AIoT-Driven Smart Ecological Restoration of Sasakia charonda Habitat

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Abstract

The Purple Emperor butterfly (Sasakia charonda) is an indicator species in Taiwan whose larvae depend on Chinese hackberry (Celtis sinensis), a tree strongly influenced by meteorological conditions. This study built an NB-IoT/MQTT-based microclimate monitoring network to collect high-precision environmental data and developed a visualized early warning platform. By integrating AI, remote sensing, and GIS, it verifies hackberry distribution and growth, assesses environmental impacts on habitat restoration, and conducts risk prediction. The framework enables data-driven habitat management, improves monitoring accuracy and efficiency, and can be applied to the Great Purple Swallowtail and other conservation targets.

Keywords: RS Imagery, GIS, Sasakia charonda restoration, AIOT, Sustainable Development

1. Introduction

Taiwan's biodiversity is threatened by climate and land-use change [1], and the Great Purple Emperor butterfly is declining due to loss of Chinese hackberry habitat [3],[4]. Using the Bai Lan Tribe as a case, this study builds a data-driven restoration framework that combines micro-meteorological monitoring, high-resolution UAV/satellite imagery [2], and machine learning (LSTM [7], GBDT [8], Random Forest [9], SVM) to assess habitat suitability and map current and potential hackberry distributions. By integrating multi-source data with AI, the framework identifies priority restoration areas, is scalable to other ecosystems, and supports biodiversity policy and sustainable habitat management [6].

2. Research Methods

This system uses solar power to provide a self-sufficient energy supply and NB-IoT for low-power, stable data transmission. Together, these enable long-term environmental monitoring in Sasakia charonda habitats while minimizing disturbance from manual observation.

2.1. *Hardware Architecture Design and Optimization*

The first-generation device had unstable networking and power, making it unsuitable for long-term use. The second-generation device (Figure 1) integrates NB-IoT and solar power, extending lifespan and reducing maintenance. With waterproof light, temperature, and humidity sensors plus a high-precision tipping-bucket rain gauge, it can reliably monitor temperature, humidity, light, and rainfall under harsh outdoor conditions.

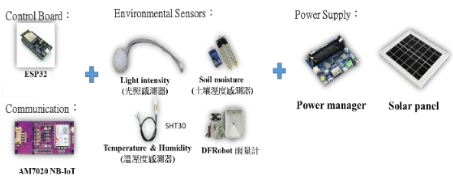

Figure 1 The second version of the device

2.2. *NB-IOT、Data Transfer*

Narrowband IoT (NB-IoT) is a low-power, wide-area LTE technology well suited to long-term sensing in remote areas. In this system, sensors send data via the lightweight MQTT protocol to a Mosquitto broker and then to a cloud database, where a web platform (Figure 2) visualizes the results, forming an efficient, scalable architecture for environmental monitoring.

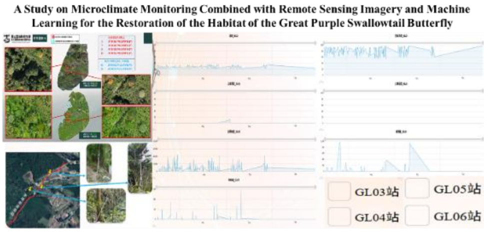

Figure 2 Visualization Interface

2.3. *Data Integration Applications*

This study uses LSTM [7] to analyze time-series climate patterns and GBDT [8] to model nonlinear relationships between environmental factors and Taiwan's endemic hackberry, predicting its potential habitat. By integrating historical and real-time meteorological data, it supports ecological restoration, conservation planning, and intelligent biodiversity monitoring.

2.4. *Collect high-resolution aerial imagery of the Bailan tribe*

Using high-resolution Pléiades, aerial, and drone imagery, this study maps vegetation and derives NDVI as key inputs. Known hackberry locations (Figure 3) and sample trees likely hosting Swallowtail larvae are identified, and relationships between tree health, environment, and larval activity are used to infer potential hackberry distribution in unsurveyed areas.

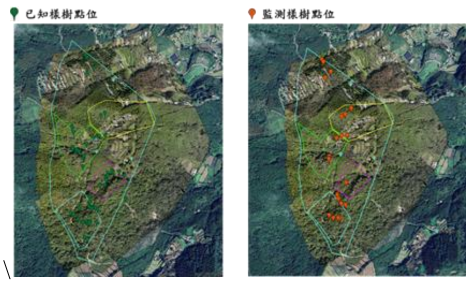

Figure 3 Known locust tree locations and monitored sample tree locations

2.5. *Model Construction and Training*

During model construction, convolutional neural networks (CNNs) [10-20] were employed to automatically classify and identify oak trees in aerial and remote sensing imagery. Long Short-Term Memory (LSTM) networks [7] and Gradient Boosted Decision Trees (GBDT) [8] were utilized to perform time series analysis on environmental data, thereby predicting the growth and distribution trends of hackberry trees.

Establish a Microclimate Data Forecasting and Analysis System

As shown in Figure 4, the system first preprocesses microclimate data (cleaning, filtering, imputing missing values, normalization), then inputs it to train machine learning models (e.g., LSTM, GBDT) on historical records with optimized parameters. The trained models use new data to predict future environmental trends, and the system outputs the results with visual analysis.

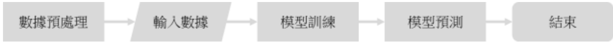

Figure 4 Research Flowchart for Microclimate Data Prediction and Analysis System

This workflow first preprocesses the data (cleaning, imputing missing values, filtering valid ranges, and standardizing features), then imports and structures it (e.g., as time series) with format checks. Next, LSTM and GBDT models are trained on historical data—LSTM for temporal trends and seasonality, GBDT for nonlinear relationships—with hyperparameter tuning and validation. Finally, the trained models are used to predict future environmental conditions, and results are visualized with charts, heatmaps, and risk alerts to support decision-making.

Establishing a System for Predicting Potential Habitats of the Celtis sinensis

The Chinese fir potential habitat system (Figure 5) uses a CNN to identify targets in UAV, aerial, and satellite imagery. Cropped, annotated, and augmented multi-source images—with multispectral indices (e.g., NDVI, EVI)—are split into training, validation, and test sets. After training, the model predicts Chinese fir distribution in unknown areas, producing potential habitat maps and reports to support habitat management and conservation.

Figure 5 Research Flowchart for the Celtis sinensis Potential Habitat Prediction System

This workflow integrates multi-source imagery for a target species, crops and standardizes it in GIS, labels trees with field validation, and augments images. The dataset is split into training, validation, and test sets, used to train and evaluate models on multispectral features (e.g., NDVI, EVI), and then applied to new imagery to generate habitat suitability maps for restoration and conservation planning.

3. Actual Case of a Micro-Weather Station Field Installation 2 - Hsinchu Bailan Tribe_Great Purple Swallowtail

This study developed a solar-powered micro-meteorological system using Arduino Nano/ESP32 and NB-IoT to continuously monitor light, temperature, humidity, and soil moisture in Great Purple Swallowtail habitats. It provides real-time environmental data, can be applied to other protected species, and, as shown in Figure 6, can be flexibly installed in complex terrain.

Figure 6 Field Installation 2-Hsinchu Bailan Tribe_Great Purple Swallowtail

4. Actual Survey of Tree Distribution Points

As shown in Figure 7, overlapping UAV flights captured high-resolution imagery on December 31, 2024 (full yellow) and May 14, 2025 (full green), with geometric and color correction for consistency. Ground plots were surveyed on December 11, 2024 to record suspected Chinese hackberry. By comparing the two periods, suspected trees were identified, field checks were planned, and location attributes and canopy boundaries were updated to improve data accuracy.

Figure 7 Establish aerial imagery mapping of the Celtis sinensis locations within the Bailan Tribe

As shown in Figure 8, this study generated a Chinese hackberry distribution basemap and multi-temporal overlay for the Bailan tribe, identifying confirmed and suspected trees and revealing patterns along transects A and B. Due to terrain, weather, and confusion with evergreen broadleaf trees, image gaps and misclassifications remain, so low-altitude resurveys, fixed monitoring in late December and May, and permanent plots recording DBH, crown size, and health are recommended to support ongoing restoration management.

Figure 8 Mark the locations of Celtis sinensis and suspected Celtis sinensis locations

This study established a distribution basemap and seasonal baseline for Chinese hackberry using multi-temporal aerial imagery and ground surveys, improving identification accuracy. Future work will implement regular resurveys and automated analysis to enhance spatiotemporal monitoring, supporting applications in restoration planning, habitat connectivity, and pest/disease monitoring.

5. Conclusion

This study built a smart ecological restoration framework that integrates NB-IoT/MQTT sensing, micro-meteorological monitoring, AI models (LSTM [7], GBDT [8]), and high-resolution drone/satellite imagery to analyze habitat conditions and map suitable areas for Chinese hackberry, supporting restoration of the Great Purple Swallowtail butterfly habitat [5]. The framework improves monitoring accuracy and efficiency, offers concrete management recommendations, and provides a replicable, scalable model for future ecological conservation and sustainable biodiversity management.

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