Integration and Intelligent Monitoring Technology System of Space-Air-Ground Remote Sensing and Its Applications

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Abstract

Multi-source remote sensing technology finds extensive application in natural resource management, ecological and environmental conservation, disaster response, and other fields. However, current challenges include shortcomings in multi-modal data governance, insufficient generalization capabilities in intelligent remote sensing interpretation, and inadequate coordination in monitoring applications. This paper focuses on the Integration and Intelligent Monitoring Technology System of Space-Air-Ground Remote Sensing, centering on three core technologies: multi-source data governance and collaborative association, component-based AI interpretation model development, and application agent construction based on multi-modal large models. It establishes a multi-modal data foundation through standardized data processing and cross-source retrieval, achieves precise multi-task interpretation via a flexible component-based architecture, and leverages application agents for natural language instruction parsing, autonomous task planning, and automated execution of multi-algorithm task chains. This forms a closed-loop"perception-cognition-decision-execution" closed-loop system. Through an applied case study of an ecological restoration project at an abandoned mine in Hunan Province, China, this research validated the feasibility and effectiveness of the system in comprehensively coordinating multi-source data, achieving intelligent identification of surface cover changes, and enabling full-cycle monitoring and evaluation. It provides efficient intelligent technical support for natural resource management.

1. Introduction

Global Earth observation is undergoing a paradigm shift from "data acquisition" to "intelligent services", characterized by online access, real-time updates, and smart applications.In recent years, global space-air-ground sensing data has become increasingly abundant. In the field of Earth Observation Satellite Remote Sensing, a diversified and multi-scale satellite observation system has been established, with core components including the U.S. Landsat and WorldView, Europe's Sentinel, and China's Ziyuan (ZY) and Gaofen (GF) series. This system offers advantages such as large-scale, all-time, all-weather, and periodic Earth observation, enabling the rapid, macroscopic, and dynamic acquisition of surface imagery. In the filed of aerial remote sensing, new equipment like unmanned aerial vehicles (UAVs), light aircraft, and aerostat have been deployed at scale. Some systems have already achieved fully intelligent operations, including autonomous inspections and self-charging capabilities. In the field of ground-based surveys, a station network has been established utilizing tower-mounted video observation and field fixed-point monitoring. This system enables comprehensive stereoscopic monitoring of ecology, atmosphere, soil, crops, and more. These sensing techniques have been widely implemented in a variety of monitoring applications, including dynamic ecological change(e.g., vegetation cover(Balata et al., 2022), biodiversity(Stephenson, 2020), soil erosion(Ji et al., 2024)), nature resource development (e.g., mineral extraction(Q. Li et al., 2024), water resource allocation(Ibrahim et al., 2024), land-use change(Schulz et al., 2021)), and disaster emergency response(e.g., forest fire monitoring (Chen and Liu, 2025), flood inundation (Gambardella et al., 2022), geological hazards (Auflič et al., 2023)).

Internationally, research in the field of integrated air-ground remote sensing monitoring exhibits characteristics of systematic and large-scale development.The European Union's Copernicus Incubation programme aims to build an integrated system of "Space-based observations + Aerial/Ground-based measurements + Data services." Through its multiple Sentinel satellites, it provides global environmental monitoring data, with its data products widely used in land, ocean, and atmospheric monitoring(Aschbacher and Milagro-Pérez, 2012). The U.S. Department of Defense has been advancing the concept of Multi-Domain Operations (MDO), which involves the integration and coordination of networks across land, sea, air, and space dimensions(Minculete, 2023). China has also established comprehensive monitoring systems such as the "Stereoscopic Remote Sensing Monitoring System of Ecological Environment with Five-Based Synergy"(Wang et al., 2024), the "Sky-space-earth-water-project"(Qian et al., 2024), and the "Forest-Grassland Ecological Network Perception System"(Zhao et al., 2024).In recent years, scholars have also begun to focus on how to achieve more comprehensive and accurate environmental perception and situational awareness by integrating data from different platforms and sensor types (Zhang et al., 2021).Based on diverse payload data from satellites and UAVs, including optical, SAR, hyperspectral, and thermal infrared imagery, scholars have conducted extensive research in land use change monitoring(Schulz et al., 2021), crop identification and monitoring(Z. Li et al., 2024), and ecological monitoring(Jiao, 2024).

However, current Space-Air-Ground remote sensing collaborative intelligent monitoring still faces shortcomings in data governance, model generalization capabilities, and collaborative applications. First, deficiencies in multi-modal data governance are prominent. Multi-modal data sources are diverse and vary in format, while inadequate data quality control, version management, and end-to-end traceability capabilities constrain comprehensive application effectiveness. Second, remote sensing intelligent interpretation suffers from insufficient generalization capabilities. Current remote sensing interpretation models predominantly focus on single-element, single-task, and single-region approaches, making cross-task reuse challenging. Concurrently, multi-modal large models remain immature, with insufficient semantic alignment and collaborative inference stability, making it difficult to meet the refined interpretation demands for monitoring various natural resource elements.Third, there is a lack of collaborative capabilities in monitoring applications. Current natural resource monitoring heavily relies on manual expertise, with insufficient adaptability and scalability for diverse scenarios. Multi-source data and various models and tools operate in "siloed" states, resulting in weak collaborative execution capabilities. There is inadequate linkage between monitoring outcomes and operational responses, hindering the formation of a closed-loop application cycle encompassing "detection, analysis, response, and feedback".

Therefore, this paper focuses on the technology system of integrated intelligent sensing in Space-Air-Ground remote sensing. By integrating data from different platforms and sensor types through deep collaboration, it establishes an integrated dispatch platform for satellites, UAVs, and tower-based video systems. Research core technologies including multi-source data governance and collaborative association, component-based AI interpretation model development, and application agent construction based on multi-modal large models. Selecting representative ecological regions, conduct full-cycle monitoring application trials of land ecological restoration changes through Space-Air-Ground collaboration to validate the feasibility of the proposed technical approach. This addresses the increasingly urgent demand for high-precision, high-frequency, near-real-time monitoring in land change surveillance, natural resource development and utilization, and disaster emergency response.

2. Methodology

This paper establishes an intelligent monitoring technology system for natural resources that integrates airborne, ground-based, and spaceborne remote sensing, as shown in Figure 1. It focuses on core technical methodologies including multi-source data governance and collaborative association, development of component-based AI interpretation models, and construction of application agents based on multi-modal large models.
First, integrate multi-source data including satellite images, UAV images, and tower-based videos. Conduct data governance and collaborative association through standardized workflows such as automated geometric correction, radiometric normalization, cloud/fog detection, and quality assessment to establish a multi-temporal image base map with unified spatio-temporal reference. Implement cross-source retrieval of satellite map images via deep hash coding, forming a multi-modal data foundation for cross-referencing and mutual verification.
Concurrently, construct a modularized multi-task intelligent remote sensing interpretation model framework.Employing a flexible encoding-decoding architecture that supports multiple backbone networks, it integrates pluggable components such as atrous spatial pyramid pooling(ASPP)(He et al., 2014), attention mechanisms, and visual Transformers(Vaswani et al., 2017). This enables the extraction of multi-scale spatial context and semantic features, supporting precise interpretation across diverse tasks including land cover classification, change detection, and object recognition.

Furthermore, by building remote sensing monitoring application agents based on multi-modal large models, a closed-loop system of "perception-cognition-decision-execution" is formed. Fine-tuned large language models interpret natural language commands, dynamically plan task chains, and intelligently allocate resources. Diverse data processing, interpretation, and analysis algorithms are encapsulated as toolkits, enabling end-to-end automation through workflow engines. Continuous model performance optimization occurs via human-machine feedback loops, achieving autonomous execution and decision support for complex remote sensing monitoring tasks.

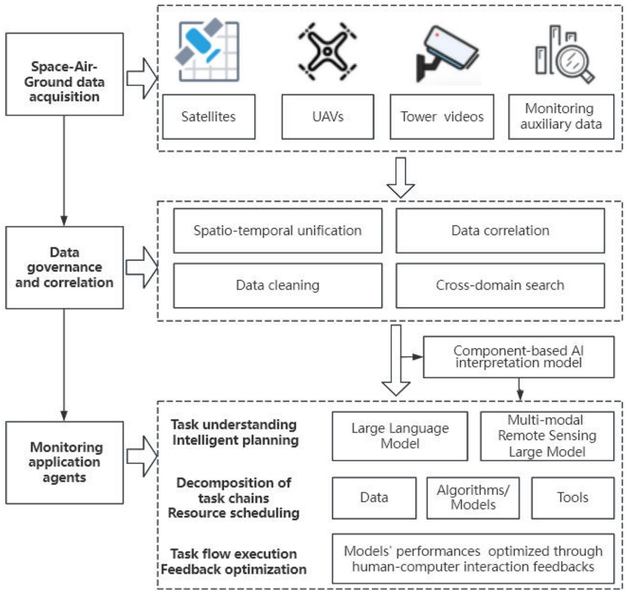

Figure 1. Integration and Intelligent Monitoring Technology System of Space-Air-Ground Remote Sensing Framework

2.1 Multi-source Data Governance and Collaborative Association

Perform spatio-temporal alignment, data cleaning, noise reduction, and quality assessment on preprocessed data from various sources and formats, including satellite imagery, UAV imagery, video footage, and vector data. Through spatio-temporal alignment, unify the coordinate systems, resolutions, data formats, and other aspects of the data to eliminate inconsistencies between datasets. Establish standardized processing workflows to automate geometric correction, radiometric normalization, cloud/fog detection, and quality assessment for multi-source data. Data cleansing employs techniques such as median filtering and topological repair to ensure data quality. At the collaborative association level, coarse-to-fine registration algorithms are utilized to achieve geographic positioning of tower videos. Cross-source retrieval of satellite images is enabled through deep hash encoding, establishing a spatio-temporal integrated, interlinked, and cross-referenced multi-modal data system. Integrate multi-source data from satellites, UAVs, and tower-based video systems to create a nationwide multi-period imagery base map with a unified spatio-temporal reference.

2.1.1 Temporal-Spatial Alignment: Unify multi-source data coordinate systems (e.g.,., WGS84). Both satellite and UAV imagery undergo correction processing and DOM image production using a unified geometric and elevation reference (control coordinate system). Employ a coarse-to-fine registration approach to establish the spatio-temporal mapping relationship between tower video locations sand UAV image features. First, based on the known high-precision GPS coordinates of the tower base station and camera installation parameters (field of view, orientation), combined with high-resolution orthophotos generated by the UAV, the approximate coverage area of the video field of view on the orthophoto is rapidly determined. A preliminary spatial correspondence is established to perform coarse registration. Subsequently, feature-based dense image registration is employed. Feature points such as SIFT or ORB are automatically extracted from key video frames and UAV imagery. The RANSAC algorithm estimates the homography matrix to perform projection transformation, achieving fine registration. This process ensures spatial alignment among satellite imagery, UAV imagery, and tower video data. The UAV camera and tower camera employ a unified communication protocol (MQT Tover TLS) and standardized BeiDou timing (error $\leqslant$ 1ms) to achieve time synchronization and multi-device coordination. Spatio-temporal alignment of multi-source data is accomplished by matching video frames with satellite overpass times (error $\leqslant$ 5 minutes).

2.1.2 Data Cleaning and Format Conversion: Image data cleaning and processing employ automated methods such as automatic image noise filtering (median filtering), cloud shadow detection, edge blur removal, and image mosaic correction. For video data, techniques including multi-frame interpolation, keyframe extraction, and GPS reconstruction are used to achieve standardized representation. For vector data, enhance interpretability through topological checks (e.g.,., polygon closure), outlier removal, coordinate system unification, and attribute field mapping. To support the collaborative application of multi-modal data, a unified format conversion mechanism is introduced to define standard representation structures for various data types. Remote sensing data such as imagery and video adopt a unified XML metadata template. Imagery data is uniformly converted to GeoTIFF format, preserving original resolution and geographic coordinate information. Video data is uniformly encoded as MP4, with key frame images extracted and tagged with temporal and spatial metadata. Vector polygons are uniformly stored in Shapefile or GeoJSON formats.

2.1.3 Cross-Source Retrieval of Airborne and Terrestrial Remote Sensing Images Based on Deep Hashing Encoding: As depicted in Figure 2, this paper investigates a cross-domain retrieval method based on deep hashing for multi-source optical remote sensing images from satellites, UAVs, and video frames. It enables retrieval across domains despite varying resolution scales and distinct spectral characteristics. This method employs a dual-branch deep learning network to synergistically process the generic spatial structures and specific spectral attributes of multi-source images. The model utilizes a weight-sharing spatial feature extraction network to uniformly encode multi-source input images, thereby extracting their shared contour and texture features. This enhances the model's adaptability to scale variations while reducing the number of parameters. Simultaneously, to address variations in the number and range of spectral bands across different imagery, the model incorporates a spectral feature extraction sub-network with non-shared weights. This sub-network configures independent channels for data from different spectral dimensions, enabling adaptive extraction of their unique spectral characteristics. Subsequently, the extracted shared spatial features are fused with the exclusive spectral features to form a unified spatio-spectral joint feature. Based on this, the hash learning module is responsible for mapping this feature into a compact binary hash code, a process involving feature dimensionality reduction and hash encoding. To further optimize the hash space and ensure that samples with identical semantics but vastly different origins (such as satellite and UAV imagery) yield hash codes that are as close as possible, this method introduces an auxiliary hash learning sub-module during the training phase. This sub-module drives the main network to learn more discriminative hash representations by constructing similarity constraints between cross-source and same-source sample pairs. Through end-to-end joint optimization of the aforementioned modules, this method generates high-quality unified hash codes for multi-source satellite imagery, UAV imagery, and tower video frames, thereby enabling efficient and accurate cross-source remote sensing image retrieval across airborne, ground-based, and satellite platforms.

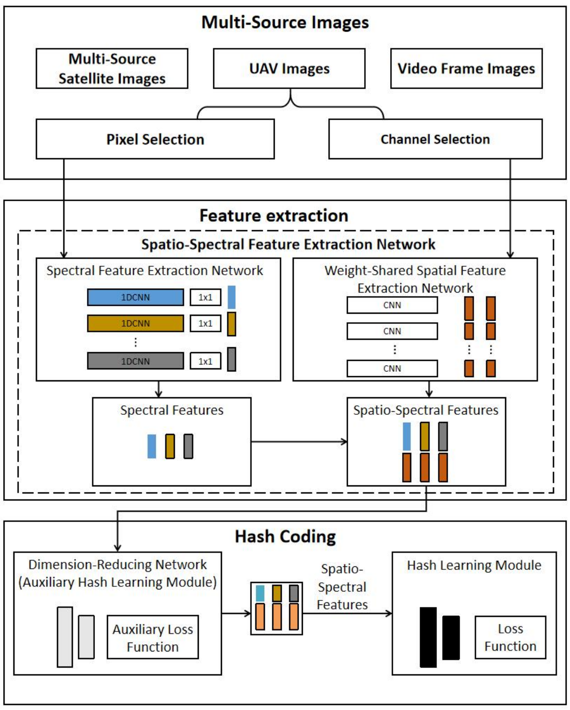

Figure 2. Cross-Source Retrieval Method for Space-Air-Ground Remote Sensing Images Based on Deep Hashing Encoding

2.2 Construction of Dynamic Base Maps for Multi-Load Remote Sensing Imagery

Based on multi-payload/multi-scale remote sensing images from resources such as Ziyuan-3, Gaofen-2, Gaofen-7, and UAVs, this system utilizes automatically generated orthophotos. Image data is filtered according to criteria including resolution, temporal phase, cloud cover, and region. The filtered imagery undergoes statistical calculations such as stretching, mosaicking, tile conversion, and service publishing. As illustrated in Figure 3, this enables the dynamic generation of monthly/quarterly/annual imagery basemaps for monitoring areas, supporting long-term time-series monitoring applications.The statistical value calculation for imagery primarily involves extracting key statistical values and indicators, such as the mean and standard deviation of radiometric information. This process ensures optimal display during image mosaicking and stretching, facilitates subsequent information extraction, and enhances the visualization quality of the imagery.

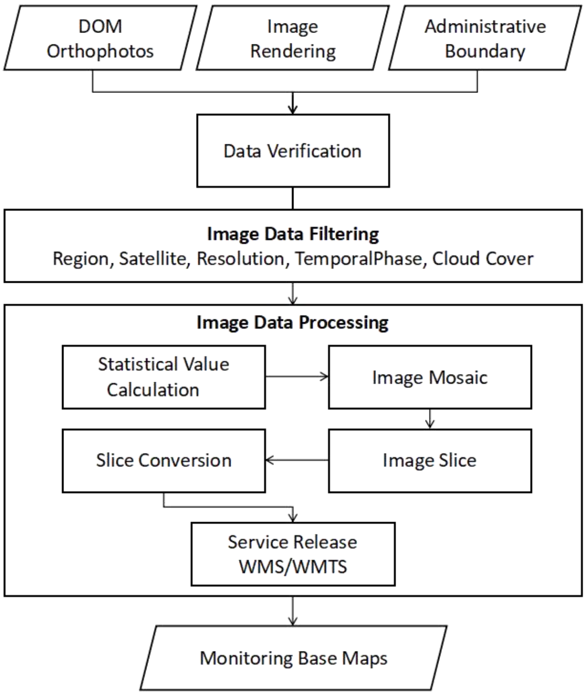

Figure 3. Dynamic Base Map Construction Technology Workflow of Multi-source Images

2.3 Component-Based AI Interpretation Model Construction

This paper aims to investigate a component-based multi-task remote sensing interpretation model framework. Based on a universal encoder-decoder architecture, the encoder supports multiple backbone networks including ResNet, DenseNet (Huang et al., 2018), and EfficientNet(Tan and Le, 2019), enabling flexible configuration according to task requirements. To enhance feature representation capabilities, the model integrates atrous spatial pyramid pooling(ASPP) attention mechanisms, and visual Transformer to effectively extract multi-scale spatial context and semantic features. The decoder progressively restores spatial details through deconvolution, feature fusion, and upsampling operations, ultimately outputting pixel-level classification maps and specific predictions such as change regions.

2.4 Construction of Intelligent Agents for Remote Sensing Monitoring Applications Based on Multi-modal Large Models

This study develops an intelligent agent for remote sensing monitoring applications with autonomous task comprehension, planning, and execution capabilities. This agent operates within a closed-loop "perception-cognition-decision-execution" framework, achieving cross-modal alignment and semantic unification of Space-Air-Ground data through multi-modal remote sensing large models, as presented in Figure 4. Subsequently, task comprehension and intelligent planning are executed. A fine-tuned large language model parses natural language instructions, dynamically decomposes task chains, and schedules resources, automatically matching optimal data, computing power, and other resources. Following this, model algorithms for data processing which including coordinate transformation, image defogging, change detection, object detection, scene classification, and video recognition, along with intelligent interpretation and spatio-temporal analysis are encapsulated into tools. Automatically select optimal tools to convert the agent-planned task chain into an executable workflow. Finally, a closed-loop learning mechanism is established, continuously optimizing model performance through human-machine interaction feedback to achieve end-to-end automated processing of complex remote sensing monitoring tasks.(Maroto-Gómez et al., 2025)

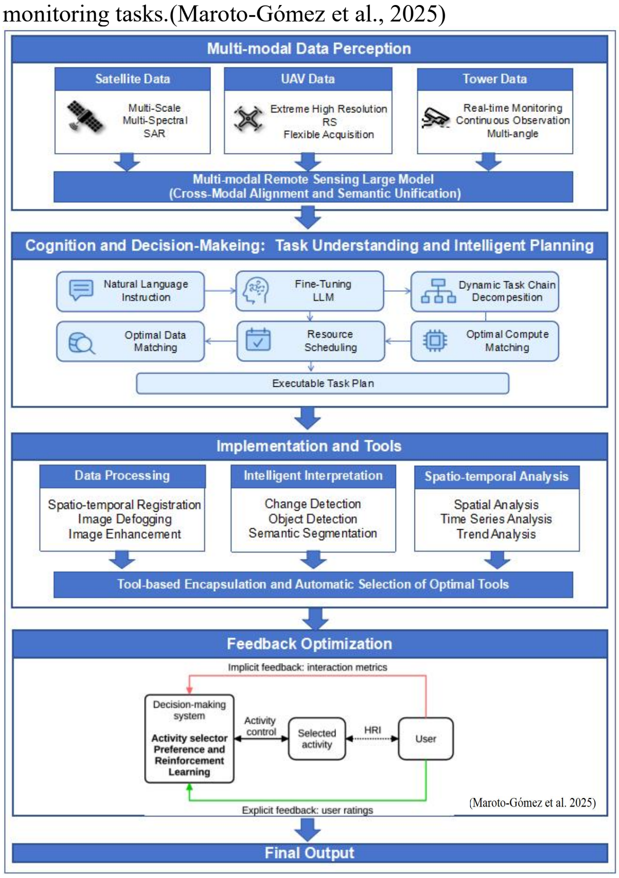

Figure 4. Technical Process for Constructing Intelligent Agents for Remote Sensing Monitoring Applications

3. Application Case study

This study demonstrates the application effectiveness of an integrated Space-Air-Ground intelligent monitoring system through a typical case study of ecological restoration project monitoring. The case site is an ecological restoration plot of an abandoned open-pit mine along the Yangtze River shoreline in Hunan Province, China, covering approximately 5.61 hectares. Originally used as a sand and gravel storage area, the site faced primary environmental issues including altered landforms and degraded landscapes due to destruction of forest and grassland vegetation, as well as land occupation and soil erosion. To harmonize with the surrounding riverfront corridor landscape, enhance ecological protection functions, and improve visual aesthetics, a vegetation restoration project was implemented on the area with poor natural recovery (approximately 0.7 hectares). Key restoration measures included site leveling and tillage, mixed grass seed broadcasting, and preservation of existing ponds.

In 2017, routine change monitoring based on satellite remote sensing images identified surface anomalies within this site along the Yangtze River shoreline management zone in Yueyang City, Hunan Province, leading to its inclusion in the ecological restoration project. During project implementation, the system continuously tracked progress using multi-source satellite imagery from resources such as Ziyuan-3 and Gaofen-2. Based on eight years of multi-temporal data, it dynamically monitored construction demolition, soil covering and greening, and vegetation planting. A UAV nest deployed approximately 3 kilometers from the site supported remote mission planning (with a flight radius of 10 kilometers). It enabled real-time data transmission for remote inspection of the restoration area and evaluation of grass planting effectiveness. Additionally, the tower-mounted cameras feature 360° rotation with a visual radius exceeding 2 kilometers. Through intelligent video processing, they automatically identify targets such as construction machinery, earth-moving zones, and forest fire hot spots while extracting their spatial coordinates. The online intelligent detection function of the tower video system precisely identifies markers like construction equipment and earth-moving activities within the restoration area, enabling remote early warning and smart supervision against re-degradation.

Based on the Integration and Intelligent Monitoring Technology System of Space-Air-Ground Remote Sensing developed in this study, an ecological restoration monitoring agent was constructed. Driven by natural language commands, this agent autonomously plans task chains, schedules multi-source data (including multi-temporal satellite images, UAV patrol images, and tower video feeds), and triggers surface cover change detection and classification models, as outlined in Figure 5. Experiments integrated the wide-area observation capability of satellite remote sensing, the high-resolution spatial detail information (such as vegetation coverage status) from UAV images, and the real-time dynamic monitoring advantages of tower videos, thereby optimizing land type recognition and interpretation models. Following ecological restoration project implementation, monitoring results revealed 4.87 hectares of new grassland and 0.74 hectares of new forestland within the site. The system achieved intelligent identification and quantitative, automated assessment of land cover types, restoration progress, and ecological recovery outcomes. Experiments demonstrate that this system offers the advantages of "rapid identification and early warning", forming an intelligent operational closed loop of "monitoring-analysis-decision making-feedback".It provides reliable technical support for the dynamic supervision of similar projects.

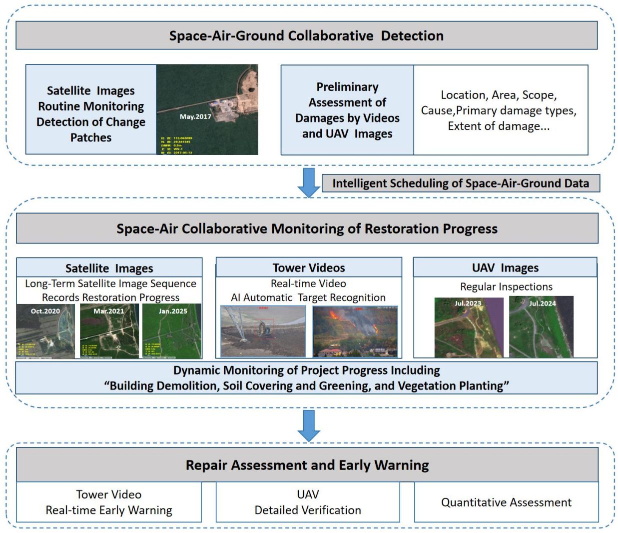

Figure 5. Technical Procedures for Monitoring Applications in Land Ecological Restoration Projects

4. Conclusions

This paper focuses on the core challenges in Integration and Intelligent Monitoring Technology System of Space-Air-Ground Remote Sensing, systematically researching and constructing a technology framework for collaborative intelligent perception. The study first addressed the challenges of inconsistent data formats and insufficient inter-source correlations across multiple data. Through standardized processes such as automated geometric correction and radiometric normalization, combined with deep hash-based cross-source retrieval technology, it established a unified spatio-temporal, inter-correlated, and cross-verifiable multimodal data foundation. Second, a modular, configurable multi-task intelligent remote sensing interpretation framework was designed, integrating multiple pluggable components to achieve precise multi-task interpretation such as feature classification and change detection. Subsequently, an application agent based on a multi-modal large model was constructed. Through natural language instruction parsing, dynamic task chain planning, and human-machine interaction feedback optimization, a complete application closed-loop was formed. This technological system has been successfully applied to the full-cycle dynamic monitoring of ecological restoration projects, enabling precise identification of newly added grasslands and woodlands. It achieves rapid and accurate recognition and quantitative assessment of land cover changes, fulfilling the goal of "early identification and early warning".This research provides a practical technical pathway to address the bottleneck issues of data, model, and application coordination in current remote sensing monitoring applications, demonstrating significant practical value. Future efforts will further explore the autonomous learning and evolutionary capabilities of intelligent agents in more complex decision-making scenarios, while expanding the system's application scope to additional fields such as natural resource management and emergency response.

Acknowledgements

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