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INTEGRATING UAV PHOTOGRAMMETRY AND DEEP LEARNING FOR VEGETATION MONITORING ON THE DRIED BED OF THE ARAL SEA

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Abstract

The dried bed of the Aral Sea is vast, hard to access and covered by sparse, mosaic vegetation that 10–30 m satellite pixels cannot resolve. We tested a workflow that combines UAV Structure-from-Motion photogrammetry, deep-learning vegetation detection, LiDAR-based 3D analysis and a continuously updated flora database. Two key sectors (1.01 km² and 0.524 km²) were surveyed with a DJI Matrice 30T, giving a ground sampling distance of 5.09 and 6.77 cm/pixel and reprojection errors of 0.847 and 0.796 pixels. A YOLOv5-based detector and a five-class CNN classifier gave preliminary active-vegetation cover of about 45% and 34%, concentrated in micro-depressions. Results are stored in a Darwin Core-compatible database published through the geoai.uz platform, which is used at least weekly by 66.5% of 287 surveyed users. A three-level monitoring system linking field plots, UAV surveys and satellite data is proposed.

Keywords: Aralkum, UAV, Structure-from-Motion, YOLOv5, convolutional neural network, LiDAR, vegetation mapping, biodiversity database.



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Introduction

Desiccation of the Aral Sea has produced the Aralkum, a desert of more than 5 million ha [1]. Since 2018, protective plantations have been established on about 1.94 million ha of the dried bed in Uzbekistan, but their condition is still assessed mainly by visual inspection, which classifies plots only as well covered, moderately covered or poorly established. Such assessments are hard to repeat and give little spatial detail.

Satellite data cover the whole region but are too coarse for this landscape. Shrubs on the seabed are typically 0.5–3 m across, so a single Sentinel-2 or Landsat pixel mixes several plants with bare saline soil. UAV imagery with centimetre resolution, combined with convolutional neural networks (CNNs), enables species-level mapping in such settings [2]. The aim of this work was to develop and test a UAV–AI workflow for quantitative vegetation monitoring in the Aralkum and to link its outputs to a continuously updated flora database.

Materials and methods

Field work was carried out within the institute's applied project on AI-based inventory of the flora of the dried Aral Sea bed. Two key sectors were surveyed: the Central sector (1.01 km²) from 156 m altitude with 270 images, and the Eastern sector (0.524 km²) from 159 m with 75 images. A DJI Matrice 30T with its wide-angle RGB camera (4000×3000 px, 1.59 µm pixel size, 4.4 mm focal length) flew pre-planned automatic routes with high forward and side overlap. A DJI Phantom 4 was used for close-range photographs of plants at observation points.

Images were processed by Structure-from-Motion (SfM) photogrammetry [3] in six steps: image quality check; alignment with tie-point extraction and self-calibration of the camera (focal length, principal point, radial distortion K1–K3);



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depth maps and dense point cloud; digital elevation model (DEM); orthomosaic; and quality assessment by reprojection error and camera position errors. No ground control points or RTK positioning were used.

Vegetation was detected with two models. The first, "YOLO Forest Detection v5", is based on the YOLOv5 architecture [4] and integrated into the geoai.uz "Tree Detection Workflow" module. It draws bounding boxes around trees and shrubs and assigns each a confidence score; a threshold of 0.8 was used to reduce false detections. The second model splits the orthomosaic into 128×128-pixel tiles, normalizes them to the 0–1 range and classifies each tile into five classes: bare soil, Haloxylon, Tamarix, salt crust and sparse grass. The classified raster was converted to vector polygons with GDAL for GIS analysis. The workflow was implemented in Python with TensorFlow/Keras, rasterio, OpenCV and GDAL.

Because the UAV sensors were RGB only, NDVI, GNDVI and SAVI were computed from Sentinel-2 imagery, while visible-band indices were used for UAV data: excess green, $ExG = 2g - r - b$, and $VARI = (G - R)/(G + R - B)$, where r , g and b are the normalized shares of the red, green and blue channels. LiDAR point clouds were processed in the geoai.uz NeuroLIDAR module, and a canopy height model was derived as $CHM = DSM - DTM$.

Results and discussion

Photogrammetric quality. All images aligned in both sectors despite the low texture of saline surfaces (Table 1). Self-calibration gave $K1 = 0.192026$, $K2 = -0.465648$ and $K3 = 0.241625$, and image residuals showed minimal deformation around the optical centre. In a larger block, all 1,578 images aligned, producing 773,745 tie points, 112.6 million dense points, a 20.5 cm DEM and a 5.12 cm orthomosaic, showing that the workflow is stable over large areas.



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Table 1. Main indicators of UAV photogrammetry in the Aralkum sectors

Indicator	Central sector	Eastern sector
Area, km ²	1.01	0.524
Flight altitude, m	156	159
Number of images	270	75
Ground sampling distance, cm/pixel	5.09	6.77
Tie points	161,323	45,645
Tie points per image	≈598	≈609
Reprojection error, pixel	0.847	0.796
Camera position error XY, m	≈1.2	1.229 / 1.309
Camera position error Z, m	≈16	10.60
Dense point cloud, million points	>25	7.28
Mean point density, points/m ²	≈25	≈14
Relative elevation range in DEM, m	30–160	100–184

Reprojection errors below 1 pixel allow plant outlines to be delineated at 5–7 cm, sufficient to resolve individual shrubs. The high vertical camera-position error (10–16 m) results from the standard GNSS receiver without ground control points. It does not affect the planimetric geometry of the orthomosaic, and therefore AI detection, but it makes absolute DEM elevations unreliable, so only relative elevations were analysed. One survey session at 150–160 m covered 0.5–1 km², which can guide the size of permanent UAV monitoring plots.

Vegetation mapping. Model outputs were overlaid on the orthomosaics, with active vegetation shown in green and stressed or sparse vegetation clusters in red. Class shares were estimated from the result maps under four colour-threshold variants (Table 2).



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Table 2. Estimated shares of vegetation classes from AI result maps

Indicator	Central sector	Eastern sector
Sector area, ha	101.0	52.4
Active vegetation, % (range; mid variant)	27–51 (45)	26–36 (34)
Active vegetation area, ha (mid variant)	≈46	≈18
Stressed or sparse vegetation, %	1.1–1.9	2.4–3.4
Bare surface, % (mid variant)	≈53	≈63

Note: shares are preliminary estimates from colour analysis of result maps; final values require pixel counts of the classified GeoTIFF output.

In the Central sector the model detected large shrub clusters that field data identify as *Haloxylon*, *Xylosalsola*, *Caroxylon* and *Calligonum* communities. In the Eastern sector vegetation was more mosaic: it clustered in micro-depressions, while elevated, wind-eroded surfaces covered by salt crust were nearly bare. This pattern matches the DEM gradients: plants are denser where water briefly accumulates. The higher share of stressed vegetation in the Eastern sector reflects its wider salt-crust surfaces and larger relief gradients.

The AI estimates exceed field estimates (10–36% cover at observation points, 35% on a saxaul plantation), probably because shadows and mixed pixels around crowns were included; calibration against field plots is therefore required. Four practical problems were identified: (1) spectral similarity of late-summer halophytes and saline soil, to be reduced by surveys in April–June, multispectral sensors and LiDAR height; (2) lack of labelled training data for Aralkum flora, to be addressed by transfer learning, expert labelling at field points and augmentation; (3) limited species-level detection of annual chenopods and grasses at 5–7 cm, to be solved by additional 20–40 m flights; and (4) shadow effects, to be reduced by flights at high sun angle. LiDAR complements optical



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data because plants with the same colour as the soil appear in point clouds as clear rises above the ground surface.

Database and platform. All records were written to a relational database with fields for a UUID identifier, scientific name, AI or expert class, WGS-84 coordinates, date, vegetation index value, image path, data source (UAV-CNN, field survey, LiDAR), update date and remarks. These fields follow Darwin Core [5] and FAIR principles [6]. Every operation is logged, and each AI detection enters the database as "UAV-CNN" and is later verified by an expert, forming a "model – expert – database" chain. Validated coordinates of 7 Red Book species and 35 other key species serve as ground truth for model testing.

A survey of 287 geoai.uz users showed that 18.1% use the platform daily, 23.7% several times a week and 24.7% weekly (66.5% at least weekly). Main purposes were GIS and map analysis (31.0%), environmental monitoring (25.8%) and research (18.1%). Mean satisfaction was 7.45 out of 10: the map interface (8.4) and data accuracy (8.1) scored highest, and mobile adaptation (6.2) and loading speed (6.9) lowest. Active users grew from 18 in January to 58 in December 2025, a 3.2-fold increase.

Monitoring system. Based on these results, a three-level system is proposed: a regional level (the whole dried seabed, Sentinel-2 and Landsat indices, at least twice a year); a site level (50–100 ha key plots, UAV, LiDAR and AI models, once or twice a year in April–June and September); and a point level (permanent plots and observation points, species composition, cover, rare species, groundwater and salinity, every spring). Point data train and test the AI models, UAV and LiDAR data serve as a reference for satellite interpretation, and satellite data scale the results to the whole Aralkum.



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Conclusions

UAV photogrammetry combined with deep learning provides centimetre-scale, repeatable vegetation maps of the Aralkum that can replace visual assessment of plantations. Future surveys should use RTK/PPK positioning or ground control points, spring flight timing, multispectral and LiDAR sensors, and formal accuracy assessment against field data. Integration of the database with the state cadastre of flora objects and adaptation of geoai.uz to mobile devices are the next practical steps.

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