time information, which limits their application and requires different strategies for different situations. When removing thick clouds, the spatial interpolation method may not work well due to the lack of cloud-free areas. Homomorphic filtering and wavelet transform may weaken background information and reduce image quality. Remote sensing data is limited by multiple resolutions, affecting information acquisition and application. Multiple resolutions are difficult to be compatible, which may change the comprehensiveness and accuracy of the data. Satellite remote sensing mainly acquires surface information, making it difficult to penetrate below the surface, limiting the understanding of the deep layers. Multiple satellites are difficult to coordinate, limiting the comprehensive coverage of specific application needs. Data fusion technology needs to solve the problems of image registration and radiation difference, which may affect the timeliness and spatial resolution. Spatial statistical methods work well for flat terrain areas, but when the terrain is complex or the occluded area is large, the interpolation accuracy may decrease.

The control and improvement of satellite remote sensing images may be a challenge for small or resource-constrained units to build and implement a comprehensive quality management system. Continuous quality inspection requires a lot of time and resources, which is a burden for units with heavy economic burdens. Technological improvements and process adjustments may require additional training and supervision. Some technical processing procedures, such as atmospheric correction and radiation calibration, require a lot of computing resources and professional knowledge.

Multi-temporal remote sensing data fusion may cause data inconsistency when fusing data, and data assimilation issues need to be considered. Deep learning and machine learning algorithms require a large number of training samples, and the generalization ability of the model needs further research [34]. Change detection technology may be limited by the spatiotemporal resolution and band settings of the data, and the data source needs to be optimized. Remote sensing mapping and spatiotemporal feature analysis face data barriers and coordination difficulties, and require the realization of full-process service capabilities. The processing of the cloud platform needs to ensure data compatibility and consistency, and achieve the continuity of observation and data sets. Object-oriented classification may require in-depth coupling of remote sensing technology and water conservancy models to achieve deeper simulation [35].

6 Conclusion

Satellite remote sensing images have become an important means for us to understand and monitor the Earth's surface. In this review, we have made efforts to improve satellite remote sensing image technology by studying data cleaning technology and data fusion technology, controlling process quality, and time series analysis methods. Through the application of data cleaning, fusion technology, process quality control, and time series analysis methods, we can solve the problems of cloud occlusion, sensor noise, and resolution limitations, which can greatly improve the quality, authenticity, clarity and integrity of images and enable wider applications. The management, economic, technical and other aspects of the problems and challenges faced by the application of the technology are also carefully analyzed. The quality management of the finished products needs to build a comprehensive quality management system, carry out process quality control, analyze the technical capabilities of the production unit, etc., all of which require careful organization, sufficient resources and professional knowledge. In addition, the capability limitations of deep learning and machine learning algorithms, the adaptability of change detection techniques, and the consistency of multi-temporal data fusion are all important issues that need further research and resolution in the remote sensing field today.

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衛星遙感影像的模型訓練研究綜述

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摘要：衛星遙感圖像是一種使用安裝在地球軌道衛星上的傳感器捕獲地球表面圖像的技術。它在許多領域發揮著至關重要的作用，包括地理信息系統、環境監測和保護、城市規劃和管理、災害應對和氣候變化研究。衛星遙感圖像的多功能性和高效性使其在現代技術中不可或缺，為地球觀測提供了宏觀和微觀的見解。隨著遙感技術的進步，其應用不斷擴大。然而，在實踐中，從衛星遙感圖像中獲得的樣本數據的質量與現實世界條件之間存在差異。這些差異可能源於雲層覆蓋、傳感器噪聲、低分辨率、季節變化或環境變化。例如，雲遮擋通常會導致無效的像素區域，而時間相位失配和原始圖像質量差會嚴重影響下遊處理。在水環境監測中，水體快速的時間變化等限製使數據采集和分析更加復雜。為了應對這些挑戰，研究人員提出了穩健的解決方案，以提高遙感圖像處理的質量和可靠性。

關鍵詞：遙感技術與運用；人工智能；遙感；遙感偵測；過程質量控製