

Artificial Intelligence-Enhanced Strategic Planning Framework for Sustainable Rehabilitation of Ecosystems and Tourist Attractions Based on Spatiotemporal Dynamics

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Abstract. The development of cities, climate change, and unsustainable activities by humans are all making natural ecosystems and tourist sites worse. This means that new, data-driven techniques are needed for sustainable rehabilitation. Conventional ecological restoration techniques frequently exhibit accuracy, flexibility, and sustained efficacy deficiencies within dynamic ecosystems. To deal with these problems, combining Artificial Intelligence (AI) with spatiotemporal analysis has become a revolutionary way to prepare for the natural world and regulate ecosystems. This study utilized artificial intelligence, unmanned aerial vehicles (UAVs), and deep Q-learning networks (DQNs) to create an effective ecological monitoring and restoration system. The main goal was to create a sustainable ecological restoration system to make the area more attractive to tourists (SRE&TA). The system got real-time tracking data from satellites, UAVs, and sensor networks that were far away. The researchers looked at the restoration projects and data from weather sensors to learn more about the restoration initiatives. The results showed that the AI system could greatly improve the efficiency of resources and environmental monitoring. DQNs automated the sustainable ecological rehabilitation system to improve tourism attraction based on spatiotemporal dynamics (SRE&TA-StD). They did this by creating personalized restoration plans. The suggested method using DQN worked for the SRE&TA-StD tests.

1 Introduction

Land degradation refers to the loss of environmental benefits caused by human activities that disrupt natural processes, leading to reduced productivity, pollution, habitat loss, and land destruction [1]. It negatively affects landscapes, wildlife, human health, and economic development at both regional and global levels [12]. Therefore, restoring land resources and associated ecosystems is essential.

Ecological rehabilitation aims to restore damaged ecosystems to their original state by integrating biological and socioeconomic knowledge to identify degradation causes and implement suitable restoration strategies [2]. The ultimate goal is to sustain ecosystem services while supporting economic and social development [9].

Previous studies have focused on infrastructure, cultural aspects, economic factors, and environmental impacts. Restoration efforts include soil and water remediation, erosion and salinity control, reforestation, and agricultural land conservation [3][10]. Cultural and social aspects, such as habitat preservation and community identity, are also considered [13]. Infrastructure improvements involve eco-friendly development, green spaces, and sustainable tourism [5].

Existing evaluation methods are limited, often relying on single-factor assessments that fail to provide comprehensive restoration strategies [4][11]. This results in ineffective rehabilitation due to insufficient analysis of biological processes [6]. Additionally, lack of community involvement reduces public acceptance [7]. Studies have also overlooked local ecological risks and human health impacts [8][16], while challenges remain in handling complex, non-linear, and diverse geographical data [14][15].

2 Proposed methodology

Developing an effective and all-encompassing ecological surveillance system involved integrating satellite imagery, UAV assessment, and surface technology for sensors with cutting-edge artificial intelligence algorithms to enable smart evaluation and continuous tracking of ecological surroundings for TA. Fig. 1 displays the AI-assisted SRE&TA system's workflow.

Sentinel-2 MSI and other high-quality multispectral and hyperspectral satellite images were used to apply various spectral indicators for ecological monitoring. Additional indices, including the Standardized Variance Moisture Indicator (SVMI) and the Standardized Construction Indicator (SCI), were combined with the

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Improved Vegetation Indicator (IVI) to provide a comprehensive assessment of water bodies, vegetation condition, and human impacts. Deep learning (DL) networks analyzed high-resolution drone images, while convolutional neural networks (CNNs), particularly Residual Networks (ResNet), were used to identify plant species, detect land-use changes, and assess erosion stages.

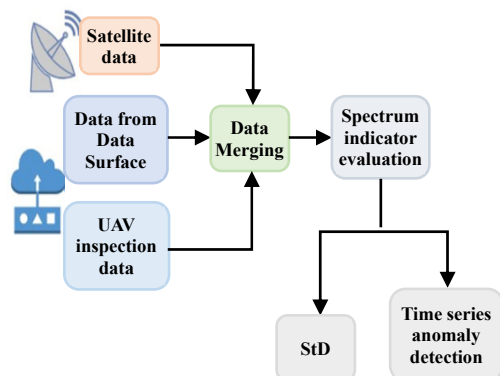


Fig. 1. AI-assisted SRE&TA system's workflow.

To ensure reproducibility and scientific rigor, the study employs well-defined deep learning models. CNNs, specifically ResNet-50, are fine-tuned for segmentation and classification of vegetation types and land-use changes using high-resolution drone imagery. In addition, DQN are utilized for adaptive decision-making in ecological restoration. The DQN state space incorporates key ecological variables such as soil type, moisture, temperature, and visitor concentration, while the action space includes restoration strategies like reforestation, soil conservation, and region-specific interventions. The reward function is designed to maximize both ecological restoration and tourism potential, enabling the system to generate efficient and sustainable restoration plans based on dynamic environmental data.

Using StD, data from satellites and UAVs was combined with data from surface sensors, including humidity, temperature, and light quality, and sent in real-time to the cloud storage system over wireless connections.

To ensure technical rigor, the study employs well-defined deep learning models. Convolutional neural networks (CNNs), particularly ResNet-50, are fine-tuned for image segmentation and classification tasks, including vegetation type identification and land-use change detection using high-resolution drone imagery. In addition, U-Net is utilized for pixel-level land cover classification. The Deep Q-Learning Network (DQN) is implemented with a state space defined by ecological parameters derived from satellite data, UAV measurements, and surface sensors, including soil type, soil moisture, temperature, visitor density, and vegetation health. The action space consists of predefined restoration strategies such as reforestation, soil conservation, and erosion control.

The reward mechanism was developed to maximize ecological restoration and tourism potential, considering ecological impact (soil health, vegetation recovery, moisture levels), tourism potential (visitor concentration), and cost efficiency. The DQN architecture featured the

input layer, the state vector, fully connected hidden layers with the ReLU activations of non-image data, and the CNN layers to work with image-based features. The output layer produced Q-values of every available action, which were also updated with experience replay and target networks to stabilize training. The Q-values were updated continually through real-time environmental feedback, and so, the system learns and agrees with the best ecological restoration strategies over time.

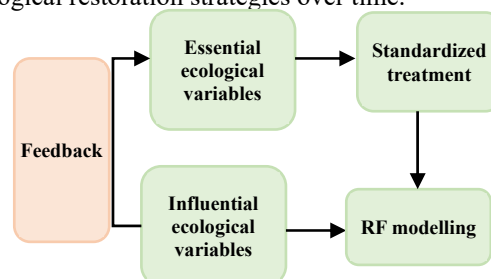


Fig. 2. SRE&TA approach.

Then, StD mining of associations, including spatiotemporal cube search, anomaly identification, and pattern evaluation, was utilized. To confirm the accuracy and generalizability of the SRE&TA-StD model, the random forest (RF) algorithm's forecasting ability, feature decision-making, model effectiveness, and variable optimization processes were all investigated throughout implementation. Fig. 2 illustrates the SRE&TA approach.

Feature engineering formed the basis of model development, with key ecological variables selected as inputs. These included soil type (encoded using soil quality categories), vegetation type (represented through one-hot encoding), moisture (median monthly rainfall), temperature (average monthly values), and tourist visitor concentration (mean daily visitors per unit area), capturing both environmental and human influences.

The model gave Characteristics at various scales equal weight thanks to normalizing persistent numerical characteristics, such as Z-score standardization. The RF technique combined many decision trees to increase forecast stability and precision. Moisture and TA visitor concentration, two environmental parameters that may be important variables, were shown to have the greatest impact on the ecological restoration effect via the study mentioned above. Further screening of the characteristics and model optimization to prevent excessive fitting and enhance accessibility are also possible.

Sustainable Ecological Rehabilitation (SRE) and, subsequently, TA have been given by

$$SRE_l = \sum a_l \times V_{pl} \quad (1)$$

SRE_l is the SRE of land type 'l.' a_l is the area for land type 'l.' V_{pl} is the cost parameter of the land type 'l.'

To generate the most optimal rehabilitation policy recommendations to various regions and issues, the fusion of DL and reinforcement learning (RL) formed an active, flexible, and highly adaptable choice-making framework that encompassed the feature representation, model specifications, policy performance, and the process of implementation. Based on the information acquired in the course of surveillance, an attribute vector of the repair area was constructed, which featured human behaviour

magnitude, constantly changing data pertaining to StD features, as well as velocity of change and periodic swings, and traditional environmental parameters. These heterogeneous attributes were represented in a continuous vector space, through encoding, by the category features.

The key algorithm, Deep Q-Network (DQN), develops the best policy, combining environmental conditions with policy-making choices. The two primary components of the model architecture were the Q-value system and the attribute extractor. A mixed description of features was created by combining fully connected layers that analyze non-image information with CNN, which processes image characteristics like plant coverage shift maps. A sequence of completely linked layers estimated the Q value for every potential action based on the attribute representations.

Learning was crucial to RL because it established an equilibrium between discovery and extraction. Recommendation of repair techniques entailed using established, successful tactics and experimenting with new ones to find potential, better solutions. An efficient incentive function considering value for money and ongoing ecological rehabilitation benefits allowed for assessing rehabilitation options. Iterative learning and online adaptation were part of the strategy suggestion process.

To minimize excessive fitting, replays of events and defined Q-targets were used, and the Q value was modified based on real impact feedback each time a

procedure was carried out. The deep RL framework could suggest the best restoration plan based on the existing environmental conditions. To maximize the approach and accomplish customized restoration, learning and adjusting to how the surroundings vary over time is possible.

3 Results and discussion

To create a complete dataset, data gathering activities concentrated on integrating data from numerous sources, including satellite imagery, remote sensing, weather data, surface surveying information, and rehabilitation program records. To ensure the quality and dependability of the study, the data pretreatment procedure closely adhered to scientific norms, which included cleaning of information, normalization, class coding, and feature refining. This study integrated multidimensional images from the Landsat 8 satellite, humidity, and average temperature archives from local weather stations, surface survey information, and files of all rehabilitation initiatives carried out over the previous five years to evaluate the efficacy of AI-SRE&TA. The information was thoroughly cleaned, normalized, class-coded, and enhanced to make a great database with a lot of information about the amount of greenery, how land is used, the types of soil, the structure of plant life, and the number of TA activities. This dataset was a great starting point for checking models and evaluating their use.

Table 1. Comparison of traditional non-ai methods and proposed ai-based framework for ecological restoration.

Aspect	Traditional non-AI Methods	Proposed AI-based Framework
Approach	Mono-factor assessments (e.g., vegetation or soil health only)	Multi-dimensional, data-driven approach (e.g., soil, moisture, vegetation, and visitor concentration)
Data Collection	Periodic field surveys and manual monitoring	Real-time data from satellites, UAVs, and surface sensors
Adaptability	Static; cannot respond dynamically to changing conditions	Adaptive; learns and updates strategies in real-time using Deep Q-Learning Networks (DQN)
Decision-Making	Reactive, based on periodic data collection	Proactive, using reinforcement learning to adjust restoration strategies based on real-time feedback
Scope of Analysis	Limited to isolated ecological factors (e.g., soil degradation)	Comprehensive, considering multiple ecological and tourism factors simultaneously
Cost and Efficiency	High costs due to manual surveys and the limited scope of data	Cost-effective by automating decisions and optimizing resource usage
Impact of Human Activity	Often ignores or inadequately considers the impact of human activities	Includes visitor concentration, ensuring sustainable tourism and ecological restoration
Outcome	Suboptimal, often with delayed intervention	Improved restoration outcomes, faster response times, and a holistic solution for ecology and tourism

Table 1 is a comparison of the performance and benefits of the traditional non-AI ecological planning techniques and the proposed AI-based model. It brings out the most significant things like the strategy, data collection techniques, flexibility, decision-making moves, scope of analysis, economic nature, influence of human activity, and the final results. The comparison shows that the AI-based framework is better in real-time decision-making, thorough analysis, cost-effectiveness, and consideration of human aspects, such as tourism, making ecological restoration strategies more effective and sustainable.

Fig. 3 indicates that the technology can support SRE and ecologically friendly farming methods. After the implementation of AI-enhanced SRE&TA, the consumption of pesticides and water for farming decreased by 20%, from 2.5 to 2 kg/mu and from 500 to 400 m³/mu, respectively. This demonstrates the value of the system towards motivating people to utilize resources in a more environmentally and cost-effective manner. The average annual rate of increase in the incomes of the farmers rose to 5 % compared to the previous 2.5 %, which is a 100 % improvement and a definite positive impact on the economy. The approach also reduced soil salinization by 10 %, which indicates that the soil is

healthier, and the land serving visitors can be used over a long period. Such findings can confirm the assumption that the SRE&TA system with AI assistance could be

effective in sustainable tourist development as well as environmental recovery.

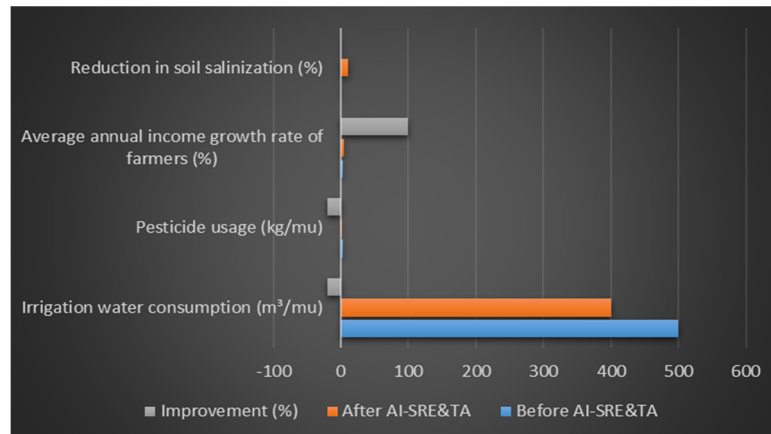


Fig. 3. Analysis of the proposed AI-SRE&TA in precision agriculture.

4 Conclusion

Conventional ways of restoring ecosystems are not always precise, flexible, and effective in the ever-changing ecosystems. The integration of artificial intelligence (AI) and spatiotemporal analysis is now a breakthrough method of understanding the natural world and managing the ecosystem. In this research, artificial intelligence, unmanned aerial vehicles (UAVs), and deep Q-learning networks (DQNs) were used to produce an effective ecological monitoring and restoration approach. This was chiefly intended to make the area more attractive to tourists through the establishment of a sustainable ecological restoration system (SRE&TA). To measure the efficiency of AI-SRE&TA, this paper combined multidimensional points of view based on data captured by the Landsat 8 satellite, humidity, and average temperature measurements by local weather stations, surface survey, and a list of all the rehabilitation projects that have been accomplished in the last five years. After installation of AI-enhanced SRE&TA, pesticides and water used in agriculture were reduced by 20 %; 2.5 to 2 kg/mu; 500 to 400 m³ to m³ respectively. This is an indication of how the system is important in ensuring that resource utilization is environmental and economically beneficial.

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