International Journal of Combinatorial Optimization Problems and Informatics, 17(1), Jan-April 2026, 355-367. ISSN: 2007-1558. https://doi.org/10.61467/2007.1558.2026.v17i1.1189

www.editada.org

Technological Development Model for Environmental Monitoring Aimed at the Conservation of the Santa María del Lago Wetland Using IoT Sensors, Satellite Imagery, and Drones

Laura Mercedes Arteaga Rojas, Griselda Cortés Barrera

[1] Politecnico Gran Colombiano, Faculty of Engineering

[2] Corporación Minuto de Dios, Faculty of Engineering

[3] Laboratorio Nacional Conahcyt en Inteligencia Artificial y Ciencia de Datos (LNC-IACD), Av. Tecnológico s/n, Col. Valle de Anáhuac, Sección Fuentes, C.P. 55210, México.

[4] Tecnológico Nacional de México, Av. Universidad 1200, Col. Xoco, Ciudad de México, Alcaldía Benito Juárez C.P. 03330.

[5] Tecnológico de Estudios Superiores de Ecatepec, Av. Tecnológico s/n, Col. Valle de Anáhuac, Sección Fuentes, C.P. 55210, México.

Larteagaa@poligran.edu.co And gcortes@tese.edu.mx

Abstract. In Bogotá, the absence of integrated data for wetland monitoring persists; therefore, a technological application structured in three phases was developed. In the first phase, information acquisition was conducted through flights using DJI Mini 2 and Phantom 4 Pro drones, with orthomosaics processed in Pix4D and WebODM, together with Landsat and Sentinel satellite imagery obtained from Google Earth Engine. In the second phase, the SIBIA platform was designed. This platform integrates Google Earth Engine panels, machine learning models implemented in Teachable Machine (a low-code environment), and their scaling in Python with OpenCV to classify vegetation and bodies of water. In the third phase, technical and community validation was carried out using IoT sensors, accuracy metrics (RMSE, MAE), and surveys with high reliability ($\alpha = 0.894$). The results indicate high model accuracy (~0.98–1.00) and the generation of quality orthomosaics. In conclusion, the tool is shown to enhance environmental management and support sustainable decision-making for urban wetlands.

Keywords: Urban wetlands; Environmental monitoring; Google Earth Engine.

Article Info

Received July 28, 2025

Accepted August 12, 2025

1 Introduction

The development and implementation of digital applications for environmental monitoring, which integrate satellite data, vegetation and urbanization indices derived from drone images, as well as IoT sensors and the participatory compilation of climate and biodiversity information by the community living near environmental reserves, still lack specialized studies and technological solutions in the context of wetlands in Bogotá, Colombia. These ecosystems are unique and play a fundamental role in urban ecological balance, since they provide multiple ecosystem services, including water filtration, microclimate regulation, mitigation of the heat island effect, provision of habitats for a wide diversity of flora and fauna species, and flood control. (Cuellar & Perez, 2023),(Hellweger et al., 2004; Zhao et al., 2024)

Moreover, evaluating the potential of these spaces for the implementation of renewable energy technologies represents a valuable opportunity to strengthen environmental sustainability and improve urban planning.

In Bogotá, Colombia, La Secretaria de Ambiente de Bogotá, (2020) has identified 15 wetlands, of which 11 are RAMSAR certified, one of the world's highest environmental awards for biodiversity conservation. However, urban expansion has caused a drastic reduction of these ecosystems, from more than 50,000 hectares in the 1950s to only 800 hectares today, representing a loss of 98% (Barros Jhon, 2020a, 2020b). Examples such as the Lago Gaitán park, the wetland in the industrial zone of Montevideo, Lake San Cristóbal, the Bonanza wetland, and the space currently occupied by the El Dorado airport show how the uncontrolled growth of the city has displaced and eliminated these bodies of water. ,(Secretaria de Ambiente de Bogotá, 2020)

This research focuses on the Santa María del Lago wetland, which covers an area of 10.8 hectares and is considered one of the most visited in the capital (Barros Jhon, 2020, 2020). This wetland is home to 319 species of flora, fauna and fungi (NaturaLista, 2022), including the emblematic yellow-billed Tingua. However, it faces significant threats such as air pollution from heavy traffic on adjacent roads (Boyacá Avenue and 80th Street) and pressure from surrounding residential and commercial areas, increasing community exposure to the adverse effects of climate change.

Despite the importance of these ecosystems, there are currently no mobile applications or technological platforms that integrate updated databases on biodiversity, climate, vegetative state, energy fitness indices and areas suitable for the implementation of renewable technologies in Bogotá's wetlands. This limitation restricts the ability of environmental authorities and community organizations to carry out informed and efficient management of these spaces. In a context where wetland loss has reached critical levels, it is important to develop technological solutions to consolidate satellite information, IoT sensors, community records and multitemporal analyses, as proposed by recent research. (Cuellar & Perez, 2023; Imdad et al., 2023a; Pan et al., 2023)

Advancing this type of application would contribute to strengthening comprehensive monitoring processes, recovering ecosystem services and evaluating the viability of clean energy projects, making a significant contribution to the conservation and resilience of urban wetlands.

2 Review Literarie

The incorporation of IoT technologies for the monitoring of aquatic ecosystems has shown significant efficiencies in the management of water resources and the automation of environmental monitoring. IoT systems in smart agriculture that made improvements of 20-46% in water use efficiency using soil moisture sensors and automatic weather stations (AWS). These systems used LoRaWAN and NB-IoT communication protocols for wide coverage, while technologies such as ZigBee and Bluetooth established short-range sensor networks with robust mesh topologies. (Quy et al., 2022)

The commercial platforms such as OnFarm, FarmX and CropX have demonstrated extensive capabilities in tree crop management and soil nutrient assessment, establishing relevant technical reference points for urban wetland monitoring. This architectural design facilitates the continuous observation of vital parameters such as pH, dissolved oxygen and water temperature, which are crucial for monitoring wetlands in urban environments. Simultaneously, advances in multispectral and multi-satellite remote sensing have transformed automated environmental monitoring through cloud processing platforms. (Quy et al., 2022)

The first research describes the development of the online platform that works as an automated mechanism within Google Earth Engine, which aggregates data from satellite missions launched by the United States, called Sentinel-1, Sentinel-2, Sentinel-3, Landsat 8/9 and VIIRS, reducing data processing time from 15 days to just 1 day. Its methodology integrated U-Net deep learning algorithms for semantic segmentation, achieving a detection probability of 77% and a false alarm rate of 12% while tracking river ice conditions. The incorporation of citizen science data through the Fresh Eyes on Ice project and the GLOBE Observer application achieved a Critical Success Index of 0.82, authenticating remote sensing results through georeferenced community contributions. This strategy encourages citizen participation in environmental monitoring, providing valuable field data for the calibration and validation of remote models. (Abdelkader et al., 2024)

Other research, using automated methodologies for the classification of wetlands, has seen significant improvements due to the implementation of sophisticated machine learning techniques. They use a tool known as Global Surface Water in Google Earth Engine to classify 11 different categories of surface water variations in the Al Shuwija wetland, examining Landsat images from 1984 to 2019 and generating vector data in both KML and Shapefile formats.(Hao et al., 2024)

Moreover, the combination of RGB images captured by drones with data from the Sentinel-2 satellite stands out, applying N-dimensional color correction and Random Forest classification with 100 trees to map seasonal plant communities. This methodology achieved an accuracy of 87%, significantly exceeding the 62% obtained with unsupervised clustering techniques such as K-means. This difference highlights the advantages of supervised hybrid models for accurate identification of plant communities within complex aquatic ecosystems, providing key solutions to the loss of 98% of these ecosystems in Bogotá since 1950. (Bhatnagar et al., 2021)

Building on the methodologies previously outlined, the study by (Pan et al., 2023) This represents a significant advancement in the analysis of urban ecosystem services (ES) through the use of high-resolution satellite imagery and spatial simulation models. By employing a mixed-methods approach that integrated tools from the InVEST model—such as modules for carbon storage, water yield, nutrient and soil retention, as well as biodiversity and recreation services—the study evaluated the spatiotemporal changes of six key ES in the Xixi urban wetland, China, over the period 1984–2018.

The findings indicate a substantial increase in carbon storage, rising from 223.25 t/ha to 368.11 t/ha, while other ecosystem services exhibited a general trend of degradation. The classification accuracies across different years ranged from 79.12% to 91.53%, with Kappa coefficients exceeding 0.70 in most instances. Moreover, positive synergies were observed between services such as biodiversity and recreation, alongside notable trade-offs between carbon storage and water yield. Redundancy analysis (RDA) revealed that the extent of impervious surface coverage—primarily from buildings and roads—was the most influential factor, accounting for up to 37% of the variance within the park and 24.8% beyond its boundaries. These results not only confirm the effectiveness of conservation policies, such as the establishment of national wetland parks, but also underscore the critical need to incorporate predictive modeling, inter-service interactions, and socio-environmental variables into sustainable urban planning frameworks. (Pan et al., 2023)

As previously outlined, the integration of Drone and satellite imagery is essential for effective wetland monitoring and conservation. Furthermore, the study conducted by (Bhatnagar et al., 2021) in the urban and peri-urban areas of Lucknow, India, offers a robust methodological framework for assessing ecosystem health. This framework is based on a hybrid approach that combines advanced geospatial tools with participatory community engagement processes, thereby enhancing both the accuracy and relevance of environmental evaluations

Specifically, they applied the Pressure-State-Response (PSR) model using remote sensor data (NDVI, MNDWI, LULC), landscape indices (FRAGSTATS) and validation using GPS points and ROC curves, evaluating 12 landscape metrics between 1998 and 2018. The results revealed a decrease of 49.93% in the area of water bodies and an increase of 162.66% in urban areas, indicating a strong anthropogenic pressure on periurban wetlands. Additionally, focal group discussions (FGD) were carried out with local communities and interviews with experts, allowing us to understand ecosystem degradation from a socio-territorial perspective.

The communities reported both economic and cultural losses, and identified several direct drivers of degradation, including the construction of roads lacking proper drainage infrastructure, the intensification of agricultural activities, and the application of pesticides in aquatic crop systems. From a governance perspective, the study underscores the critical role of sustainable public policies, integrated land use planning, and ecological restoration efforts. Notably, it proposes the Wetland Ecosystem Health Index (WEHI) as a comprehensive and integrative tool for monitoring and decision-making. These findings not only complement and enhance prior research conducted in our local context but also illustrate that wetland degradation is not an isolated occurrence. Rather, it represents a global manifestation of unsustainable urban development patterns and governance models that systematically marginalize community voices. (Imdad et al., 2023)

Finally, it is worth highlighting another study conducted in the wetlands of Bogotá, which employed satellite imagery to analyze land use and land cover dynamics. This research is particularly notable for its application of the combined Markov-Future model to predict changes between 1998 and 2034. The findings project that by 2034, wetlands will comprise less than 2% of the city's total surface area. This alarming projection is driven by a significant decline in cultivated land (from 21.4% to 12.71%) and wetland areas (from 2.6% to 1.97%), juxtaposed with the expansion of urbanized zones, which are expected to increase from 70% to 78%. (Cuellar & Perez, 2023)

These findings underscore theneed to incorporate comprehensive conservation strategies and innovative technologies to counteract the accelerated degradation of these ecosystems. Collectively, the studies reviewed establish a robust foundation for the development of integrated technological solutions that leverage satellite imagery, RGB drone data, community-sourced records, and multitemporal analyses, with the overarching goal of enhancing continuous environmental monitoring and evidence-based ecosystem management.

3 Methodology

The methodological approach is structured into four sequential stages encompassing data acquisition, the development of the SIBIA platform, system validation, and predictive analytics. As illustrated as in Figure 1, the environmental monitoring system implementation model is divided into three main components: (1) data collection through drone-based imagery and satellite-based spatial delimitation; (2) technological development involving software architecture and system deployment; and (3) technical and operational validation through field testing, which includes the use of IoT sensors, drone operations, and community-based surveys.

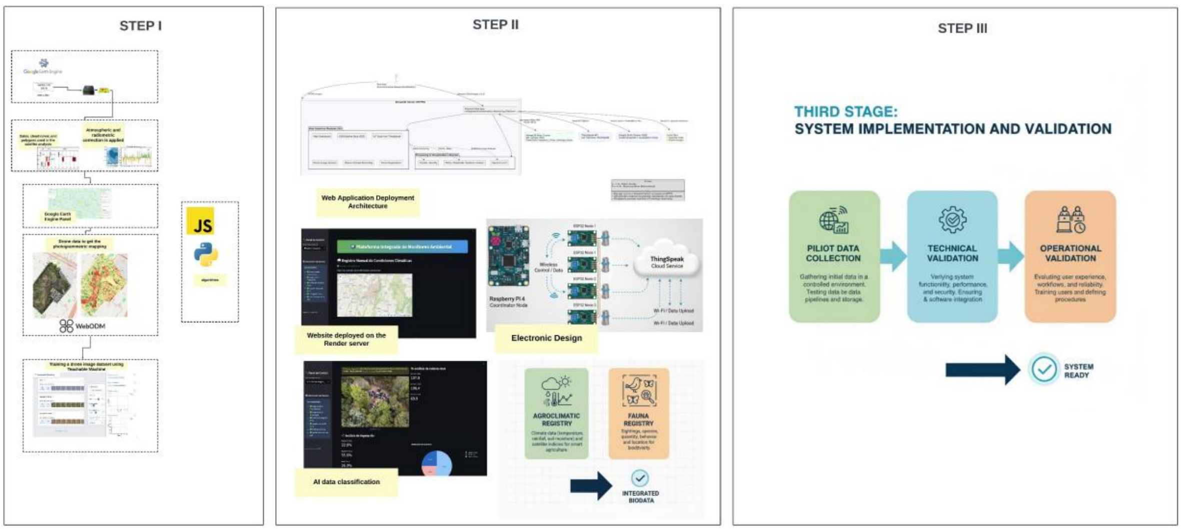


Fig.1. Environmental monitoring system implementation model that includes three stages: (1) drone data collection and satellite delimitation; (2) technological development with software architecture and deployment; and (3) technical and operational validation through field tests with IoT sensors, drones, and community surveys.

3.1 Methodological Framework of Phase One

The catalog of satellite imagery datasets for the construction of the panels was compiled using the Google Earth Engine (GEE) platform. From these inputs, panels of vegetation indices, meteorological variables, radiation data and aptitude index were generated. With this information, models were trained using the Teachable Machine web platform, designed within a low-code environment, aimed at classifying images of water, healthy vegetation and sparse vegetation.

Likewise, during the first phase of the environmental monitoring model, the DJI Mini 2 and DJI Phantom 4 Pro platforms were configured for data acquisition and automated mapping using the Map Pilot Pro and Pix4D applications. The study area, covering approximately 50 square meters within the Santa María del Lago wetland, served as the test site. This stage integrated high-resolution drone imagery (Phantom 4 Pro and DJI Mini 2) with satellite image time series from missions such as Landsat and Sentinel, allowing for a comprehensive photogrammetric analysis of the area. Subsequently, the process continued with the preparation of materials, followed by the execution of the monitoring phase.

In this context, low-altitude aerial photogrammetry was conducted through controlled drone flights, with the flight altitude restricted to 50 meters due to the strategic location of the Santa María del Lago wetland, which lies in proximity to El Dorado International Airport. This operational constraint was implemented in accordance with regulatory guidelines for drone usage near airport zones, which recommend maintaining altitudes between 50 and 60 meters to ensure airspace safety. As a result, orthorectified images were obtained, accurately capturing the current conditions of the vegetation cover, water surface, and surrounding urban structures within the wetland area, located in Bogotá, Colombia. (Bhatnagar et al., 2021; Bonilla et al., 2023)

In addition, based on the processing of the data obtained from the orthophotos and vegetation indices generated by the Pix4D and WebODM platforms, the training of models in Teachable Machine was carried out. This process was carried out by classifying the information according to the type of vegetation index corresponding healthy, dense vegetation or areas with the presence of water, based on the data captured by the drones.

Besides that, the collected data included spatial geometry information, such as boundary polygons and reference points—which are essential for accurate environmental characterization. The precise location and spatial extent of the wetland were georeferenced and compiled in Table 1, which presents the coordinates and vertices delineating the perimeter of the study area.

Table 1. Coordinates of the Santa María del Lago Wetland

Places	Latitude °	Longitude°
Humedal Santa Maria del Lago	4.694907558821093°	-74.09325799258°

3.2 Methodological Framework of Phase two

The second phase involved the design and development of the Integrated System for Biodiversity, Agriculture, and Environment (SIBIA). This platform was conceived to support the collection, analysis, and dissemination of critical information related to biodiversity, agricultural practices, and environmental conditions. Beyond merely capturing data, SIBIA integrates a wide range of information sources, enabling a comprehensive understanding of the complex interactions between ecosystems and human activities. By leveraging this technological framework, the system aims to foster informed, evidence-based decision-making processes that contribute to biodiversity conservation and the sustainable management of agricultural resources.

In the figure associated with the software architecture and deployment of the web application, you can see the different stages and components that make up the data capture process, illustrating how the different elements of the system are interconnected. This visual representation makes it easier to understand the complexity of SIBIA and its ability to adapt to specific research and environmental management needs. SIBIA is proposed as an innovative solution to face environmental challenges, promoting collaboration between communities and authorities in the management and conservation of wetlands, as in Figure 2. Software architecture.

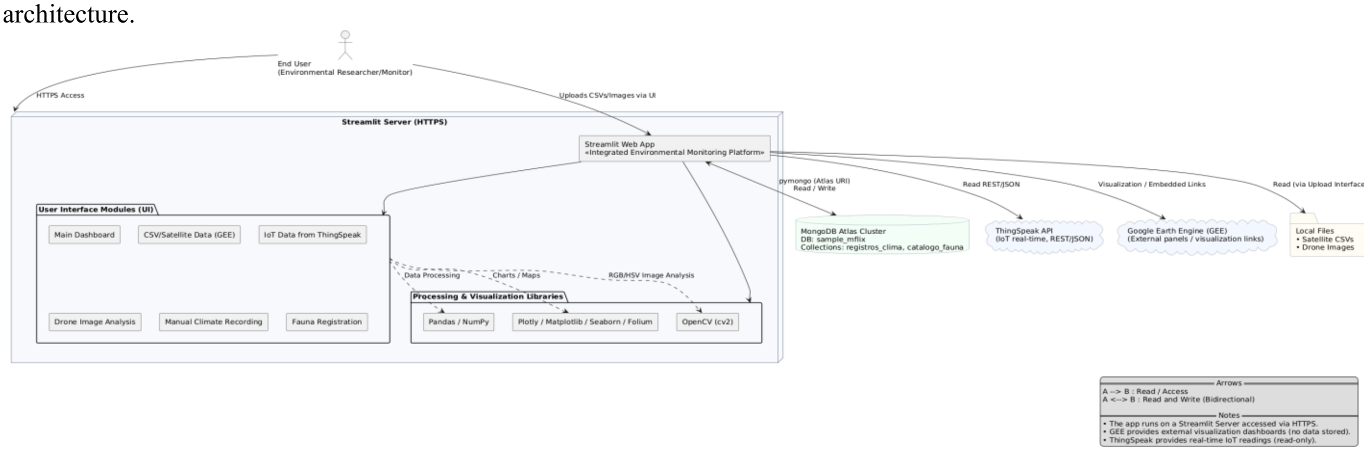


Fig.2. Web Application Deployment Architecture

This system integrates a variety of modules and sources of information, taking advantage of the Google Earth Engine (GEE) platform to offer a comprehensive approach to the management and analysis of geospatial data. The components of the system are broken down as follows: The initial module includes the energy aptitude index and the satellite vegetative indices (adaptable to different regions): it facilitates the acquisition of Satellite Images Collection: This module emphasizes the collection and processing of satellite images from Landsat 7 and 8, MODIS, SENTINEL 2A and 2B satellites; as well as data from the ECMWF ERa5-LAND (Solar Radiation) satellite, the USGS SRTM satellite (Elevation Model), meteorological data on rainfall and temperature MODIS and IDAHO, allowing users to access both visual and quantitative data regarding the Earth's surface over time. By using GEE, users can access an extensive archive of historical and contemporary images, facilitating the temporal analysis and evaluation of environmental changes. (Avtar et al., 2022; Navarro Rau et al., 2025; Shuai & Qian, 2011)

This module calculates the energy fitness index, which incorporates variables such as soil slope, vegetation cover and climate information, weighted using the AHP (Analytical Hierarchy Process) methodology. This index allows the spatial classification of the territory with respect to its suitability for the deployment of low-impact renewable technologies, such as solar energy systems. It also has the GEE interactive panel, particularly the NDVI (Normalized Differential Vegetation Index) and NDWI (Normalized Differential Water Index) indices, historical solar radiation data, and object detection (building roofs). This module is scalable and customizable to other areas and ecosystems, thus expanding the platform's capabilities to cover diverse geographical scenarios. The equations of the vegetative index: This approach allows us to evaluate the feasibility of implementing sustainable energy solutions in wetlands, contributing to the conservation and efficient management of these vital ecosystems (Avtar et al., 2014, 2022)

The study applies remote sensing indices to assess ecosystem integrity and guide sustainable energy planning. Among these, the Normalized Difference Vegetation Index (NDVI) serves to characterize vegetation density and vigor; higher values denote robust and healthy cover, whereas lower ones indicate deterioration or fragmentation. This information proves essential for identifying ecological zones that warrant conservation, as well as areas with potential for renewable energy integration. In parallel, the Normalized Difference Water Index (NDWI) distinguishes regions with water accumulation from those that are comparatively dry, a distinction crucial for effective management of water resources and the protection of biodiversity.

Building on these layers of analysis, the Energy Aptitude Index (IAE) combines variables related to terrain slope, vegetation, and solar radiation to determine the suitability of deploying renewable energy systems. The framework prioritizes landscapes with gentler slopes and higher solar input, ensuring that technological initiatives remain compatible with conservation principles, particularly within sensitive ecosystems such as urban wetlands.

Finally, the study employed a curated dataset of roughly 400 scenes encompassing NDVI, NDWI, and meteorological variables to conduct predictive modeling. Using machine learning techniques—specifically the Random Forest algorithm—it generated forecasts describing the evolution of vegetation indices and the IAE over time. Comparative tests among multiple algorithms allowed the identification of the most precise and stable model for anticipating future ecological conditions within wetland systems (Avtar et al., 2022; Navarro Rau et al., 2025; Shuai & Qian, 2011)

The second module centers on the application of image processing techniques using OpenCV to train and classify polygons based on indices of interest within the targeted orthomosaics, in conjunction with machine learning algorithms. This methodology enables the accurate identification of various vegetation types, such as dry, dense, and sparse vegetation—among others. Furthermore, the module performs a comparative analysis between current data and historical vegetative information obtained in Module One, thereby providing a detailed assessment of vegetative and/or urban conditions within the study area using the RGB scale. This analytical capability not only facilitates the detection of alterations in vegetation cover but also plays a crucial role in supporting evidence-based decision-making for environmental management and ecosystem preservation.

The third module is dedicated to the visualization and real-time acquisition of data generated by Internet of Things (IoT) devices used for environmental monitoring. These sensors enhance the understanding of local environmental phenomena and their dynamic interactions. The implemented system includes two ESP32 T18 modules, each connected to microcontrollers interfaced with MQ135 and DHT11 sensors, and networked through a Raspberry Pi 4 running Node-RED. These configurations capture key environmental parameters, including temperature, relative humidity, CO_2 concentration, and soil moisture.

Data transmission occurs every two hours between 9:00 a.m. and 11:00 a.m. from February to June. Field visits and sensor operation are contingent upon weather conditions, as exposure to rain and other environmental factors may damage the monitoring equipment. Additionally, a third ESP32 T18 module equipped with DHT11 and MQ135 sensors is mounted on the DJI Phantom 4 Pro drone, enabling airborne data collection during 15-minute monitoring flights. The architecture of the IoT network, illustrating the connection between the Raspberry Pi 4 and the ESP32 T18 nodes for data transmission to ThingSpeak, is depicted in Figure 3.

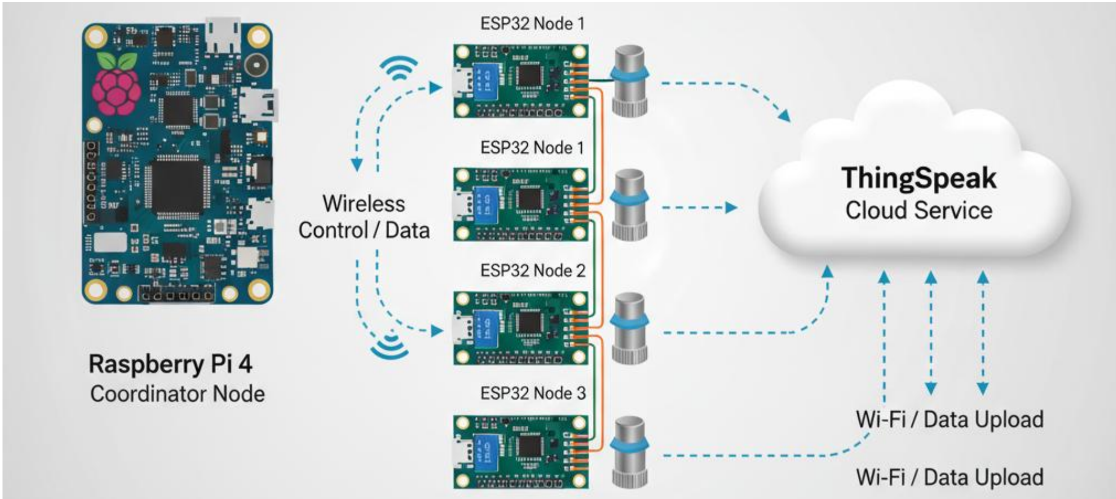


Fig.2. IoT network scheme between Raspberry Pi 4 and ESP32 T18 nodes with DHT11 and MQ135 sensors for data transmission to ThingSpeak

3.3 Methodological Framework of Phase three

During the third phase of the model, the implementation and field validation of the system were conducted through pilot data collection trials involving IoT sensors, drone-based imaging, and community surveys with a sample of 100 participants. The validation process was structured into two distinct levels. First, a technical validation was performed to assess the accuracy of data acquisition. In the case of drone-based data, previously georeferenced coordinates were compared to those generated in the photogrammetric model using WebODM and Pix4D software. The root mean square error (RMSE) was calculated to evaluate spatial accuracy, with the photogrammetric outputs considered independent of the SIBIA platform itself.

For the IoT sensor network, environmental variables such as temperature, relative humidity, and CO_2 levels recorded by ESP32 T18 microcontrollers were evaluated against data from nearby meteorological stations—specifically those managed by IDEAM. The mean absolute error (MAE) was calculated, and the sensors' responsiveness to actual environmental changes was verified. Second, an operational validation of the IoT network was carried out through continuous node connectivity testing on scheduled monitoring days from February to June, while accounting for the specific climatic constraints of the wetland environment. Key performance indicators included the successful transmission rate, average communication latency to the MongoDB Atlas database, and the percentage of data loss observed throughout the monitoring period. (Bonilla et al., 2023; Navarro Rau et al., 2025; Shuai & Qian, 2011; Venturini et al., 2023)

To validate the technological platform from the perspective of end-users, a structured questionnaire was administered to 100 individuals who visited the Santa María del Lago wetland between February and June. This instrument was designed to assess participants' experiences with the platform, specifically regarding its usability and the perceived reliability of the data displayed through the community-based forms. The evaluation focused on key aspects such as ease of use, clarity of the information presented, perceived accuracy of data captured by drones and IoT sensors, and the overall acceptance of the platform as a participatory tool for environmental monitoring. Statistical validation was performed through a reliability analysis using Cronbach's Alpha, and the questionnaire was structured into five main sections:

- User Identification
- Record of observed species.
- Perceived weather conditions.
- Evaluation of the state of the wetland (water, vegetation, fauna).
- Perception of environmental conditions (air quality, noise, thermal comfort).
- Each section will include Likert-type items (scale from 1 to 5) to measure: Frequency, Degree of perception, Level of satisfaction, Confidence in observation, Calculation of Cronbach's Alpha: The validation of the internal consistency of the questionnaire will be carried out by applying the equation of Cronbach's Alpha

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$$

Where:
N = Number of items
$\bar{c}$ = Average covariance between items
$\bar{v}$ = Average variance of items

Interpretation of values:
$\alpha \geq 0.9$: Excellent reliability
$0.8 \leq \alpha < 0.9$: Good reliability
$0.7 \leq \alpha < 0.8$: Aceptable
$\alpha < 0.7$: Questionable or insufficient

4 Results

These could be presented in tabular or graph form, with appropriate statistical evaluation. Discussion of results. Statement of conclusions drawn from the work.

4.1 Phase One Results: Drone Data Collection and Satellite Missions

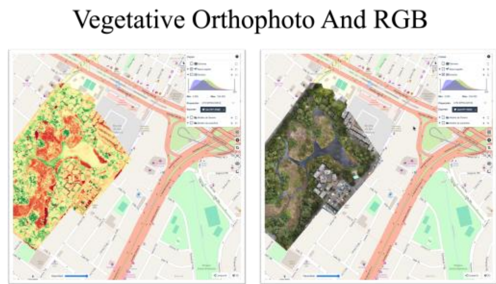
The resultsobtained through photogrammetric processing with Pix4D and WebODM, based on images captured with the DJI Phantom 4 Pro drone, evidenced the generation of high-precision orthomosaics and digital surface models (Figure 4a). In this regard, a total RMS of 0.065 m was achieved, with specific errors of 0.053 m on the X axis, 0.033 m on the Y axis and 0.125 m on the Z axis, without requiring terrestrial control points (GCP). The horizontal accuracy (CE90) was 0.307 m and the vertical (LE90) accuracy was 0.702 m, thus validating the cartographic quality of the products generated. As a result, these inputs allow for detailed and reliable monitoring of the vegetation cover and the spatial structure of the wetland, effectively complementing the multitemporal satellite analysis with high-resolution information obtained at the local level. (Bhatnagar et al., 2021b; Bonilla et al., 2023b)

In parallel, the processing of satellite imagery for the Santa María del Lago wetland using QGIS software facilitated the development of detailed maps of NDVI and NDWI indices (Figure 4b).

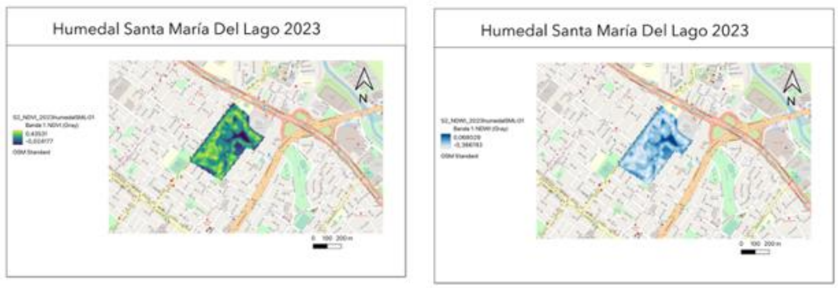
These maps reveal significant spatiotemporal variations in vegetation cover and water content within the wetland, influenced by meteorological phenomena observed between 1986 and 2023. Notably, substantial declines in vegetation were recorded in the years 1994, 2006, and 2015, corresponding to periods of reduced precipitation, whereas the year 2000 exhibited peaks in vegetative growth associated with intermittent rainfall events.

Likewise, multi-temporal analyses with data from MODIS and IDOH satellite sensors between 2002 and 2023 confirmed a sustained trend of vegetation decline. Particularly in 2023, the NDVI fell to values close to 0.3, indicating dry vegetation, and the NDWI stood at -0.25, reflecting a low accumulation of water. These patterns correlate with the effects of the El Niño phenomenon, as reported by IDEAM [25], characterized by reduced rainfall between 10 mm and 75 mm and high temperatures, which reached up to 31.5 °C in 2020 and 30.6 °C in 2023.

Finally, a simple linear regression model was applied, which yielded a coefficient of determination (R^2) of 0.11. Although this value reflects a low initial explanatory capacity, it constitutes a useful preliminary basis for the development of future predictive models with machine learning techniques, aimed at anticipating changes in the ecological dynamics of the wetland under different climate scenarios.



(a)



(b)

Fig.4. Orthomosaic and vegetative indices of the Santa Maria del Lago wetland from pix4D and webODM software (a) and wetland maps acquired from GEE (b).

In addition, we trained a supervised image-classification model in Teachable Machine using both satellite and drone imagery. The dataset comprised 255 scenes labeled water (NDWI-oriented samples), 339 scenes labeled dense vegetation (high-NDVI patterns), and 221 scenes labeled sparse/dry vegetation (low-NDVI patterns). Using the advanced settings shown (50 epochs, batch size 16, learning rate 0.001), the training reached near-perfect convergence with accuracy ~1.00 across epochs. The per-class precision reported by the tool was very high, with water ≈ 1.00, dense vegetation ≈ 0.99, and sparse/dry vegetation ≈ 0.98; the confusion matrix was diagonal-dominant, indicating negligible misclassifications overall and minor confusions primarily between the two vegetation classes, while water was almost never confused with vegetation. These results confirm that the classifier reliably separates hydric surfaces from vegetated areas and is sufficiently sensitive to discriminate canopy density in both satellite and low-altitude (drone) scenes.

4.2 Results of Phase Two: Integrated Environmental Monitoring Platform

The second phase of the project resulted in the development of the Integrated Environmental Monitoring Platform, composed of different interconnected modules that allow the collection, visualization and analysis of environmental data from various sources. These include Google Earth Engine (GEE), Internet of Things (IoT) sensors (Abdelkader et al., 2024; Imdad et al., 2023). And community-entered records. Each module plays a specific role, contributing in a complementary way to the strengthening of the monitoring system.
First, the community dashboard module provides an overview of community-reported data, which includes climate variables and wildlife records. This data is stored in a MongoDB Atlas cluster and presented through an interactive dashboard that allows it to be consulted and analyzed in an accessible way.

Second, GEE panels integrate historical information from this platform, making it possible to analyze variables such as vegetative state, weather conditions, and solar radiation levels. These panels allow the data to be graphed, downloaded and thematic maps adapted to the user's interests, providing a multi-temporal perspective to the monitoring.

For its part, the IoT monitoring module, implemented with the ThingSpeak platform, connects humidity, temperature and air quality sensors through ESP32 microcontrollers linked to a Raspberry Pi 4. This component enables real-time visualization of the captured data, which is essential for continuous and local monitoring of environmental conditions. (Abdelkader et al., 2024b; Zhao et al., 2024)

Moreover, the drone image analysis module allows the study of vegetation cover from orthorectified images. These images, previously processed, can be uploaded to the system to apply algorithms for the detection of vegetative, urban and water areas, from orthomosaics generated by drone flights.

Finally, the georeferenced manual registration module allows the entry of climate data obtained in the field through digital forms, as well as the documentation of wildlife sightings through photographs and GPS location. This function is essential to integrate community knowledge and enrich environmental monitoring from a participatory perspective.
Together, these five modules form a robust platform that strengthens participatory environmental monitoring and facilitates evidence-based decision-making. Figure 5 graphically illustrates the modular structure of the SIBIA web platform and its integrated functionality.

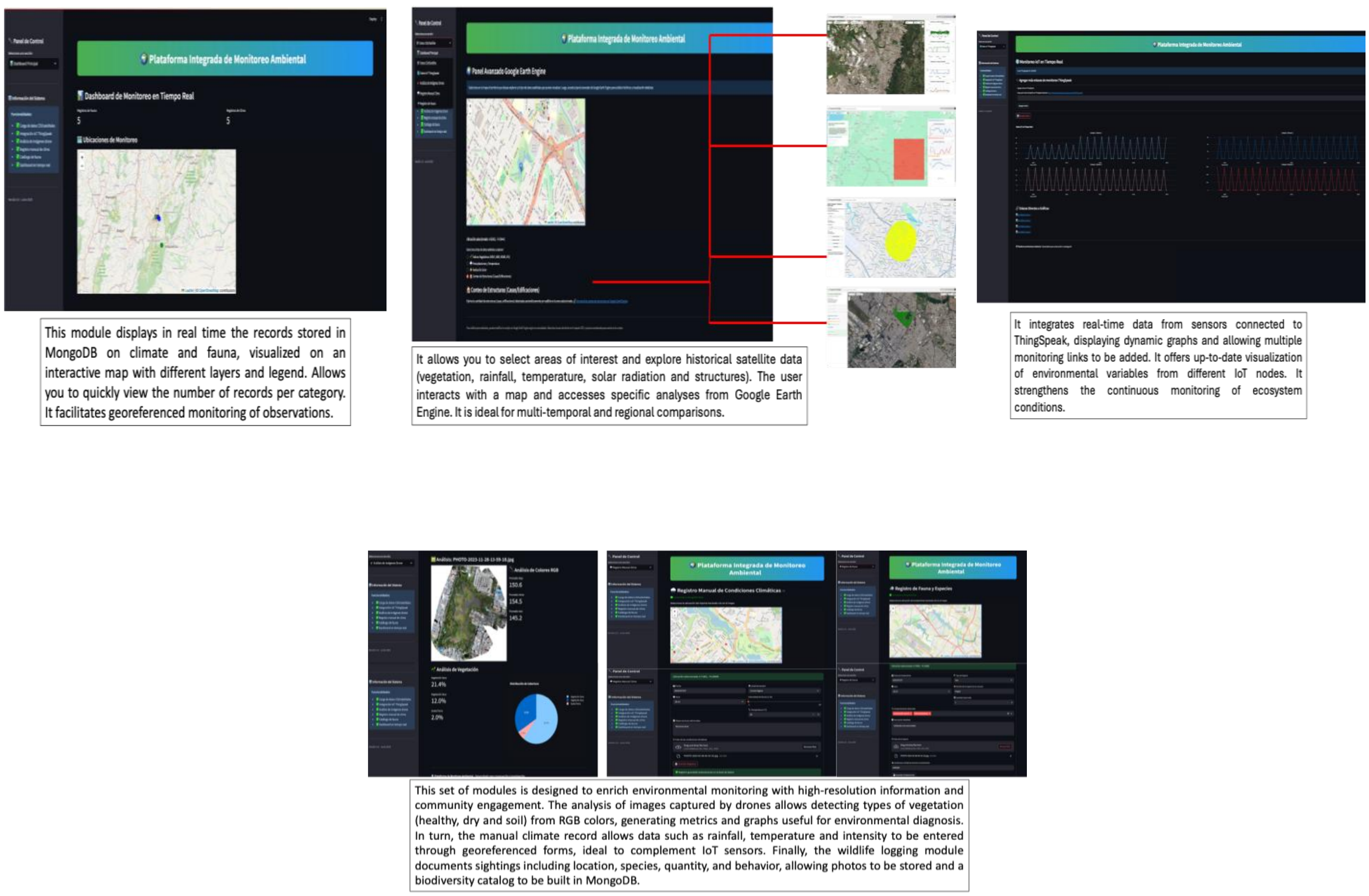


Fig.5. Modules of the SIBIA web platform.
Link : https://geodata-jltw.onrender.com/

In the second phase of the study, we analyzed NDVI and NDWI for Santa María del Lago using SIBIA: years 1994, 2006, and 2015 showed low or absent rainfall with marked NDVI declines and relative NDWI increases—evidence of reduced vegetation and greater water exposure—whereas 2000 exhibited partial rainfall, a peak NDVI, and low NDWI, suggesting a favorable phenological response to moderate moisture. These patterns align with El Niño/La Niña influences; the 2002–2023 comparison highlights 2023 as critical (average NDVI ≈ 0.3—dry vegetation—and NDWI = −0.25, with 10–75 mm rainfall). Historically (1986–2023), vegetation hovered at 0.2–0.3, with notable dips in 1994, 2005, and 2015; projections indicate possible vegetation advance into current water areas by 2026, 2036, and 2056. A multi-criteria synthesis reports average NDVI = 0.38, mean slope 0.70°, and territorial suitability 0.47, classifying 100% of the wetland as low suitability for direct energy infrastructure, though peripheral opportunities for low-impact pilots and residual bioenergy remain under strict sustainability criterio. (Navarro Rau et al., 2025)

Complementarily, a classifier trained in Teachable Machine (satellite/drone scenes) is integrated into the Python application via OpenCV to scale inference on imagery, supporting rapid screening of water vs. dense vs. sparse vegetation in operational workflows.

4.3 Results of Phase Three: Multi-Source Technical Validation of Environmental Monitoring with Photogrammetry, IoT Sensors and Community Perception in the Santa María del Lago Wetland

In the third phase, corresponding to the technical validation of the data captured with DJI Phantom 4 Pro and DJI Mini 2 drones, photogrammetric processing was carried out using the specialized platforms Pix4D and WebODM. This procedure generated orthomosaics and high-resolution digital surface models (MDS). According to accuracy reports, the total root mean square error (RMS) was 0.412 meters for the GPS/GCP data, and 0.065 meters for the reconstructed 3D model. Specifically, RMS errors were 0.053 m on the X-axis, 0.033 m on the Y-axis, and 0.125 m on the Z-axis. The absolute horizontal accuracy (CE90) was 0.307 meters and the vertical accuracy (LE90) was 0.702 meters, which validates the reliability of the model for environmental applications and multitemporal analysis.
The quality of the data obtained is attributed to adequate flight planning, high overlap between images and correct configuration of processing parameters, which allowed acceptable levels of accuracy to be achieved without requiring external ground control points. (Navarro Rau et al., 2025)

This validation was carried out between February and June 2025, with monitoring sessions scheduled according to the climatic conditions of the ecosystem. During this period, the average relative humidity was 76.4%, with variations between 68% and 85%, consistent with environments of high vegetation cover. In terms of air quality, measurements from the MQ135 sensor revealed carbon dioxide (CO_2) concentrations between 528 and 570 ppm, averaging 552 ppm, which is within acceptable ranges for ecosystems with abundant plant activity and low pollutant sources (Quy et al., 2022; Shuai & Qian, 2011)

As a final point, the results of the statistical analysis of the questionnaire applied to the community reflect a Cronbach's alpha value of 0.894, which indicates a very good reliability and internal consistency among the items evaluated. This indicator confirms that the instrument's questions are conceptually aligned and measure related constructs. Likewise, the correlation heat map shows strong positive relationships between most of the questions, especially those related to the frequency of visits, the perception of environmental conditions and the observation of species. This suggests that participants who frequently visit the wetland tend to perceive their conditions more consistently. No negative correlations or significant weak relationships were identified, reaffirming the consistency of the questionnaire. Consequently, it is considered that the instrument is valid for community perception studies and can be applied in future monitoring processes in urban wetlands. (Imdad et al., 2023)

—

5 Conclusions

The implementation of the technological monitoring model in the Santa María del Lago wetland demonstrated high spatial precision through drone-based photogrammetry. Using DJI Phantom 4 Pro and DJI Mini 2 platforms, the model achieved a total root mean square error (RMSE) of 0.065 m, with axis-specific errors of 0.053 m (X), 0.033 m (Y), and 0.125 m (Z), and horizontal (CE90) and vertical (LE90) accuracies of 0.307 m and 0.702 m, respectively. These values validate the cartographic reliability of the orthomosaics and digital surface models generated without the use of ground control points. Additionally, the monitoring system integrated IoT data collected from ESP32 sensors, which registered carbon dioxide levels between 528 and 570 ppm (average 552 ppm), and a relative humidity range between 68% and 85%, aligning with high vegetative cover conditions.

The analysis of NDVI and NDWI indices between 1986 and 2023 revealed significant ecosystem degradation, particularly in 2023 when NDVI dropped to ~0.3 and NDWI to -0.25—indicators of dry vegetation and low water accumulation—corresponding with extreme climate conditions during El Niño events. Although the average Energy Fitness Index for the wetland was 0.47, limiting large-scale renewable energy deployment, specific peripheral areas showed potential for experimental low-impact applications. The platform's usability and community relevance were also confirmed, with a structured perception survey yielding a Cronbach’s Alpha of 0.894. Overall, the integration of drones, satellite data, IoT, and citizen science provides a replicable model to strengthen urban wetland conservation strategies under increasing climate and anthropogenic pressures.

6 Acknowledgement

This work was supported by the Tecnológico de Estudios Superiores de Ecatepec (TESE) in collaboration with SECIHTI through grant ApoyoLN-2025-C-73. H. Sossa gratefully acknowledges the support received from the Instituto Politécnico Nacional (IPN) and CONAHCyT for making this research possible. The authors also wish to express their sincere gratitude to the researchers and students whose valuable contributions were essential to the development of this work at the Laboratorio Nacional CONAHCyT en Inteligencia Artificial y Ciencia de Datos (LNC-IACD).

Additionally, the authors extend their appreciation to the Politécnico Grancolombiano University and the Corporación Universitaria Minuto de Dios (UNIMINUTO) for their academic collaboration, support in technological resources, and encouragement in advancing interdisciplinary research and innovation initiatives across Latin America.

References

Abdelkader, M., Bravo Mendez, J. H., Temimi, M., Brown, D. R. N., Spellman, K. V., Arp, C. D., Bondurant, A., & Kohl, H. (2024). A Google Earth Engine platform to integrate multi-satellite and citizen science data for the monitoring of river ice dynamics. *Remote Sensing, 16*(8), 1368. https://doi.org/10.3390/rs16081368

Avtar, R., Saito, O., Singh, G., Kobayashi, H., Ali, Y., Herath, S., & Takeuchi, K. (2014). Monitoring responses of terrestrial ecosystem to climate variations using multi-temporal remote sensing data in Ghana. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2014)*. IEEE. https://doi.org/10.1109/IGARSS.2014.6946535

Avtar, R., Yunus, A. P., Saito, O., Kharrazi, A., Kumar, P., & Takeuchi, K. (2022). Multi-temporal remote sensing data to monitor terrestrial ecosystem responses to climate variations in Ghana. *Geocarto International, 37*(2), 498–514. https://doi.org/10.1080/10106049.2020.1723716

Barros, J. (2020). *Especial: El preocupante ranking de los humedales de Bogotá*. Revista Semana. https://www.semana.com/impacto/informe-especial/articulo/especial-el-preocupante-ranking-de-los-humedales-de-bogota/56731/

Barros, J. (2020, April 12). *Cuatro humedales bogotanos sucumben ante las basuras, cemento, ruido e incendios*. Revista Semana. https://www.semana.com/medio-ambiente/articulo/cuatro-humedales-bogotanos-sucumben-ante-las-basuras-cemento-ruido-e-incendios/49524/

Bhatnagar, S., Gill, L., Regan, S., Waldren, S., & Ghosh, B. (2021). A nested drone-satellite approach to monitoring the ecological conditions of wetlands. *ISPRS Journal of Photogrammetry and Remote Sensing, 174*, 151–165. https://doi.org/10.1016/j.isprsjprs.2021.01.012

Bonilla, C., Brentan, B., Montalvo, I., Ayala-Cabrera, D., & Izquierdo, J. (2023). Digitalization of water distribution systems in small cities, a tool for verification and hydraulic analysis: A case study of Pamplona, Colombia. *Water, 15*(21), 3824. https://doi.org/10.3390/w15213824

Cuellar, Y., & Perez, L. (2023). Multitemporal modeling and simulation of the complex dynamics in urban wetlands: The case of Bogotá, Colombia. *Scientific Reports, 13*(1), 36600. https://doi.org/10.1038/s41598-023-36600-8

Das, N., & Mehrotra, S. (2021). Wetlands in urban contexts: A case of Bhoj Wetland. In *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2021)*. IEEE. https://doi.org/10.1109/IGARSS47720.2021.9554693

Hao, Z., Cai, X., Ge, Y., Foody, G. M., Li, X., Yin, Z., Du, Y., & Ling, F. (2024). Resolving data gaps in global surface water monthly records through a self-supervised deep learning strategy. *Journal of Hydrology, 640*, 131673. https://doi.org/10.1016/j.jhydrol.2024.131673

Hellweger, F. L., Schlosser, P., Lall, U., & Weissel, J. K. (2004). Use of satellite imagery for water quality studies in New York Harbor. *Estuarine, Coastal and Shelf Science, 61*(3), 437–448. https://doi.org/10.1016/j.ecss.2004.06.019

IDEAM. (2023). IDEAM Informe 2023.

Imdad, K., Sahana, M., Ravetz, J., Areendran, G., Gautam, O., Dwivedi, S., Chaudhary, A., & Sajjad, H. (2023). A sustainable solution to manage ecosystem health of wetlands in urban and peri-urban areas of Lucknow district, India using geospatial techniques and community-based pragmatic approach. *Journal of Cleaner Production, 414*, 137646. https://doi.org/10.1016/j.jclepro.2023.137646

iNaturalist Colombia. (n.d.). *Humedal Santa María del Lago* [Proyecto de ciencia ciudadana]. Retrieved March 15, 2025, from https://colombia.inaturalist.org/projects/humedal-santa-maria-del-lago?tab=stats

Navarro Rau, M. F., Calamari, N. C., Navarro, C. S., Enriquez, A., Mosciaro, M. J., Saucedo, G., Barrios, R., Curcio, M., Dieta, V., Martínez, G. G., Iturralde Elortegui, M. del R., Michard, N. J., Paredes, P., Umaña, F., Alday, S., Pezzola, A., Vidal, C., Winschel, C., Franco, S. A., … Kurtz, D. B. (2025). Advancing wetland mapping in Argentina: A probabilistic approach integrating remote sensing, machine learning, and cloud computing towards sustainable ecosystem monitoring. *Watershed Ecology and the Environment, 7*, 144–158. https://doi.org/10.1016/j.wsee.2025.04.001

Pan, M., Hu, T., Zhan, J., Hao, Y., Li, X., & Zhang, L. (2023). Unveiling spatiotemporal dynamics and factors influencing the provision of urban wetland ecosystem services using high-resolution images. *Ecological Indicators, 151*, 110305. https://doi.org/10.1016/j.ecolind.2023.110305

Quy, V. K., Hau, N. Van, Anh, D. Van, Quy, N. M., Ban, N. T., Lanza, S., Randazzo, G., & Muzirafuti, A. (2022). IoT-enabled smart agriculture: Architecture, applications, and challenges. *Applied Sciences, 12*(7), 3396. https://doi.org/10.3390/app12073396

Secretaria de Ambiente de Bogotá. (2020). Humedales de Bogotá.

Shuai, X., & Qian, H. (2011). Design of wetland monitoring system based on the Internet of Things. *Procedia Environmental Sciences, 10*(Part B), 1046–1051. https://doi.org/10.1016/j.proenv.2011.09.167

Venturini, V., Marchetti, Z. Y., Walker, E., & Fagioli, G. (2023). Performance analysis of machine learning techniques to identify aquatic vegetation with Sentinel-2 bands. *Ecología Austral, 33*(3), 743–756. https://doi.org/10.25260/EA.23.33.3.0.1960

Zhao, Y., He, X., Pan, S., Bai, Y., Wang, D., Li, T., Gong, F., & Zhang, X. (2024). Satellite retrievals of water quality for diverse inland waters from Sentinel-2 images: An example from Zhejiang Province, China. *International Journal of Applied Earth Observation and Geoinformation, 132*, 104048. https://doi.org/10.1016/j.jag.2024.104048