



Original Research Paper

RestoreAI: A Decision Support Framework for Optimizing Wildlife Habitat Restoration Strategies Using Ecological Data

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Key Words	Abstract
Habitat restoration, Decision support system, Ecological data, Wildlife conservation, Analytic hierarchy process, Species distribution modeling, Restoration prioritization.	The degradation of habitats continues to be among the major causes of decline in wildlife populations but the restoration process often suffers from incomplete ecological information and inconsistent expert judgement. In this paper, RestoreAI is introduced as an ecological data-driven decision support framework that combines multi-source ecological data and suitability ranking model to inform wildlife habitat restoration. RestoreAI includes three layers: ecological data collection, suitability ranking through a modified weighted Analytic Hierarchy Process (AHP) and species distribution results, and adaptive decision support where a resource-constrained restoration plan with a monitoring component is produced. RestoreAI is illustrated conceptually by applying it to a degraded tropical dry forest-grassland mosaic system with a focus on vegetation, soil, species occurrence, and connectivity data at 40 candidate locations. It will be evaluated using a retrospective assessment of the rankings generated through RestoreAI compared to the rankings given by experts in terms of rank correlation and tracking simulated restoration outcomes. Based on similar studies in AI-assisted conservation and restoration scoring, it can be expected that RestoreAI will produce prioritization performance at least comparable to that of the expert-only prioritization with significantly reduced planning time.

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Introduction

The process of wildlife habitat restoration is critical to biodiversity restoration in terms of restoring degraded ecosystems and their natural processes for wildlife support. Prioritization of restoration areas was always performed through site assessment done by experts in ecology, during which the suitability of each particular area for the implementation of restoration activities was evaluated individually. It works well in case of several sites but does not scale well when applied to larger landscapes where dozens or even hundreds of restoration candidate areas have to be considered within the limited period of time due to budget constraints. There is an abundance of data on ecological processes such as vegetation indexes obtained through remote sensing, the condition of soil, and species distribution, as well as data on connectivity, which makes it possible to perform prioritization systematically with the help of AI analytics (Bhakhar et al., 2025). RestoreAI is introduced in this paper as a decision support system framework which formalizes the prioritization process by using a structured multi-criteria scoring model together with species distribution modeling, applied on an example of a degraded landscape. Instead of making ecological data gathering and prioritization process two disconnected steps, RestoreAI binds them through an explicit scoring model, which allows for replicating, auditing and updating the results based on new data (Ullah et al., 2025; Reddy, 2026). This paper has three goals: (i) to analyze existing gaps in the use of ecological data for

restoration prioritization; (ii) to describe data pipeline, scoring model and validation approach of the RestoreAI framework in an example landscape case study; (iii) to analyze the expected performance of RestoreAI versus traditional expert-based prioritization.

These Contributions of the Research Include:

First, this research provides an objective and replicable method to perform the task of restoration prioritization by formulating it as a MCDA problem. Thus, the problem is specified in terms of the criteria used, their weights, and the exact algorithm to be applied. Second, SDM outputs are incorporated into the process of scoring of sites, allowing for a direct connection between suitability score and expected benefit to the target species of interest. Third, a testable method of validation is outlined – rank correlation with expert scoring and retrospective validation.

In the rest of the paper, the following structure is followed: Section II provides background information on ecological data, AI-driven conservation planning, and multi-criteria restoration prioritization literature. Section III introduces the landscape of the study, the sources of data, the scoring algorithm based on the AHP and SDM methods, and the validation technique. Section IV presents the expected or simulated results.

Literature Review

Studies carried out through the application of AI in ecosystem management have shown that predictive analytics through remote sensing and field ecology data can consistently identify degraded sites and their restoration potential as opposed to manual approaches, especially when assessing large or diverse landscapes (Bhakhar et al., 2025). General studies on the application of AI in biodiversity conservation show different methodologies that incorporate the use of classical ecological surveys with modern computational technology; however, the current applications only make use of one data type, such as only vegetation cover (Ullah et al., 2025). Literature in biodiversity conservation strategy stresses that in developing an effective biodiversity conservation strategy, both ecological and social considerations should be considered in tandem, and any technical approaches to prioritization should be wary of feasibility issues (Reddy, 2026). Literature in restoration sciences, on the other hand, shows that there is huge variability in terms of the success rate of restoration, depending greatly on the initial conditions of the site in question (Jain et al., 2023). Previous research on ecosystem recovery in complicated environments has revealed that landscape connectivity and climate exposure are also key factors determining the success of the restoration, making it possible to consider the use of such criteria as part of the scoring process and not as secondary elements (Saikanth et al., 2025). Previous research has indicated that using the decision-making approach for assessing landscape suitability for

restoration based on criteria combining ecological and socio-economic parameters is more efficient in comparison to informal decision-making processes or expert opinions (Bhatt et al., 2020). Multi-criteria decision analysis tools, including AHP, are widely used in land-use and conservation planning in order to integrate heterogeneous indicators in one score but have a very limited number of applications in prioritizing wildlife habitats using the SDM approach. This lack of experience in applying such an approach to wildlife restoration prioritization led to the creation of the RestoreAI method.

Materials and Methods

3.1 Case Study Landscape and Data Sources

RestorationAI is illustrated with a hypothetical yet representative degraded tropical dry forest-grassland mosaic landscape covering an area of about 500 km², which has been fragmented into 40 potential restoration areas of varying sizes (1–5 km²), which range in degradation intensity from freshly cleared areas to partially restored secondary vegetation. Four types of ecological data have been collected from each site:

- Vegetation condition: normalized difference vegetation index (NDVI) and canopy cover extracted from Sentinel-2 satellite images (10 m spatial resolution, composite images from recent dry and wet seasons).
- Soil condition: soil organic carbon and erosion risk index from field soil sampling (composite soil sample per site)

complemented by soil organic carbon map (SoilGrids raster data).

- Species occurrence and habitat suitability: records of occurrences for a selected number of indicator species (a threatened ungulate and two forest birds) from field observations and camera traps used for building a MaxEnt species distribution model and calculating the habitat suitability index (0–1 per site).
- Landscape connectivity: least-cost path connectivity to the closest intact patch of habitat based on a resistance surface representing different land cover classes.

3.2 Restore AI Framework Architecture

RestoreAI comprises three layers. Ecological data acquisition layer transforms the four data categories listed above to site-level indicators normalized between 0 and 1. Restoration suitability modeling layer aggregates these indicators based on weighted Analytic Hierarchy Process, where criteria weights (vegetation condition, soil condition, species habitat suitability, and connectivity) are obtained through pairwise comparisons, and consistency ratios are calculated to validate criteria weights ($CR < 0.1$). Final score of the AHP process is aggregated multiplicatively with species habitat suitability indicator obtained by the MaxEnt model, thus providing a single value Restoration Priority Score (RPS) for each site. Adaptive decision support layer ranks all 40 sites by RPS values, implements a budget constraint (i.e., restoration of the top N sites that can be restored within a certain funding envelope), and

generates a restoration plan, as well as a monitoring schedule for vegetation and species indicators after interventions.

3.3 Validation Approach

Two validation methods have been suggested to measure the prioritization effectiveness of RestoreAI. The first involves a comparison of the RPS ranking for the 40 locations with an expert-elicited priority ranking, which is generated independently (with the aid of structured elicitation by three restoration ecologists) using Spearman's rank correlation coefficient with ρ being the performance measure. The second involves a retrospective outcome tracking analysis based on data from previous restoration projects on comparable landscapes, where sites that were selected for restoration through expert prioritization will be compared with a retrospective RestoreAI ranking of the same set of sites.

Results

Given that RestoreAI has not been tested in a live field program, the following results have been obtained based on the design of the case study and previous publications of AI-assisted conservation scoring systems.

4.1 Expected Performance of Prioritization

From the comparison to other AHP-SDM-based approaches, it can be concluded that RestoreAI's Restoration Priority Score would demonstrate moderate to strong correlation with expert assessments (expected $\rho \approx 0.65$ – 0.80), with higher correlation expected for the sites on the two extreme ends of the

degradation scale (severely degraded and intact) and lesser correlation for the moderately degraded sites.

4.2 Comparing with Expert-Only Prioritization

While expert prioritization is still important in providing local expertise and community consideration which may not be included in remote sensing data, it is also expected to produce less consistent results (i.e., lower inter-expert consistency) in repeated elicitations than the reliable RPS ranking.

4.3 Expected Efficiency Gains

Considering the comparison of the time involved during the planning phase in similar applications, it is anticipated that RestoreAI will cut down the time for site evaluation significantly more than would manual expert evaluation of all 40 sites, providing an auditable criteria-based rationale for the ranking of each site.

Discussion

5.1 Implications of Habitat Restoration

Through the integration of a multi-criteria algorithm and species distribution modeling, the use of RestoreAI will enable the practitioner to justify the choice of the restoration location transparently for funding agencies and other regulators, as well as to adjust priorities continuously based on newly collected ecological information (Bhatt et al., 2020).

5.2 Shortcomings of the Restore AI Framework

Firstly, the accuracy of the framework will depend on the quality and availability of the input data; areas that have few observations will generate inaccurate outputs from the SDM step. Secondly, the subjective factor is present in the application of the AHP method, since it is based on expert pairwise comparisons. Finally, socio-economic factors or land tenure restrictions are not considered within the proposed framework, while they play an important role in the success of habitat restoration initiatives (Reddy, 2026; Jain et al., 2023).

5.3 Recommendations for Future Research

The future work may involve the use of RestoreAI on an actual landscape where a restoration program is in place in order to validate the suggested approach, fine-tune the AHP weights with expert consultation, and include socio-economic and land tenure information in the suitability score calculation (Reddy, 2026; Bhatt et al., 2020). Future application will also help evaluate the effectiveness of the feedback loop of the framework in terms of early restoration success or failure detection (Saikanth et al., 2025).

Conclusion

RestoreAI is defined as a framework for habitat restoration that provides decision support for choosing priority sites for the restoration by means of an integrated approach using a weighted AHP scoring model combined with a species distribution model. This framework uses information on ecology, environment and habitat suitability for making systematic decisions about

restoration. In contrast to conceptual approaches, RestoreAI describes its sources of data, criteria for the analysis, as well as the algorithm for calculating the scores. Moreover, this framework includes the procedures for validation based on rank correlation of priorities chosen by experts and the results of previous restoration projects. In this way, RestoreAI allows for finding out which sites have the greatest potential for habitat improvement through restoration due to the inclusion of multiple ecological criteria. Data-driven analysis makes it possible to minimize subjectivity while using expert ecological knowledge. Even though RestoreAI still needs to be tested and used in practice, in order to prove its reliability, it offers a good basis for decision-making regarding habitat restoration. Thus, RestoreAI illustrates the application of artificial intelligence and multi-criteria decision analysis in habitat restoration planning and optimization of resource allocation.

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