RESEARCH ARTICLE

Ecological environment restoration technology for tourist attractions based on spatiotemporal evolution and artificial intelligence

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With the increasing demand for sustainable ecosystem management, artificial intelligence (AI) offers unprecedented opportunities for enhancing ecological restoration efforts. This study leveraged AI, unmanned aerial vehicles (UAVs), and deep Q-learning networks (DQNs) to develop an integrated system for ecological monitoring and restoration. The research focused on developing an AI-assisted environmental monitoring system and an ecological restoration model. The system integrated satellite remote sensing, UAV inspections, and ground sensor networks to provide comprehensive real-time monitoring data. Additionally, historical data from restoration initiatives and meteorological stations were analyzed alongside the collected data. The study demonstrated the effectiveness of the developed AI system in improving environmental governance and resource utilization efficiency. Key findings included an increase in vegetation coverage from 0.30 to 0.65, representing an improvement of 116.7%; a reduction in soil erosion from 0.25 to 0.10, indicating a 60% decrease; and a significant decrease in water turbidity from 25 NTU to 10 NTU, corresponding to a 60% reduction. This research highlighted the significant role of AI in ecological environment restoration. By integrating various data sources and employing advanced machine learning techniques, the system could predict restoration outcomes and optimize strategies based on feature importance. The personalized restoration strategy recommendation system powered by DQNs enabled dynamic optimization and environmental adaptability. The empirical evidence from urban transportation and agricultural irrigation applications underscored the transformative impact of AI technology on improving environmental management and resource efficiency.

Keywords: spatiotemporal evolution; artificial intelligence; tourist attractions; ecological environment restoration.

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Introduction

With the robust growth of global tourism, tourist attractions have become vital showcases for natural and cultural resources. However, this has led to unprecedented ecological pressures, manifesting in various forms such as biodiversity loss, water pollution, soil erosion, vegetation cover decline, and landscape fragmentation. Excessive tourist activities cause issues like path erosion, garbage accumulation, and noise pollution, which not only degrade wildlife habitats but also diminish tourist experiences. These impacts pose serious threats to the ecological balance of scenic areas and the long-term sustainability of the tourism economy, especially in ecologically sensitive regions like alpine ecosystems, wetlands, and tropical rainforests, where effective management and restoration measures are urgently needed [1].

Long-term monitoring data on vegetation cover show that vegetation cover in the core tourist area and its surrounding areas has decreased by about 10% in the past 30 years, especially in the most frequent tourist sites such as main entrances and observation platforms with a decrease of up to 15%. Soil erosion depth increases obviously on both sides of slope and footpath, increasing about 2 cm every year on average, which not only affects terrain stability, but also may lead to soil erosion and affect water conservation [2]. Due to domestic sewage discharge and garbage dumping, the water quality of rivers and lakes near tourist activity areas deteriorated, showing that the dissolved oxygen content decreased, and the ammonia nitrogen concentration increased. As habitat fragmentation and anthropogenic disturbance intensify, endemic native species such as certain rare birds and insects experience population decline and biodiversity loss. Direct contact and trampling by tourists have resulted in wear and tear on the fragile surfaces of some monuments, which over time may cause irreversible damage to Machu Picchu's cultural heritage (Urubamba, Cusco Region, Peru) [3, 4].

The ecological environment is the foundation of tourism development, crucial for attracting tourists and supporting local communities' well-being and socio-economic stability. To address these challenges, the utilization of high-tech tools, particularly spatiotemporal analysis and artificial intelligence, is imperative [5, 6]. These technologies enable precise identification of ecological issues, prediction of trends, and formulation of efficient remediation strategies, facilitating more scientifically informed, forward-looking, and effective environmental management practices [7]. The widespread applications of spatiotemporal analysis in natural resource management and ecological environment monitoring have been seen in recent years [8]. By integrating multi-source data, these technologies can dynamically track and analyze ecosystem changes. However, there remains a gap in their comprehensive application for the ecological restoration of tourist attractions, particularly in strategy formulation and effect evaluation [9]. The rapid advancement of Geographic Information Systems (GIS), Remote Sensing (RS), and Global Positioning Systems (GPS) has significantly enhanced spatiotemporal analysis capabilities, transforming them into powerful tools for ecological environment change assessment. Studies have shown that integrating multiple remote sensing data and GIS platforms can effectively monitor the dynamic changes of ecological environments in tourist attractions and accurately describe their spatial distribution characteristics [10]. For instance, the use of long-term satellite imagery and spectral analysis methods has provided detailed insights into vegetation cover dynamics, highlighting the patterns of ecological recovery and degradation [11]. The emergence of spatiotemporal big data and the integration of machine learning technologies such as the combination of random forest (RF) algorithms and time series analysis models offer new opportunities for predicting ecosystem trends. Techniques like Convolutional Neural Networks (CNNs) and other deep learning networks have improved the accuracy and efficiency of ecological element recognition in high-resolution remote sensing images. Furthermore, the combination of spatiotemporal data mining with artificial intelligence algorithms has enabled predictive identification of ecological risk areas and provided data-driven support for preventive measures [12].

Artificial intelligence (AI), particularly deep learning and neural network models, is reshaping ecological risk assessment and intelligent early warning systems. For example, deep learning-driven frameworks enable rapid and accurate classification of ecological degradation states, enhancing the timeliness and accuracy of assessments. The integration of continuous data streams from Internet of Things (IoT) sensors with advanced AI algorithms shows potential for proactive identification of ecological risks, providing valuable time for preventive measures. Machine learning and satellite remote sensing data analysis have also been utilized in early forest fire warning systems, improving disaster response efficiency and preparedness [13]. In the field of ecological restoration, the innovative application of machine learning and deep learning models is leading to more scientific and personalized restoration strategies. Researchers are leveraging big data to guide ecological restoration through intelligent means. Techniques like reinforcement learning have demonstrated potential in optimizing water resources management strategies, addressing water scarcity issues under climate change. Machine learning algorithms have been used to analyze historical restoration cases, extracting key elements of successful restoration, and providing a scientific basis for customizing strategies. The use of deep reinforcement learning (DRL) has shown promise in autonomously exploring and determining the most effective restoration paths through virtual experimentation, reducing costs and risks [14, 15].

This study was dedicated to exploring and verifying an innovative methodology for ecological environment restoration of tourist attractions, the core of which laid in the integration of in-depth analysis of spatiotemporal dimensions and advanced artificial intelligence technology, aiming to cope with the ecological degradation challenges faced by current tourist destinations and ensure the harmonious coexistence of long-term prosperity of tourism and natural environment. Specifically, the study aimed to achieve the following core objectives [16], which included to deeply understand and quantitatively evaluate the ecological environment of tourist attractions, comprehensively expose ecological dynamics and potential risks, and accurately evaluate the impact of ecological health and tourist activities through high-precision spatiotemporal analysis technology. An intelligent monitoring system integrated with AI algorithm was constructed, which not only tracked ecological environment parameters in real time, but also predicted ecological degradation trends, issued early warning signals in time, and provided solid scientific support for rapid intervention. Further, machine learning and deep learning technology were used to analyze rich repair cases, optimize and generate personalized repair strategies, and ensure that the repair measures for the uniqueness of each scenic spot achieved the highest efficiency and effect [17, 18]. The spatiotemporal analysis was employed to track changes over time and space. The artificial intelligence, particularly machine learning and deep learning algorithms, were used to process large volumes of data efficiently. Additionally, GIS, RS, and GPS were integrated to create comprehensive models for ecological environment monitoring and assessment. These tools enabled the development of intelligent early warning systems and data-driven decision support mechanisms, which were crucial for formulating effective ecological restoration strategies [19]. This research was significant not only for its practical implications but also for its contribution to the scientific community. By combining cutting-edge technologies with traditional ecological restoration practices, the research aimed to advance the field of environmental science and management. The results would provide a solid foundation for future studies and might lead to the development of new, more efficient approaches to managing human impacts on the natural environment. Furthermore, the results of this study could have far-reaching effects, influencing policymaking and guiding sustainable development practices globally [20].

Materials and methods

Research site

Machu Picchu (Urubamba, Cusco Region, Peru) is in the Peruvian Andes, approximately 75 kilometers (47 miles) northwest of Cusco. Situated on a ridge above the Urubamba River at an elevation of about 2,430 meters (7,970 feet), the site is characterized by a subtropical humid climate with distinct seasons. Despite visitor limitations to 2,500 people per day, the high volume of tourists poses a significant threat to the fragile archaeological site [21]. Activities such as walking tours, photography, and guided tours have resulted in soil erosion and structural damage. Additionally, waste disposal, water consumption, and impacts on local wildlife are pressing concerns. As a treasure house of biodiversity, the ecological environment of Machu Picchu is critical for the preservation of both the heritage site and the surrounding ecosystem [22].

Data and resources

The data used in this study were sourced from several reputable databases and online resources. Geospatial data were obtained from the National Aeronautics and Space Administration (NASA) Earth Observing System Data and Information System (EOSDIS), provided by NASA (Washington, D.C., USA) (https://earthdata.nasa.gov/). For remote sensing imagery, data were sourced from the European Space Agency (ESA) Sentinel Hub (European Space Agency, Frascati, Lazio, Italy) (https://sentinel.esa.int/web/sentinel/home). Historical climate data were retrieved from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) (NOAA, Asheville, North Carolina, USA) (https://www.ncei.noaa.gov/) [23, 24]. In this study, a variety of advanced remote sensing and machine learning techniques were utilized to monitor and assess the ecological environment of Machu Picchu. For vegetation health assessment, the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) were calculated using Sentinel-2 Multi-Spectral Instrument (MSI) data obtained from ESA. To highlight water features and identify built-up areas, the Normalized Difference Water Index (NDWI) and the Normalized Difference Built-up Index (NDBI) were computed and used, respectively. Both derived from Sentinel-2 MSI data. For time series forecasting of visitor trends and potential impacts on the site, the AutoRegressive Integrated Moving Average (ARIMA) model was applied to leverage historical data and implement it using Python library statsmodels (https://www.statsmodels.org/stable/index.html). To analyze the high-resolution imagery, CNNs were employed and implemented using TensorFlow (https://www.tensorflow.org/) and PyTorch (https://pytorch.org/). Specifically, the VGG-16 architecture was utilized, for which pre-trained models and documentation could be found at the TensorFlow Model Garden (https://github.com/tensorflow/models/tree/master/research/slim), and the ResNet architecture, for which pre-trained models and documentation were available at the PyTorch Model Zoo (https://pytorch.org/vision/stable/models.html). For detailed analysis and change detection, Unmanned Aerial Vehicle (UAV) imagery with Sentinel-2 MSI data was integrated and processed using Pix4D (https://pix4d.com/). To handle categorical data, One-Hot Encoding was implemented using pandas (https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html). Finally, to optimize decision-making processes, a Deep Q-Network (DQN) was implemented using TensorFlow Reinforcement Learning (https://www.tensorflow.org/reinforcement_learning) to automate the selection of appropriate conservation measures based on the ecological conditions detected by the models [25, 26].

Spatiotemporal evolution analysis

The remote sensing satellite images such as Landsat series over the past 30 years were collected, as well as ground-based observations such as climate data recorded by weather stations, visitor statistics, vegetation cover, and soil erosion. Radiometric correction, geometric correction, and atmospheric correction were applied to the remote sensing image, and then image cropping was performed to preserve only the study area. NDVI was used to calculate vegetation cover and assess soil erosion changes through difference analysis. ARIMA model was used to analyze the change trend of vegetation coverage and tourist number with time. Rigorous mathematical models and analytical methods were used to analyze the temporal and spatial evolution of Machu Picchu's ecological

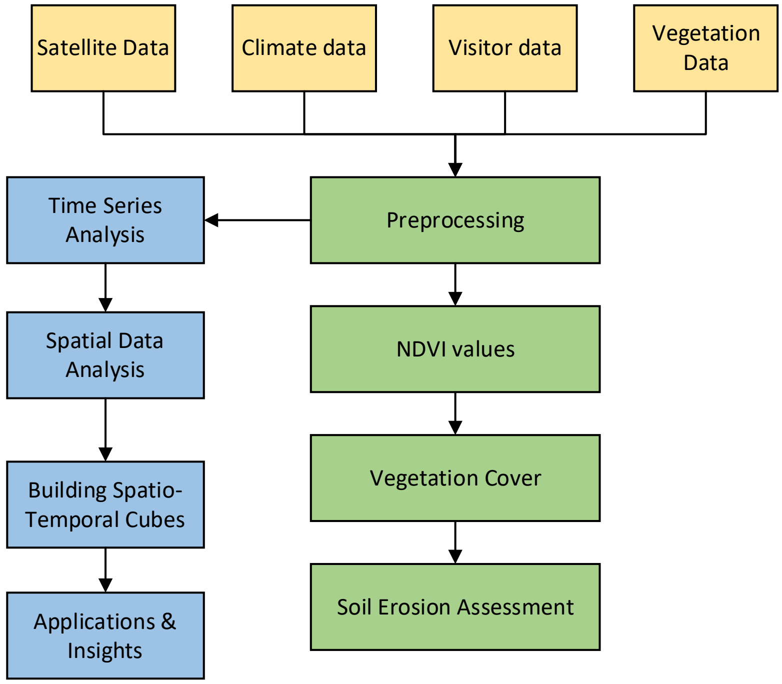

Figure 1. Specific flow of spatiotemporal evolution analysis.

environment. The NDVI coverage was shown in Equation 1 [27].

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

ARIMA is a classical statistical model widely used in time series analysis and prediction. It combines autoregression (AR), differential integration (I), and moving average (MA) processes, hence the name ARIMA model. The general form of the ARIMA model was shown in Equation 2 [23].

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \quad (2)$$

where B was the lag operator. y_t was the observed value of the time series at time t. ϕ and θ were autoregressive and moving average polynomials, respectively. d was the difference order. ε_t was the white noise sequence. Future trends could be predicted by fitting series such as vegetation coverage or visitor numbers. For spatial data, ordinary kriging interpolation (OK) was used to estimate the value of unknown points, and its equation was given in Equation 3 [28].

$$Z(s_0) = \sum_{i=1}^{n} \lambda_i Z(s_i) + m \quad (3)$$

where, s was the value of the point to be evaluated. λ_i was the kriging weight. $Z(s_i)$ was the value of the neighboring known point. m was the trend term. The weights were determined by minimizing the error variance. Building spatiotemporal cube model was an advanced process of organizing and analyzing spatiotemporal data, which skillfully integrated time series and geographical information and provided an intuitive and efficient framework for understanding dynamic changes. In this process, the spatial data layers of each moment were carefully arranged like slices of time, stacked one by one, and finally constructed into a three-dimensional, multidimensional data matrix. This organization not only preserved the temporal order of the data and ensured the consistency of dynamic evolution, but also captured the geographical distribution and diffusion patterns of phenomena or events through spatial dimensions. The space-time cube model was like a three-dimensional time camera, which frozen the geographical snapshot of each moment, and then connected through the axis of time, so that the story of data unfolded slowly from a dynamic and four-dimensional perspective, providing researchers with an all-round and multi-level data exploration platform (Figure 1).

Problem identification and cause analysis

The ecological environment problems of Machu Picchu were mainly manifested in the decline of vegetation coverage, soil erosion, water quality, biodiversity threat, and cultural heritage damage. The main causes of these problems were excessive tourism, inadequate management, inadequate infrastructure, climate change, and insufficient public awareness. Machu Picchu is a world-class tourist destination, and the continuous growth of visitor numbers exceeds the carrying capacity of natural and cultural heritage, leading directly to vegetation destruction, soil erosion, and pressure on cultural heritage. The lack of effective tourist management measures such as flow restriction, reasonable distribution of tourists, and tourism activity design with less impact on the environment makes environmental pressure concentrated in specific areas. The sewage treatment system and garbage treatment facilities are backward and cannot effectively treat the waste generated by increasing tourists, resulting in water pollution and environmental degradation. Frequent extreme weather events caused by global climate change such as heavy rainfall and drought, aggravate soil erosion and vegetation cover reduction, although not directly caused by tourism activities, but closely related to climate change trends caused by human activities. The lack of awareness of environmental protection among tourists and residents leads to uncivilized tourism behaviors such as littering and illegal picking of plants, which cause additional burdens on the ecological environment [29]. The ecological environment of Machu Picchu is a complex and systematic problem, involving tourism management, infrastructure construction, climate change, and social culture. Therefore, addressing these issues requires interdisciplinary, multidimensional collaboration, and innovative strategies that focus on both short-term mitigation measures and long-term sustainable development strategies.

AI-assisted environmental monitoring system

To build an efficient and comprehensive environmental monitoring system, the satellite remote sensing, unmanned aerial vehicle inspection, and ground sensor technology were deeply integrated and combined with advanced AI algorithm to achieve real-time monitoring and intelligent analysis of Machu Picchu ecological environment. The flow chart of AI-assisted environmental monitoring system was shown in Figure 2. Using high-resolution multispectral and hyperspectral satellite data such as Sentinel-2 MSI, various spectral indices for environmental monitoring were applied. In addition to NDVI and Enhanced Vegetation Index (EVI), other indices such as Normalized Difference Moisture Index (NDWI) and Normalized Building Index (NDBI) were introduced to provide a more comprehensive assessment of vegetation status, water body distribution, and human impacts. Images taken by high-resolution cameras carried by drones were recognized and analyzed through deep learning networks. Convolutional neural network (CNN) architectures including Visual Geometry Group 16 (VGG-16) or Residual Network (ResNet) were employed to identify vegetation types, land cover changes, and erosion levels. The basic computational unit of CNN was convolutional layer, and its forward propagation formula could be simplified as equation 4 [30].

$$O_j = f(b_j + \sum_i W_{ij} \cdot X_i) \quad (4)$$

where X_i was the input feature map. W_{ij} was the convolution kernel weight. b_j was the bias term. f was the activation function. O was the

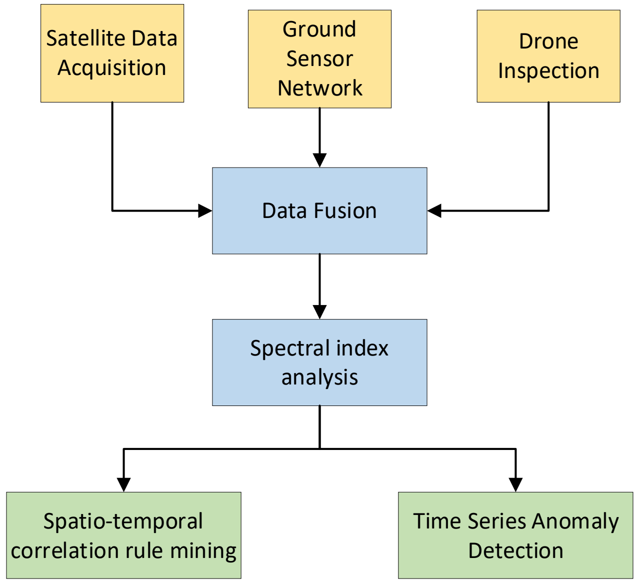

Figure 2. AI-assisted environmental monitoring system.

output feature map. Data collected by ground sensors such as soil moisture, temperature, light intensity were transmitted to the cloud database in real time *via* wireless networks and were integrated with satellite and UAV data through spatiotemporal fusion technology. Anomaly detection and trend analysis were then performed by using spatiotemporal association rule mining algorithms such as spatiotemporal cube query. The time series anomaly detection formula was expressed as below.

$$z_t = \frac{x_t \hat{\mu}_t}{\hat{\sigma}_t} \quad (5)$$

where z_t was the current observation. x_t and $\hat{\mu}_t$ were the predicted mean and standard deviation at time t, respectively. $\hat{\sigma}_t$ was the normalized scores used to identify anomalies.

Ecological environment restoration model

When constructing the ecological environment restoration model, the prediction ability of random forest algorithm and the process of feature selection, model optimization, and parameter optimization were all explored to ensure the accuracy and generalization ability of the model. The ecological restoration process was shown in Figure 3.

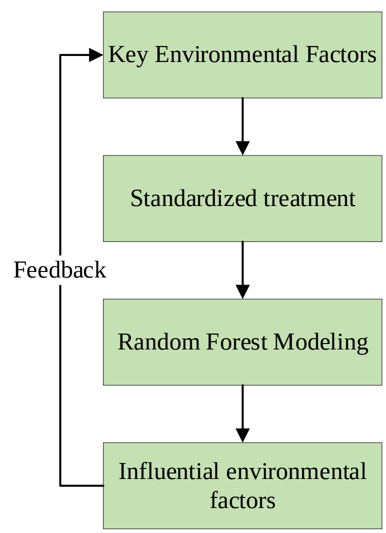

Figure 3. Ecological restoration process.

Feature engineering was the cornerstone of model construction, while the right features could significantly improve model performance. In this study, the following key environmental factors were selected as model inputs, which included (1) soil type defined by numeric type characteristics coded by soil texture classification; (2) vegetation type identified by using One-Hot coding to convert each type of vegetation into a single hot vector; (3) precipitation determined using average monthly precipitation taken directly as a continuous numerical feature; (4) temperature using mean monthly temperature as a continuous numerical feature; and (5) visitor density identified using average daily number of visitors per unit area, reflecting anthropogenic pressure. Normalization of continuous numerical features, such as Z-score normalization, ensured that features at different scales had equal importance in the model. Random forest algorithm improved the stability and accuracy of prediction by integrating multiple decision trees. Each tree was trained independently on randomly selected sample subsets and feature subsets, and its prediction function could be expressed as equation 6.

$$f(x)=\frac{1}{T}\sum_{t=1}^{T}h_t(x;\Theta_t) \tag{6}$$

where *T* was the number of trees in the forest. Θ_t was the prediction output of tree t. h_t was based on a set of tree parameters $\sum_{t=1}^{T}h_t(x;\Theta_t)$ including tree structure like node split points, split features, thresholds, *etc*. A powerful feature of random forests was the feature importance assessment. At each split, features were ranked according to their split gain such as Gini impurity reduction or information gain. The model ultimately aggregated the gains of features in all trees to determine global importance. The specific calculation formula was shown below.

$$Importance(feature_i)=\frac{\sum_{t=1}^{T}\mathrm{Gain}_t(feature_i)}{\sum_{j=1}^{F}\sum_{t=1}^{T}\mathrm{Gain}_t(feature_j)} \tag{7}$$

where $feature_i$ was the gain from splitting in tree t. *F* was the total number of features. Through the above assessment, the environmental factors that had the most influence on the ecological restoration effect such as precipitation and visitor density could be identified, which might be key variables. The features could be further screened, models could be optimized to avoid over-fitting and improve interpretability.

Personalized repair strategy recommendations

The fusion of deep learning and reinforcement learning provided a dynamic, flexible, and highly adaptive decision-making framework that included feature representation, model architecture, policy optimization, and policy execution processes to achieve optimal repair policy recommendations for different regions and problems. Based on the collected monitoring data, a feature vector of the repair area was constructed with the characteristics of traditional environmental factors, dynamic information of spatiotemporal characteristics such as change rate and seasonal fluctuation, and human activity intensity. To handle these multimodal features, embedding was applied to convert the categorical features into dense representations in a continuous vector space as follows.

$$e_{cat}=EmbeddingLayer(category) \tag{8}$$

where *category* was the original category feature and $EmbeddingLayer$ was the corresponding embedding vector. Deep Q-Network (DQN) was used as the core algorithm, combining the environmental states and policy action selection to learn the optimal policy. The model architecture consisted of two main parts of feature extractor and Q-value network. CNN used to process image features such as vegetation coverage change maps was combined with fully connected layers used to process non-image features to form a hybrid feature representation (Equation 9). Based on the feature representation *h*, the *Q* value for each possible action was predicted through a series of fully connected layers shown in equation 10.

$$h = ReLU(ConvLayer(s_{img}) + DenseLayer(s_{non-img}) \quad (9)$$

$$Q(s,a) = DenseLayer(h) \quad (10)$$

At the heart of reinforcement, learning laid the balance between exploration and exploitation. In repair strategy recommendation, this meant both trying new strategies to discover possible better solutions and taking advantage of known effective strategies. The ε-greedy policy was used to achieve this equilibrium as shown in equation 11.

$$a_t = \begin{cases} \text{random action} & \text{with probability ò} \\ \text{argmax}_a Q(s_t, a) & \text{otherwise} \end{cases} \quad (11)$$

where “random action” was the probability of randomly choosing an action in the current state. $Q(s_t, a)$ decreased with time and depended more on the current optimal policy. The evaluation of restoration strategies was achieved through a well-designed reward function that considered long-term ecological restoration benefits and cost-effectiveness. Assuming an immediate reward, the total return could be described by the Bellman equation below.

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \quad (12)$$

where r_{t+k} was the discount factor that guaranteed a reduction in the present value of future rewards. The strategy recommendation process included iterative learning and online adjustment. Every time an action was performed, the *Q* value was updated according to actual effect feedback, and overfitting was reduced through experience replay and fixed Q-targets. The updated formula was shown as equation 13.

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)] \quad (13)$$

where α was the learning rate. *a'* was the possible action in the next state. Through the deep reinforcement learning framework, the optimal repair strategy could be intelligently recommended based on the current environmental state. In addition, the environmental changes over time could be learned and adapted to optimize the strategy and achieve personalized repair.

Data collection and processing

Data collection efforts focused on Machu Picchu and its surrounding areas with a timeline spanning from 2010 to 2027 with the integration of multiple data sources including satellite remote sensing data, meteorological data, ground survey data, and restoration project archives to construct a comprehensive dataset. The data preprocessing process strictly followed scientific standards including data cleaning, standardization, category coding, and feature refinement, ensuring the accuracy and reliability of the analysis.

Results and discussion

Satellite platforms and data collection

The Landsat 8 and Sentinel-2 satellites were two of the most important earth observation platforms for remote sensing. Landsat 8 launched by the National Aeronautics and Space Administration (NASA, USA) in 2013 collected high-resolution multispectral images of the earth's surface, enabling scientists and researchers to monitor changes in land use, vegetation, and water resources over time. Sentinel-2, part of the European Space Agency's (ESA) Copernicus program, was launched in 2015 and 2017 with Sentinel-2A and Sentinel-2B, respectively, which provided high-resolution optical imagery with a wide swath width, facilitating detailed monitoring of agricultural practices, forest management, and environmental changes. To assess the effectiveness of AI technology in ecological restoration, this study combined multispectral images from Landsat 8 and Sentinel-2 satellites, monthly precipitation and mean temperature records from nearby meteorological stations,

Table 1. Comparison of sample size before and after data cleaning.

Data type	Sample size before cleaning	Sample size after cleaning	Reduction ratio
satellite remote sensing	1,200	115	5%
meteorological	1,200	118	1.67%
ground survey	100	95	5%

Table 2. Overview of cross-validation results.

Model type	Folding number	Accuracy	Precision rate	Recall rate	F1 score
Random forest	Fold 1	0.87	0.85	0.86	0.86
Random forest	Fold 2	0.89	0.90	0.88	0.89
Random forest	Fold 3	0.86	0.84	0.85	0.84
Random forest	Fold 4	0.88	0.87	0.86	0.86
Random forest	Fold 5	0.90	0.91	0.89	0.90
Average		0.88	0.87	0.87	0.87

ground survey data, and archives of all restoration initiatives implemented over the past decade. The data underwent rigorous data cleansing, standardization, category coding, and feature refinement to build a high-quality dataset, which contained abundant information of vegetation coverage, land use dynamics, soil types, vegetation composition, tourist activity frequency and provided a solid foundation for model validation and application analysis. The sample size before and after data cleaning was compared (Table 1). The random forest (RF) model performed in a 5-fold cross-validation. Each fold's accuracy, precision, recall, F1 scores, and their average values were calculated (Table 2). The average accuracy, precision, recall, and F1 score were 0.88, 0.87, 0.87, and 0.87, respectively, which indicated the stability and generalization of the model.

Evaluation of model performance

(1) Analysis of feature importance

The feature importance score showed that precipitation was the most important feature with a score of 0.28. Soil type was next with a score of 0.25. The importance scores of visitor density, average temperature, and vegetation type were 0.20, 0.15, and 0.12, respectively. These scores were helpful to identify the environmental factors that contributed most to model predictions and provided guidance for subsequent policy optimization.

(2) Comparative model assessment

The Scikit-learn library, a globally renowned and community-maintained machine learning resource (https://scikit-learn.org/), was utilized to implement and evaluate three distinct machine learning models including random forest (RF), support vector machine (SVM), and logistic regression. Each model was trained on a dataset derived from Sentinel-2 MSI data and ground truth information. The RF and SVM models implemented *via* Scikit-learn

Table 3. Comparison of urban traffic congestion management system before and after optimization.

Indicators	Before optimization	After optimization	Improvement
Average commute time (minutes)	45	35	-22.22%
Traffic delay index	1.25	0.98	-21.60%
Average vehicle speed (km/h)	20	25	+25.00%
Air Quality Index (AQI)	85	70	-17.65%
Public Satisfaction Survey Score (/10)	5.8	7.2	+24.14%

demonstrated their capabilities in handling complex, high-dimensional data. For performance assessment, the area under the curve of the receiver operating characteristic (AUC-ROC) metric was applied and calculated using Scikit-learn's "roc_auc_score" function, providing a scalar value that encapsulated the classifiers' true positive and false positive rates across various thresholds, thereby offering a comprehensive evaluation of each model's efficacy. The results showed that the RF model had an accuracy of 0.87, precision of 0.86, recall of 0.86, F1 score of 0.86, and AUC-ROC of 0.92. The SVM model performed slightly worse than RF with an accuracy of 0.84, precision of 0.83, recall of 0.84, F1 score of 0.83, and AUC-ROC of 0.88, while the logistic regression model demonstrated an accuracy of 0.82, precision of 0.81, recall of 0.82, F1 score of 0.81, and AUC-ROC of 0.85. The results indicated the advantages of the RF model over other models.

Assessment of ecological restoration impact

Vegetation coverage being measured as a fraction (0 to 1) increased from 0.30 to 0.65 with an improvement of 116.7%. Soil erosion degree that was expressed in t/(km²·a) decreased from 0.25 to 0.10 with a 60% reduction. Nephelometric turbidity unit (NTU) is a measure of the clarity of water, where a lower value indicates clearer water. The results showed that water quality index (turbidity) was reduced from 25 to 10 NTU with a reduction of 60%. The results showed that the application of AI technology to ecological environment restoration had achieved significant improvements.

Case analysis

To more intuitively illustrate the process of case application and effect analysis, two representative scenarios were selected with one as the optimization of urban traffic congestion management system and the other as the promotion and use of agricultural precision irrigation system. Both cases aimed to use advanced data analytics and intelligent algorithms to solve long-standing socio-economic problems and improve public well-being and resource efficiency. The results showed that, by introducing intelligent signal control, real-time road condition prediction, and travel suggestions, it not only significantly shortened the average commuting time of citizens and reduced the traffic delay index, but also increased the vehicle speed and reduced the air pollution caused by long idle time. In addition, public satisfaction with traffic conditions had increased significantly, reflecting the positive effect of system optimization on improving quality of life (Table 3). The extension effect of agricultural precision irrigation systems demonstrated that, through the integration of soil moisture monitoring, meteorological prediction, and crop growth model, the system realized accurate control of irrigation, effectively improved crop yield, and greatly reduced the consumption of water resources and pesticides, which was of great significance to environmental protection and sustainable development (Table 4). Through the application and effect analysis of two cases, the results confirmed that technological innovation and intelligent solutions had great potential in solving practical problems.

Table 4. Popularization effect analysis of agricultural precision irrigation system.

Indicators	Before promotion	After promotion	Improvement
Average crop yield (kg/mu)	3,000	3,500	+16.67%
Irrigation water consumption (m^3/mu)	500	400	-20.00%
Pesticide usage (kg/mu)	2.5	2.0	-20.00%
Average annual income growth rate of farmers (%)	2.5	5.0	+100.00%
Reduction in soil salinization (%)	-	10	N/A

The optimization of urban traffic congestion management system not only relieved traffic pressure, but also indirectly improved air quality and residents' life quality. The promotion of agricultural precision irrigation system ensured food security and promoted efficient utilization of resources, further significantly increased farmers' economic benefits, reflecting the broad prospects of science and technology enabling agriculture.

Conclusion

By integrating AI technology with ecological restoration strategies, this study demonstrated the great potential of technology in modernizing environmental governance and improving ecological restoration efficiency and sustainability. AI-assisted environmental monitoring system provided accurate and timely information support for environmental management through multi-source data fusion and intelligent analysis. The ecological environment restoration model, especially the prediction model based on random forest, not only improved the prediction accuracy, but also provided scientific basis for formulating targeted restoration measures through feature importance analysis. A personalized repair strategy recommendation framework was further proposed, which used deep reinforcement learning to realize adaptive optimization of strategies, which provided innovative paths for solving complex and dynamic environmental problems. Empirical studies and case studies demonstrated that AI technology could significantly improve the ecological environment in practical applications such as shortening urban commuting time, reducing traffic delays, increasing agricultural production, while reducing resource consumption. These positive results were directly related to public well-being and economic development. In addition, the case also highlighted the role of technology in improving public satisfaction and promoting environmental quality, providing strong evidence for the harmonious coexistence of ecological environment protection and social economy. AI-based ecological environment restoration technology was feasible in theory and showed strong application potential and significant social and economic value in practice.

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