Multi-dimensional Model-driven Digital Twin for River Greening

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Abstract

In this paper, for the problems of low efficiency, high cost, and difficult assessment in the traditional river greening maintenance and supervision mode, a digital twin system construction scheme for river greening based on multidimensional modeling and remote sensing technology is proposed. The system utilizes multidimensional data such as high-resolution remote sensing images, Sentinel-2 data, ground survey data and management information, and combines artificial intelligence techniques such as object-oriented classification and deep learning to realize the automated extraction of river greening information and the dynamic monitoring of green plant growth. Meanwhile, a greening survey APP and a greening maintenance supervision information system were developed to realize efficient integration of internal and external data and information sharing, and to provide decision support for river greening management through data visualization, statistical analysis and other functions. Taking Beijing LS River as an example, the research results show that the system can effectively improve the efficiency and precision of river greening maintenance and supervision, reduce the labor cost, provide technical support for the refined management of river greening, and has important application value and promotion significance.

1. Introduction

In recent years, with the acceleration of urbanization, the ecological function and landscape value of urban river greening have been increasingly valued. Remote sensing technology has become an important means of investigating and monitoring urban river greening due to its large range, spatiotemporal continuity and high efficiency. The research mainly uses high-resolution satellites (such as Sentinel-2, Landsat-8, Gaofen-2), drone aerial photography, lidar and other multi-source remote sensing data, combined with ground measurements and GIS analysis, to achieve multi-scale, spatiotemporal dynamic monitoring of urban river greening(Agustiyara, 2025; Hislop, 2025; Fiorentini, 2023; Pace, 2022). Deep learning, machine learning (such as random forests, support vector machines), multi-scale feature fusion, time series analysis and other methods have been widely used in remote sensing surveys of urban riverside greening, significantly improving the accuracy and efficiency of vegetation type identification, health status assessment, and spatial distribution extraction (Boon,2024; Xu, 2020; Cheng, 2023; Hu, 2024; Huang, 2024; Tong, 2024). Multi-source data fusion has become the key to improving species identification and structural parameter inversion capabilities (Degerickx, 2020; Rusnák, 2022).

This study aims to leverage digital twin technology for river greening management, constructing a system based on multi-dimensional models and remote sensing technology. This system aims to improve efficiency, accuracy, and cost-effectiveness while providing technical support for refined river greening management.

2. Material and Methods

2.1 Study Area

The study focuses on the LS River, the main drainage and landscape river in the southwest urban area of Beijing. The LS River runs through urban functional areas such as the New Shougang High-end Industrial Service Area, the Lize Business District, the Yizhuang Development Zone, the Bohai Rim High-end Headquarters Zone, and the Universal Studios, with a basin area of approximately 695km2. The river management area has a wide variety of greening types and complex structures, including trees, shrubs, grass-lands, aquatic plants, etc., making it an important ecological corridor and landscape resource in Beijing. The study area primarily focuses on the vicinity of the LS River's main stream, which extends for a total length of 68.41km.

2.2 Data

2.2.1 Remote sensing imagery data

Remote Sensing Data Source for Greening Information Extraction: Given the rapid changes in vegetation during the growing season and the complex species and planting structures of urban river Greening, very high requirements are placed on the spatial resolution and timeliness of remote sensing imagery. Therefore, multispectral satellite imagery data with a spatial resolution better than 1m, covering the Greening maintenance area of the LS River, and acquired during different seasons, was used for Greening information extraction to obtain identification and spatial distribution information for tree, shrub, grassland, and aquatic plant types. This study selected GF-2 multispectral satellite remote sensing imagery as the data source, with data acquisition times in January and July 2023. Imagery with good quality and less than 1% cloud cover was selected for both periods.

Figure 1. GF-2 Satellite Imagery of LS River (July 2023)

Remote Sensing Data Source for Dynamic Monitoring of Plant Growth: Dynamic monitoring of plant growth requires the accumulation of multi-year continuous remote sensing imagery with high revisit frequency. The complexity of urban river Greening information also places high demands on image resolution. Therefore, Sentinel-2 multispectral satellite remote sensing imagery was selected. Its 5-day revisit cycle, 13 spectral bands, and 10-meter spatial resolution meet the needs of dynamic monitoring of plant growth. Multi-temporal Sentinel-2 data with good quality and less than 1% cloud cover from January 2022 to November 2023 were downloaded from the European Space Agency website (https://scihub.copernicus.eu/dhus/#/home). Vegetation indices were calculated to analyze the spatiotemporal variation patterns of plant growth.

Figure 2. Sentinel-2 Satellite Imagery of LS River.(August 2023)

2.2.2 Ground survey data: Ground survey data was mainly collected through the Greening survey APP, including information such as Greening type, quantity, area, distribution, height, planting year, and management attributes, which was used to verify and supplement the results of remote sensing extraction.

2.2.3 Management information data: Management information data included river greening project information, management office information, personnel information, etc., which was used to construct the management attribute layer of the digital twin model.

2.3 Methods

2.3.1 Technological Route: This technology roadmap outlines the process of constructing a digital twin system for river greening management, starting with data acquisition and preprocessing, followed by remote sensing data extraction using object-oriented classification, deep learning model training, and manual interpretation correction. The extracted information is then integrated with ground survey data and management information to build a comprehensive multi-dimensional model. This model forms the foundation for the digital twin system, which provides visualization and analysis capabilities to support informed decision-making for greening planning, maintenance, and resource allocation.

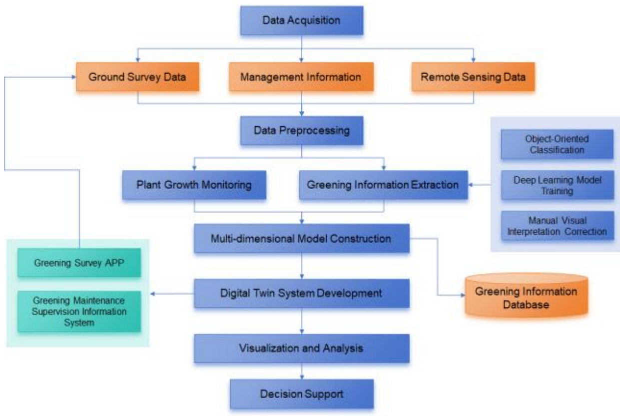


Figure 3. Technical Flowchart of Constructing a Digital Twin System for River Greening Management.

2.3.2 Remote Sensing Data Preprocessing: This study utilizes GF-2 and Sentinel-2 data, and preprocesses the data to ensure data quality and consistency, providing a reliable data foundation for subsequent Greening information extraction and plant growth monitoring. The preprocessing process mainly includes the following steps.

Radiometric Calibration: Converting the digital count values of remote sensing imagery into radiance values to eliminate sensor and atmospheric effects, making different temporal images comparable.

Atmospheric Correction: Removing the effects of atmospheric scattering and absorption to restore the true reflectance of the ground surface, improving the accuracy and authenticity of the imagery. This study uses the FLAASH atmospheric correction model, which can effectively remove the effects of atmospheric scattering and absorption, improving the accuracy and authenticity of the imagery.

Geometric Correction: Projecting remote sensing imagery onto a unified coordinate system to eliminate geometric distortions and ensure geometric accuracy. This study uses RPC parameters and ground control points for geometric correction to ensure that the geometric accuracy of the imagery meets the requirements of subsequent analysis.

Image Fusion: Fusing high-resolution panchromatic imagery with multispectral imagery to improve the spatial resolution of the imagery and enhance the interpretability and distinguishability of the imagery. This study uses the IHS transform method for image fusion to improve the spatial resolution of the imagery and enhance the interpretability and distinguishability of the imagery.

Mosaic Color Correction: Stitching multiple images into a complete image and performing color correction to eliminate color differences between images and ensure overall consistency. This study uses the mosaic module in ENVI software for image mosaicking and PhotoShop software for color correction to ensure overall consistency of the imagery.

2.3.3 Greening Information Extraction Methods: Based on GF-2 multispectral satellite data, this study employs a technical approach of "image segmentation - rule extraction - deep learning training - classification fusion - human-computer interaction correction" to extract Greening information, including trees, shrubs, grasslands, and aquatic plants. The process encompasses key stages such as multi-scale image object construction, rule-set-driven preliminary ground object classification, deep learning sample preparation, model training optimization, classification result fusion, and post-processing correction.

Multi-scale Image Object Construction: High-resolution remote sensing image data is loaded, and image objects are generated using a multi-scale segmentation algorithm. By optimizing parameter combinations such as spectral heterogeneity and shape factors, the optimal segmentation scale that adapts to the characteristics of river Greening ground objects is determined. Subsets of samples can be extracted from typical areas for model training.

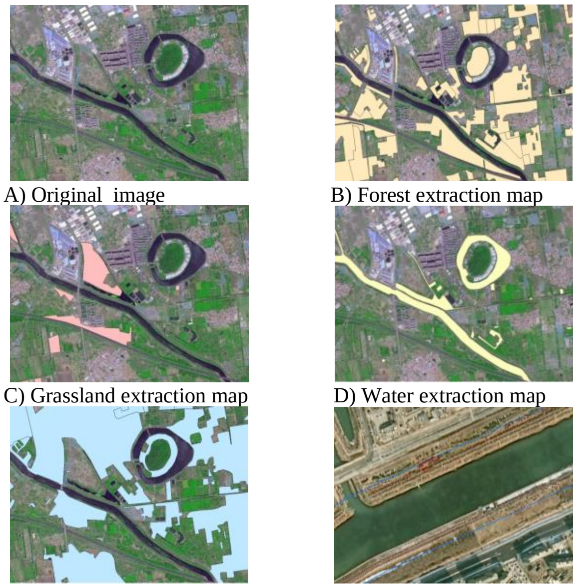
Object-Oriented Rule Set Construction and Ground Object Classification: A hierarchical classification rule system is constructed based on ground object spectral characteristics (such as NDVI, EVI values), geometric characteristics (such as shape index, compactness), and spatial contextual relationships. A rule-set-driven decision tree classification method is used to achieve preliminary semantic annotation of ground objects.

Deep Learning Training Sample Preparation: The preliminary results of object-oriented classification are manually verified, and training datasets with semantic labels are exported according to ground object categories (such as trees, shrubs, grasslands, aquatic plants, etc.). A standardized preprocessing process (such as data augmentation, normalization) is used to generate input samples suitable for deep learning models.

Deep Learning Model Training and Parameter Optimization: Based on the labelled sample set, convolutional neural networks (such as U-Net, DeepLab, etc.) or Transformer architectures are used for model training. Network hyperparameters (such as learning rate, number of iterations) are optimized through cross-validation to generate a set of neural network parameters with spatial semantic understanding capabilities.

Classification Result Fusion and Decision-Level Optimization: The trained model is applied to the entire image to generate a pixel-level classification probability map. Through a decision-level fusion strategy, the deep learning classification results are coupled with the object-oriented image object characteristics. Finally, semantic mapping and spatial aggregation of ground object categories are achieved on the object-oriented classification platform.

Human-Computer Interaction Correction and Accuracy Verification: Visual interpretation is used to perform a global check of the deep learning classification results. Misclassified patches (such as misjudging riverbank bare land as herbaceous vegetation) are manually corrected, and special ground objects missed by the model (such as sparsely distributed saplings) are supplemented. This interactive correction mechanism effectively improves the overall accuracy (OA) and Kappa coefficient of Greening information extraction, ensuring the reliability of the results.



A) Original image; B) Forest extraction map; C) Grassland extraction map; D) Water extraction map; E) Building extraction map; F) Tree point extraction map

Figure 4. Remote Sensing Extraction Sample Map

2.3.4 Plant Growth Monitoring Methods

Spectral Characteristic Analysis and Index Calculation: The spectral characteristics of plant growth processes, including trees, shrubs, grasslands, and aquatic plants, are analyzed. Using bands B4 (red light, 665nm) and B8 (near-infrared, 833nm) of Sentinel-2, the NDVI formula is:

$$I_{NDV} = \frac{P_{nir} - P_{red}}{P_{nir} + P_{red}} \tag{1}$$

where P_{nir} = surface reflectance in the near-infrared band

P_{red} = surface reflectance in the red band

Growth Status Assessment: Based on the extracted vegetation index, a vegetation coverage inversion model is constructed using the pixel bisection method. The formula for vegetation coverage is:

$$C_{FV} = \frac{S - S_{soil}}{S_{veg} - S_{soil}} \tag{2}$$

where S_{soil} = pixel value of pure bare soil

S_{veg} = pixel value of pure vegetation

S = Vegetation index of a pixel

The 5% to 95% quantiles of the NDVI values are used as thresholds based on the NDVI statistical histogram. Based on the quantified vegetation coverage results, combined with vegetation growth characteristics and phenological laws, different growth levels are divided: low-density coverage, low-medium density coverage, medium density coverage, high-density coverage, and bare land. The vegetation growth characteristics from 2022-2023 are analyzed, and the area proportions of different growth levels are statistically analyzed to assess plant growth status.

This translation provides a more detailed and academically appropriate rendering of the original Chinese text. Remember to cite any specific algorithms or methods used.

2.3.5 Multi-dimensional Model Construction: This study proposes a novel method for constructing a multi-dimensional model of river Greening, integrating diverse data sources and leveraging advanced technologies to create a comprehensive digital twin model. This model integrates multi-dimensional data, including remote sensing data, ground survey data, and management information, and utilizes advanced techniques such as object-oriented classification, deep learning, data fusion, and GIS technology to construct a digital twin model of river Greening.

Data Integration and Fusion: The model integrates multi-dimensional data from remote sensing, ground surveys, and management information to create a comprehensive representation of river Greening. Remote sensing data provides spatial information on Greening type, area, quantity, distribution, and plant growth dynamics. Ground survey data provides detailed information on individual plants, such as species, quantity, diameter at breast height, height, and planting year. Management information provides background information on Greening management, such as project information, management office information, and maintenance personnel information.

Model Structure and Functionality: The model adopts a hierarchical structure, including a base layer, a Greening layer, and a management layer. The base layer represents the physical environment of the river Greening, the Greening layer represents the vegetation within the Greening, and the management layer represents the management aspects of the Greening. This hierarchical structure allows for a comprehensive and dynamic representation of river Greening, enabling users to explore different aspects of the Greening and make informed decisions based on the integrated data.

Advanced Technologies: The model utilizes advanced technologies such as object-oriented classification, deep learning, data fusion, and GIS technology to enhance the accuracy and comprehensiveness of the model. Object-oriented classification is used to extract detailed information from high-resolution imagery; deep learning models are used to further improve the accuracy of vegetation classification; data fusion techniques are used to integrate data from different sources; and GIS technology is used to create a spatial representation of the Greening.

Digital Twin System Development: To achieve real-time monitoring, simulation, and management of river Greening information, this study developed two key systems: a Greening Survey APP and a Greening Maintenance Supervision Information System. These two systems exchange data through a central database, forming the core components of the river Greening digital twin system.

The Greening Survey APP is a mobile application designed to improve field survey efficiency and data accuracy. The APP integrates GPS positioning, map display, graphic editing, attribute collection, and photo upload functions, facilitating field personnel in collecting and verifying Greening information on-site. The APP can upload collected data to the central database in real-time and synchronize data with the desktop system.

The Greening Maintenance Supervision Information System is a desktop application based on GIS technology, used for visualizing, querying, statistically analyzing, and managing river Greening information. The system can load multi-dimensional data such as remote sensing data, ground survey data, and management information, and provides decision support for river Greening management through data visualization and statistical analysis functions. The system also has user management, task allocation, and result review functions, facilitating management personnel in managing Greening maintenance work in a unified manner.

This translation aims for a more formal and detailed explanation suitable for an academic paper. Remember to include figures as referenced in the text to illustrate the system architecture.

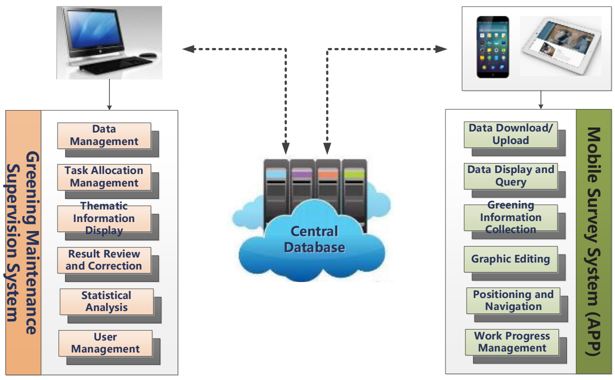


Figure 5. System Architecture Diagram

3. Results and Discussion

3.1 River greening Information Extraction Results

Based on high-resolution remote sensing imagery, this study achieved high-precision extraction of river Greening Greening information by integrating object-oriented classification and deep learning techniques. The study successfully completed the spatial identification and classification of typical vegetation categories such as trees, shrubs, grasslands, and aquatic plants, constructing a digital representation model of river Greening features.

Quantitatively assessed by the confusion matrix, the overall classification accuracy (OA) of this method reached 92.3%, and the Kappa coefficient was 0.901, with producer's accuracy for trees, shrubs, grasslands, and aquatic plants being 94.7%, 91.2%, 89.8%, and 90.5%, respectively, and user's accuracy being 93.1%, 90.6%, 90.2%, and 91.3%, respectively, demonstrating stable and excellent classification performance for different vegetation types. In terms of spatial distribution characterization, the study accurately captured the continuity features of vegetation belts along the river and quantified the coverage area of each vegetation type, with trees accounting for 38.6%, shrubs 25.4%, grasslands 22.3%, and aquatic plants 13.7%.

Through comparative validation with ground survey data, the spatial consistency between the study's extraction results and field measurement data reached 91.8%, and the relative area error was controlled within ±5.2%, verifying the effectiveness and reliability of the method. This technical framework effectively integrates the advantages of object-oriented classification in spatial structure representation and the capability of deep learning to extract complex semantic features, successfully breaking through the classification bottlenecks of single techniques in water-vegetation transition zones and mixed areas of artificial and natural vegetation, providing an innovative interdisciplinary solution for application scenarios such as river ecological environment monitoring and greening planning.

3.2 Dynamic Plant Growth Monitoring Results

Based on 23 periods of Sentinel-2 imagery from January 2022 to November 2023, NDVI and vegetation coverage were calculated respectively.

3.2.1 Seasonal Dynamic Characteristics: Vegetation coverage for each time phase was inverted using the 5% and 95% confidence interval parameters determined from the NDVI histogram (Table 1). The results show significant seasonal fluctuations in NDVI values, with the average NDVI during the growing season (May-September) ranging from 0.952 to 0.968, peaking in July 2023 (0.9689), corresponding to the period of vigorous vegetation growth. The average NDVI during the dormant season (October-April of the following year) ranged from 0.917 to 0.941, dropping to a trough in February 2023 (0.9228), which is consistent with the phenological pattern of "tree leaf fall - shrub wilting - grassland senescence" in the dormant season.

Time	$NDVI_{min}$	$NDVI_{max}$	Time	$NDVI_{min}$	$NDVI_{max}$
Jan 2022	0.0014	0.9174	Jan 2023	0.0016	0.9179
Feb 2022	0.0033	0.9225	Feb 2023	0.0035	0.9228
Mar 2022	0.0042	0.9320	Mar 2023	0.0044	0.9324
Apr 2022	0.0065	0.9484	Apr 2023	0.0066	0.9490
May 2022	0.0079	0.9544	May 2023	0.0080	0.9550
Jun 2022	0.0090	0.9649	Jun 2023	0.0091	0.9677
Jul 2022	0.0095	0.9684	Jul 2023	0.0097	0.9689
Aug 2022	0.0084	0.9547	Aug 2023	0.0082	0.9520
Sep 2022	0.0075	0.9423	Sep 2023	0.0073	0.9415
Oct 2022	0.0054	0.9352	Oct 2023	0.0054	0.9354
Nov 2022	0.0032	0.9205	Nov 2023	0.0034	0.9185
Dec 2022	0.0021	0.9166			

Table 1: NDVI Values at 5% and 95% Confidence Intervals

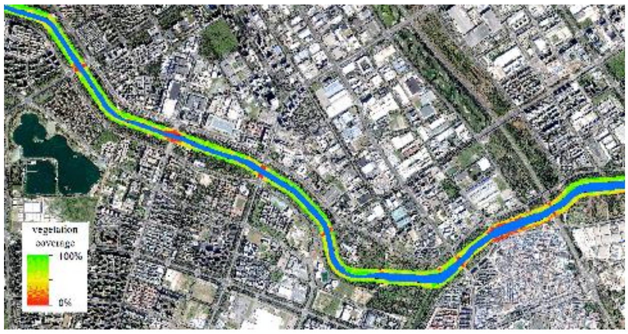


Figure 6. Partial Remote Sensing Monitoring Image of Vegetation Growth in LS River, June 2023

Vegetation Coverage Range	Vegetation Coverage Level
(0,0.1]	Bare Land
(0.1,0.3]	Low Density Coverage
(0.3,0.45]	Low-Medium Density Coverage
(0.45,0.6]	Medium Density Coverage
(0.6,1]	High Density Coverage

Table 2: Vegetation Coverage Level Classification

3.2.2 Graded Statistics of Vegetation Coverage: Coverage was divided into 5 levels according to the standard in Table 2, and growth status was assessed by statistically analyzing the area proportion of different growth levels (Table 3). The results show that during the 2023 growing season (May-September), the area proportion of high coverage (>0.6) reached 17.42%-28.49%, among which, the Majuqiao Management Office area, due to its high tree density (28326 trees, accounting for 62.21% of the total), showed a significantly higher proportion of high coverage area than the Dahongmen Management Office area (13.72%). Notably, the proportion of high coverage area in August 2023 reached 28.49%, an increase of 12.51% compared to the same period in 2022, attributed to the vegetation maturation effect of the Phase II Greening Project (3662 trees).

Time	Bare Land		Low Density Coverage		Low-Medium Density Coverage		Medium Density Coverage		Medium Density Coverage	
	Area (㎡)	Percentage (%)	Area (㎡)	Percentage (%)	Area (㎡)	Percentage (%)	Area (㎡)	Percentage (%)	Area (㎡)	Percentage (%)
Jan 2022	783963	15.15	3231066	62.44	1158092	22.38	1552	0.03	0	0
Feb 2022	627688	12.13	3368713	65.1	1175686	22.72	2070	0.04	517	0.01
Mar 2022	461063	8.91	2748787	53.12	1917734	37.06	46055	0.89	517	0.01
Apr 2022	182666	3.53	2610623	50.45	1815793	35.09	565074	10.92	517	0.01
May 2022	129884	2.51	1456671	28.15	2246843	43.42	1170511	22.62	170764	3.3
Jun 2022	172834	3.34	1134289	21.92	1596387	30.85	1706090	32.97	565592	10.93
Jul 2022	291852	5.64	1151882	22.26	1196902	23.13	1784228	34.48	749810	14.49
Aug 2022	126262	2.44	971804	18.78	1498586	28.96	1751110	33.84	826913	15.98
Sep 2022	183183	3.54	1207769	23.34	1764564	34.1	1181378	22.83	837780	16.19
Oct 2022	239070	4.62	1647099	31.83	1811653	35.01	1085647	20.98	391205	7.56
Nov 2022	350843	6.78	2816058	54.42	1065983	20.6	527817	10.2	413974	8
Dec 2022	801557	15.49	3011143	58.19	528852	10.22	626136	12.1	206987	4

https://doi.org/10.5194/isprs-archives-XLVIII-4-W14-2025-129-2025 |

Jan 2023	709965	13.72	2281514	44.09	837780	16.19	879695	17	465721	9
Feb 2023	994055	19.21	2805191	54.21	749293	14.48	447609	8.65	178526	3.45
Mar 2023	970769	18.76	2895230	55.95	911778	17.62	241657	4.67	155240	3
Apr 2023	202847	3.92	1147743	22.18	1546193	29.88	1535843	29.68	742048	14.34
May 2023	170764	3.3	942308	18.21	1505313	29.09	1654861	31.98	901428	17.42
Jun 2023	161967	3.13	967664	18.7	1596387	30.85	1617086	31.25	831570	16.07
Jul 2023	184218	3.56	747223	14.44	1453048	28.08	1826660	35.3	963524	18.62
Aug 2023	123157	2.38	440882	8.52	1202077	23.23	1934293	37.38	1474265	28.49
Sep 2023	157828	3.05	978531	18.91	1334031	25.78	1775948	34.32	927819	17.93
Oct 2023	405694	7.84	800522	15.47	1905832	36.83	1562752	30.2	499874	9.66
Nov 2023	299614	5.79	1294186	25.01	2144902	41.45	1175168	22.71	260804	5.04

Table 3: Vegetation Coverage Area Statistics

3.3 Digital Twin System Construction Results

This study successfully constructed a digital twin system for river Greening Greening based on multi-dimensional models and remote sensing technology. This system serves as an integrated platform, achieving a dynamic, real-time virtual mapping of the LS River's greening status. The core of the system lies in its meticulously designed architecture and the seamless integration of multi-source heterogeneous data.

The system architecture adopts a typical client-server model with a central database at its core, connecting the mobile-based Greening Survey APP and the desktop/web-based Greening Maintenance Supervision Information System. This architecture ensures real-time synchronization and efficient flow of data between field collection and indoor management.

3.3.1 Multi-dimensional Data Integration and Model Construction: The construction of the digital twin model is pivotal to the system. It creatively integrates data from three primary dimensions

Spatial Dimension: Spatial distribution of Greening (polygons or points for trees, shrubs, grasslands, aquatic plants) extracted from high-resolution remote sensing imagery, along with fundamental river geographic information.

Attribute Dimension: Detailed attribute information combined from remote sensing extraction results and data collected via the ground survey APP, including plant species, quantity, area, height, diameter at breast height, planting year, health status, as well as associated projects and management units. This rich attribute data provides spatial objects with a true "digital identity."

Temporal Dimension: Dynamic changes in plant growth monitored using multi-temporal Sentinel-2 imagery (e.g., NDVI, vegetation coverage), and temporal information recorded through the APP such as survey time and maintenance records, enabling the digital twin to possess the characteristic of temporal evolution.

By converging these multi-dimensional data into a unified Greening information database and establishing relationships between data, the system constructs a digital model capable of comprehensively reflecting the physical entities of the river Greening Greening and their dynamic changes.

3.3.2 Core Functionality Implementation: The successfully constructed digital twin system realizes its application value through the following key functionalities.

Visualization and Interaction: The Greening Maintenance Supervision Information System can load and display the integrated multi-dimensional data, including remote sensing base maps, Greening thematic maps, plant growth maps, etc. Utilizing GIS technology, users can intuitively browse Greening distribution in a 2D/3D environment, query detailed attributes of any patch or plant, achieving deep interaction with the digital twin model.

Dynamic Monitoring and Update: The system is capable of periodically processing new remote sensing data for plant growth monitoring and receiving the latest data collected from field operations via the Greening Survey APP (e.g., newly added Greening, status changes, maintenance records), dynamically updating the digital twin model to ensure high synchronization with the real world.

Statistical Analysis and Decision Support: The system provides powerful statistical analysis functions, allowing for Greening resource statistics, growth status analysis, survey progress analysis, etc., across dimensions such as Greening type, management unit, and project . These quantitative analysis results provide a basis for scientific decision-making by management personnel.

Task Management and Result Review: The system supports task assignment and result review processes, closely integrating field surveys with indoor management, thereby improving work efficiency and data quality.

In summary, the digital twin system constructed in this study not only integrates multi-source remote sensing, ground survey, and management data but also achieves a comprehensive, dynamic, and interactive digital mapping of the river Greening status through advanced model construction and system development, providing a solid technical foundation for refined and intelligent river Greening maintenance and management..

Figure 7. Multidimensional Greening Data Analysis

Figure 8. Panel of Greening Maintenance Supervision System

3.4 Digital Twin System Application Effects

The river Greening Greening digital twin system constructed in this study has demonstrated significant application effects in the maintenance and management of the LS River, primarily reflected in the following aspects.

Firstly, it has significantly improved the efficiency of data acquisition and updating while reducing labor costs. Traditional Greening surveys rely heavily on manual field work and paper records, which are inefficient and prone to errors. With the developed Greening Survey APP, field personnel can directly adjust Greening patch boundaries, collect attribute information (including type, quantity, height, diameter at breast height, etc.), upload photos, and synchronize data to the central database in real-time. The research report indicates that during a 30-day survey period, 41 personnel completed detailed surveys of 1344 Greening patches.This significantly improved work efficiency and effectively reduced labor input compared to traditional methods.

Secondly, it has enhanced the accuracy and timeliness of Greening information. The system adopts a technical route combining "remote sensing intelligent extraction - ground survey verification - manual interpretation correction" , fully leveraging the macro perspective of high-resolution remote sensing imagery and the detailed nature of ground surveys. Remote sensing extraction provides preliminary high-precision results of Greening distribution, while the ground survey APP is used for on-site verification, correction, and supplementation of detailed attribute information difficult to obtain from remote sensing (such as tree species, diameter at breast height, planting year, etc.). This indoor-outdoor collaborative mechanism ensures the accuracy and timeliness of both spatial and attribute data for Greening, laying a solid foundation for refined management.

Thirdly, it has strengthened the dynamic monitoring capability of plant growth. Based on the dynamic monitoring of NDVI and vegetation coverage using multi-temporal Sentinel-2 imagery , the system can periodically assess the growth status of green plants and identify areas with abnormal growth or degradation. This enables management departments to timely detect potential pest infestations, drought stress, or other health issues, shifting from passive response to proactive early warning and intervention, ensuring the health of green plants.

Finally, it has optimized management decisions and information sharing. The Greening Maintenance Supervision Information System provides powerful data visualization, spatial querying, and statistical analysis functions. Management personnel can intuitively view the distribution and statistical information of Greening resources across different Greening types, management areas, and project categories, performing multi-dimensional data analysis. The system also supports task assignment and result review, promoting the standardization and informatization of management processes, providing data support for scientifically formulating maintenance plans, evaluating maintenance effectiveness, and facilitating information sharing among different management levels.

4. Conclusions

This study successfully constructed a digital twin system for river greening, demonstrating its effectiveness in improving efficiency, accuracy, and cost-effectiveness of management. The system's integration of multi-dimensional models and remote sensing technology offers a powerful tool for achieving intelligent and sustainable development of river greening management. Future research can explore further integration with technologies like the Internet of Things and big data to enhance the system's capabilities.

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