American Journal of Biodiversity
https://biojournals.us/index.php/AJB
ISSN: 2997-3600

Designing A Dynamic Digital Database for Long-Term Monitoring of the Aral Sea Bed Ecosystem using Artificial Intelligence and Geo-Information Systems

Umidkhon Uzbekov [1], Sadriddinov Bobur [3], Nuriddin Samatov [2], Jurabek Tulaev [2]
[1] PhD Candidate, "TIIAME" National Research University
[2] Junior Researcher, Research Institute of Environment and Nature Conservation Technologies
[3] PhD Candidate, Research Institute of Environment and Nature Conservation Technologies

Received: 2025, 15, Jun
Accepted: 2025, 21, Jul
Published: 2025, 23, Aug

Annotation: This study presents the development of a centralized, dynamically updateable digital database designed to store, analyze, and visualize ecological information from the dried Aral Sea bed (Orolbo'yi). The database integrates AI-based classification outputs, satellite image-derived indicators, field survey data, and geospatial attributes into a structured, relational platform. Developed in parallel with vegetation and habitat mapping efforts, the database enables systematic storage of species-specific data, environmental parameters, and spatial coordinates. Its functionality supports user-friendly access, efficient querying, and long-term tracking of biodiversity and restoration progress. This tool is positioned to serve researchers, policymakers, and environmental managers in building adaptive management strategies and ecological forecasting for one of Central Asia's most vulnerable environments.

Keywords: Digital database, AI

monitoring, Aral Sea bed, ecological inventory, GIS, restoration tracking, biodiversity management.

Introduction

The environmental degradation of the Aral Sea, once the fourth-largest inland water body in the world, has transformed the regional landscape and created one of the most urgent ecological crises in Central Asia [1]. As the sea began to shrink in the second half of the 20th century, vast portions of its former seabed became exposed, resulting in the formation of the Aralkum desert, locally referred to as the Orolboʻyi. This new terrain is characterized by extreme salinity, wind erosion, and a fragile emerging ecosystem. Monitoring such a complex and rapidly transforming environment poses significant challenges for traditional ecological research methods [2].

The Orolboʻyi region is now the focus of national and international restoration efforts aimed at mitigating environmental damage, improving local livelihoods, and recovering biodiversity. These efforts include large-scale afforestation programs, habitat stabilization measures, and biodiversity tracking projects [3]. However, given the size of the affected area and the dynamic nature of environmental changes occurring there, managing and analyzing ecological information has become increasingly difficult using conventional tools. Data collection is often fragmented, updates are irregular, and spatial coverage is insufficient to inform timely and adaptive decision-making.

In response to these limitations, a digital ecological database was designed and implemented as part of a scientific initiative led by the Research Institute of Environment and Nature Conservation Technologies. The primary aim of the database is to consolidate various types of ecological information—such as satellite-derived vegetation indices, geo-referenced species data, and AI-based classification results—into a single, accessible system [4]. Unlike isolated datasets or paper-based records, this database allows for centralized storage, visualization, and regular updating of large-scale ecological observations.

The technological foundation of this system relies on the integration of remote sensing platforms, geographic information systems (GIS), and artificial intelligence algorithms [5]. Together, these tools enable real-time vegetation monitoring, automated detection of plant communities, and identification of ecological changes in the Orolboʻyi landscape. The database also supports ongoing inventory activities by systematically cataloging plant and animal species observed during field expeditions.

By bridging data collection, processing, and storage within a unified digital framework, the platform enhances the scientific and operational capacity to track the success of restoration initiatives across the dried seabed. It offers both researchers and policy stakeholders a reliable mechanism for long-term ecological monitoring and helps to ensure that future interventions are based on current, validated, and spatially coherent environmental information.

Materials and Methods

The foundation of the ecological database was built through the integration of satellite remote sensing data, field observations, and artificial intelligence-based classification outputs. The primary satellite imagery used in the study was obtained from the MODIS and Landsat platforms via the USGS Earth Explorer service [6]. These images, covering the years 2000 to 2024, were specifically selected to coincide with the vegetation peak season in the Orolboʻyi region—typically occurring in May and June. This time window allowed researchers to capture the maximum expression of green biomass across the dried seabed.

All downloaded imagery underwent preprocessing using the Google Earth Engine cloud platform. The imagery was filtered for cloud cover, corrected for atmospheric distortions, and calibrated for reflectance. Two key vegetation indicators were calculated from the processed images: the Normalized Difference Vegetation Index (NDVI) and the Leaf Area Index (LAI) [7, 8]. NDVI values were computed using the red and near-infrared spectral bands, while LAI values were derived from NDVI through an empirically established exponential relationship. These indices served as essential metrics for evaluating vegetation health, density, and distribution across the region.

Alongside satellite analysis, field expeditions were conducted across selected zones within the Orolboʻyi landscape. Field teams used handheld GPS devices and drone-mounted cameras to document plant species, landform types, and microclimatic features. These observations provided spatial reference points for verifying satellite-derived vegetation patterns and were later used to calibrate classification algorithms. In addition to visual documentation, researchers recorded environmental conditions such as soil salinity, surface texture, and moisture presence to better understand the factors influencing plant growth and distribution.

To classify vegetation types more efficiently, the project employed convolutional neural networks (CNNs), which are a form of deep learning models capable of recognizing patterns in complex image datasets [3, 5]. The CNN models were trained using tagged image samples of dominant flora in the region, such as *Haloxylon*, *Tamarix*, and *Calligonum*. Although no specific accuracy metrics were detailed in the project reports, the models were described as effective in separating major plant types and estimating spatial extents of each category. The results of the AI-based classifications were cross-referenced with field data and satellite outputs to ensure consistency and eliminate significant discrepancies.

All collected data—whether from fieldwork, AI classification, or satellite analysis—were compiled into a relational digital database developed in a SQL-compatible format. Each entry in the database contains geographic coordinates, observation dates, species identification (if available), NDVI and LAI values, and metadata on image sources [2, 8]. This structure allows for fast querying, easy visualization, and future integration with external data sources such as government mapping portals. Furthermore, the database was designed to support annual updates by incorporating new imagery and additional field records as they become available, ensuring that the platform remains dynamic and useful for long-term monitoring of ecological restoration in the Aral Sea basin.

Results and Discussion

The digital database developed for the Orolboʻyi region represents a major step forward in organizing, storing, and analyzing ecological data from one of the most environmentally complex regions in Uzbekistan (Figure 1). Its initial structure was populated with processed satellite imagery, field observations, and outputs from AI-based classification models, creating a multi-layered inventory of both natural and introduced vegetation. The spatial reference system embedded in the database ensures that all data entries are traceable to specific locations within the Aral Sea bed, allowing for time-series comparisons and zonal analysis of ecological change.

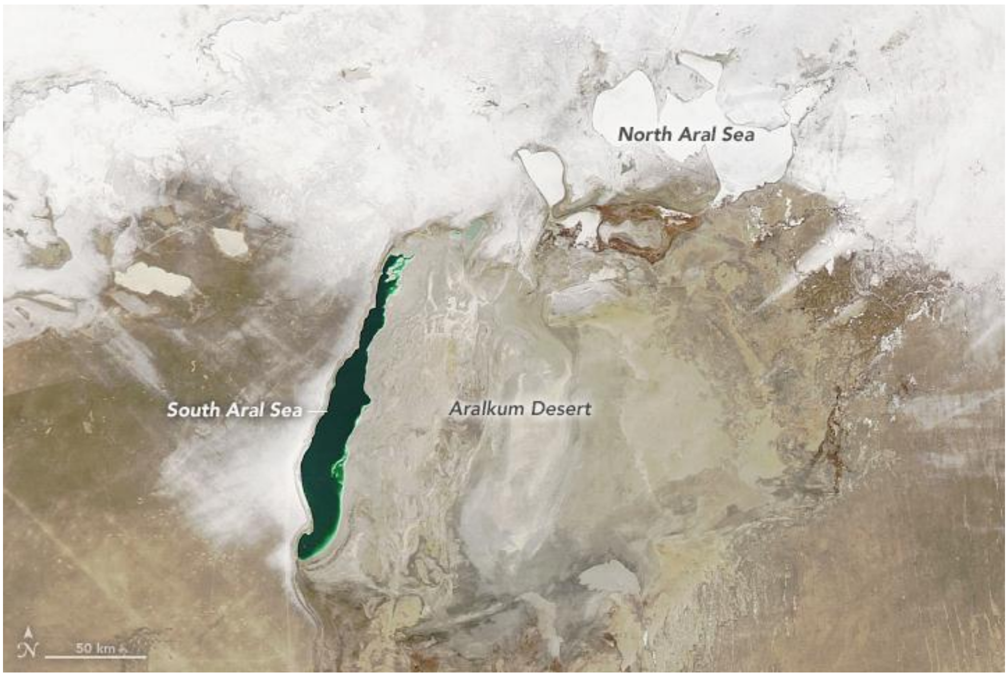

Figure 1. Digital database image of the Aral Sea.

One of the most important results of this work is the successful integration of NDVI and LAI indices into the database, allowing users to track vegetation performance over a 24-year period. The NDVI values, which reflect the relative greenness of surface cover, ranged from near-zero values in barren areas to above 0.3 in zones with established plantings of *Haloxylon* and other halophyte species. These values were calculated across the entire Karakalpakstan section of the dried Aral Sea bed using Landsat imagery, and their spatial patterns were verified with field observations taken in May and June of 2024.

The LAI index, derived from NDVI, offered an additional layer of insight into canopy development and biomass density. Although LAI values remained relatively low throughout the region due to the early stage of vegetation establishment, they helped distinguish between scattered seedlings and denser plantations. The use of LAI in the database also supports future monitoring of canopy growth, especially in afforestation areas that are expected to mature over the next decade.

The AI-based classification component contributed significantly to the structure and richness of the database. By training convolutional neural networks on field-labeled imagery, researchers were able to classify vegetation into major groups, including woody shrubs, low-stature grasses, and open soil or barren land. These classification layers were not used in isolation but were combined with field data and image metadata to verify their accuracy. Although no quantitative confusion matrices were included in the reports, the consistency of AI outputs with field observations suggests a high level of reliability for identifying large-scale patterns.

A particularly valuable feature of the system is its capability to accommodate ecological variability across space and time. The database is not static; it is designed to be regularly updated with new satellite imagery, drone footage, and ground survey results. This functionality ensures that restoration efforts—such as those under the "Yashil Makon" initiative—can be monitored on an annual or seasonal basis, and that their ecological effects can be measured precisely using both visual and numerical data.

One of the outputs stored in the database includes processed image layers representing the green cover status of the region in 2000 and 2020 (Figure 2). These layers were generated using the same methods and data sources, allowing for consistent comparison over time. The result is a highly interpretable visual representation of vegetation recovery, highlighting where greening has occurred and where barren land persists. These layers can be exported as maps or integrated into policy reports, making the database valuable not only for scientific research but also for decision-making.

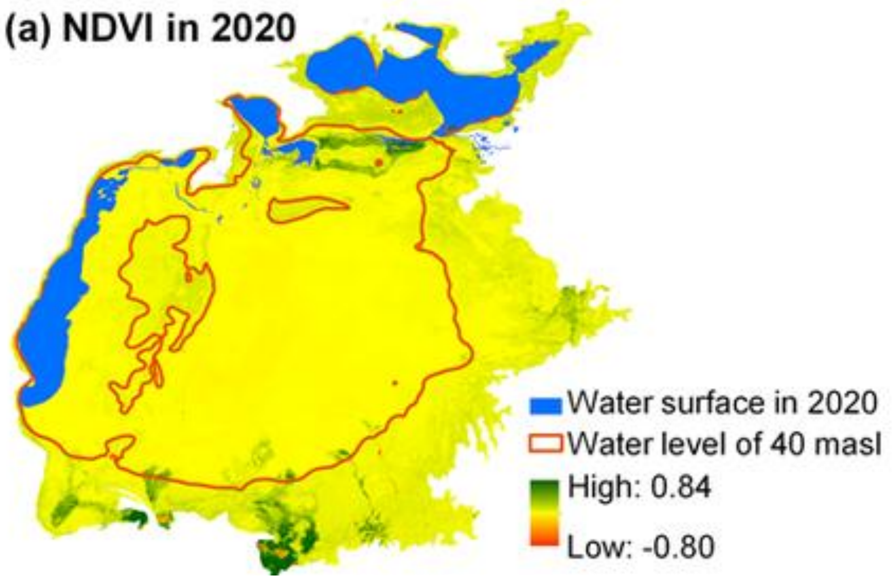

Figure 2. The NDVI state of the Aral Sea in 2020.

Field expeditions provided critical support for validating the AI classifications and satellite interpretations (Figure 3). During on-site surveys, researchers used GPS devices to tag observations of key species and landscape features. These georeferenced records were entered directly into the database and matched with satellite observations from the same location and date. In some cases, inconsistencies in NDVI readings prompted deeper investigation, helping refine both the database structure and the classification logic.

In addition to vegetation data, the database includes environmental descriptors for each observation point, such as soil type, terrain form, elevation band, and proximity to water channels. This information was compiled during the field campaigns and serves as a contextual layer for interpreting vegetation health. For instance, many of the areas with the highest NDVI values were located in shallow depressions or along dried streambeds, where soil moisture tends to accumulate. This spatial relationship can now be quantified and used to prioritize future planting zones.

Figure 3. Scenes from the fieldwork.

Although the primary focus of the database is floristic inventory, preliminary modules were also developed to record faunal observations and potential habitat zones. These are especially useful for projecting future wildlife recolonization patterns, particularly in regions where plant cover is expanding. Population modeling, based on classical ecological equations, can also be supported by linking animal sightings to vegetation trends. This opens the door for multi-species ecosystem monitoring, extending the usefulness of the platform well beyond plant-based assessments.

The establishment of a centralized, dynamic, and regularly updateable digital database for the Orolboʻyi region offers a powerful tool for ecological restoration planning, scientific analysis, and long-term environmental governance. It combines multiple sources of information into a coherent system, provides structured access to validated spatial data, and supports the design and evaluation of climate-adaptive land use strategies. Its continued maintenance and expansion will be essential to ensure that restoration policies in the Aral Sea basin are informed by the most current and accurate ecological data available.

Conclusions

The development of a dynamic ecological database for the Aral Sea bed marks a foundational advancement in how restoration and biodiversity monitoring can be conducted in post-disaster landscapes. In a region as ecologically sensitive and spatially vast as the Orolboʻyi, traditional monitoring methods have proven insufficient in capturing the full complexity of environmental change. This study demonstrates that through the integration of remote sensing, artificial intelligence, and ground-based observations, a scalable and reliable digital platform can be established to support ongoing restoration activities.

One of the key achievements of the project is the successful unification of diverse data types—satellite imagery, AI-based classification outputs, field measurements, and spatial metadata—into a structured and updateable system. This enables consistent tracking of vegetation trends, provides insight into spatial variation across the former seabed, and supports habitat modeling and long-term planning. The use of NDVI and LAI indices allows restoration teams and researchers to measure progress at both macro and micro scales, while field validation ensures the accuracy and credibility of model outputs.

Equally important is the adaptability of the system. Designed to be updated annually, the database allows for new imagery and field data to be continuously added without disrupting its structure. This makes it especially valuable in a climate-vulnerable region where environmental conditions and vegetation patterns can shift rapidly. The inclusion of AI-assisted classifications and ecological indicators also prepares the platform for more advanced modeling in future phases, including predictive habitat suitability and species distribution forecasts.

Beyond its scientific utility, the database has direct practical implications for policymakers and environmental agencies. It supports transparent reporting, prioritization of afforestation zones, evaluation of ecosystem health, and coordination of restoration activities across different sectors. As climate-related risks grow more complex, such integrated systems will be essential for designing flexible and evidence-based responses to desertification and biodiversity loss.

In conclusion, the creation of a centralized, updateable, and scientifically grounded ecological database for the Orolboʻyi region offers a replicable model for post-crisis landscape monitoring. It not only documents current progress but also enables future adaptive management, contributing to both national restoration strategies and broader regional efforts to restore ecological balance in the former Aral Sea basin.

Acknowledgements

This research was carried out within the framework of the targeted applied project No. ALM-202403110248, funded by the Agency for Innovative Development under the Ministry of Higher Education, Science and Innovations of the Republic of Uzbekistan. The authors gratefully acknowledge the support provided by the funding agency, as well as the contributions of all research team members and international partners involved in the field expedition and data analysis.

References

1. Krapivin, V., & Shutko, A. M. (2012). *Information technologies for remote monitoring of the environment*. Springer Science & Business Media.
2. Kara, D. E., Himmelstoss, T., Betz-Nutz, S., Altmann, M., Rom, J., Haas, F., ... & Becht, M. (2024). Long-term suspended sediment monitoring in upper Kaunertal, Austria: Examining trigger mechanisms of high transport events.
3. Lausch, A., Schaepman, M. E., Skidmore, A. K., Truckenbrodt, S. C., Hacker, J. M., Baade, J., ... & Thiel, C. (2020). Linking the remote sensing of geodiversity and traits relevant to biodiversity—part II: geomorphology, terrain and surfaces. *Remote sensing*, *12*(22), 3690.
4. Benmokhtar, S., Robin, M., Maanan, M., & Bazairi, H. (2021). Mapping and quantification of the dwarf eelgrass Zostera noltei using a Random Forest Algorithm on a SPOT 7 Satellite Image. *ISPRS International Journal of Geo-Information*, *10*(5), 313.
5. Kairanbayeva, A., Nurpeissova, G., Zhantayev, Z., Shults, R., Panyukova, D., Kiyalbay, S., & Panyukov, K. (2022). Impact of landscape factors on automobile road deformation patterns—a case study of the almaty mountain road. *Sustainability*, *14*(22), 15466.
6. Varotsos, C. A., & Krapivin, V. F. (2020). *Microwave remote sensing tools in environmental science* (Vol. 3). New York, NY, USA: Springer International Publishing.
7. Löw, F., Biradar, C., Dubovyk, O., Fliemann, E., Akramkhanov, A., Narvaez Vallejo, A., & Waldner, F. (2018). Regional-scale monitoring of cropland intensity and productivity with multi-source satellite image time series. *GIScience & Remote Sensing*, *55*(4), 539-567.
8. Ndehedehe, C. (2022). *Satellite remote sensing of Terrestrial Hydrology* (Vol. 15). Springer.