International Cartographic Association
Association Cartographique Internationale

An Open-Source YOLO & QGIS Workflow for Geospatial Object Detection

Jakub Šperka [a,*], Renata Ďuračiová [a], Tibor Lieskovský [a]

[a] *Department of Theoretical Geodesy and Geoinformatics, Faculty of Civil Engineering, Slovak University of Technology in Bratislava, Jakub Šperka – jakub.sperka@stuba.sk, Renata Ďuračiová – renata.duraciova@stuba.sk, Tibor Lieskovský – tibor.lieskovsky@stuba.sk*

* Corresponding author

Keywords: geospatial object detection, Open-Source GIS, computer vision, deep learning, remote sensing

Abstract:

The increasing availability of open geospatial data and open-source software has created new opportunities for integrating machine learning into GIS workflows. Object detection models have demonstrated strong performance in computer vision tasks, yet their adoption within geospatial analysis pipelines remains limited. This work presents an open-source workflow that bridges the gap between deep learning and GIS, with emphasis on reproducibility, scalability and integration into GIS-based analytical workflows.

The proposed approach is demonstrated on two distinct types of geospatial data. The first dataset consists of digital feature models (DFM) with specialized visualization for archaeological features from Lieskovský et al. (2022), derived from airborne laser scanning (ALS), used for enhancing microtopographic features displayed in Figure 1. The second dataset includes airborne orthophoto mosaics (GKÚ Bratislava, NLC) used for detecting swimming pools in both urban and rural environments displayed in Figure 2. These datasets represent fundamentally different data characteristics, combining elevation-based and spectral information, and allow evaluation of the workflow's generalization capability and scalability.

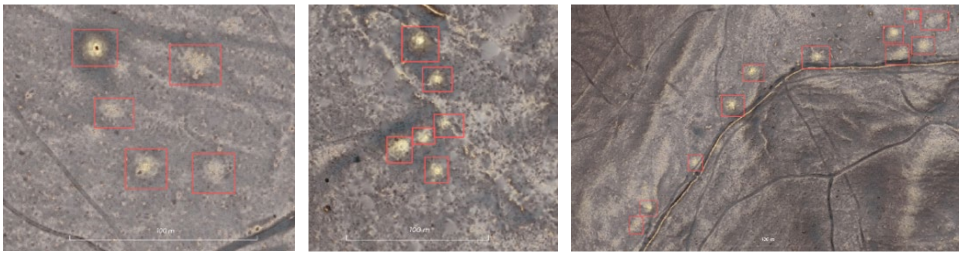

Figure 1. Training batch example of archaeological burial mounds with annotated bounding boxes.

Figure 2. Training batch example of pools with annotated bounding boxes.

Raster data are divided into 640×640-pixel tiles and corresponding annotations are converted into YOLO-format bounding boxes using custom Python scripts. The models are trained on balanced datasets using standard augmentation techniques. Large-area inference is performed using a sliding-window approach, followed by IoU-based filtering and non-maximum suppression (NMS). Detection results are transformed back into geospatial coordinates and stored in GeoPackage format for GIS integration, visualization, and validation. The workflow is implemented entirely using open-source tools, Python libraries, and the Ultralytics YOLOv26 framework, providing a reproducible and scalable solution for geospatial object detection. The workflow scripts will be published as open-source resources in future via GitHub repository.

Abstracts of the International Cartographic Association, 12, 134, 2026
European Cartographic Conference – EuroCarto 2026, 8–11 September 2026, Brno, Czech Republic.
https://doi.org/10.5194/ica-abs-12-134-2026

The prototype models achieved moderate to good performance on the validation and test datasets according to standard object detection metrics based on Bundzel et al. (2020). The numerical comparison of detection performance metrics is presented in Table 1.

Dataset	Precision	Recall	F1-score	mAP50
Mounds (Validation)	0.898	0.687	0.778	0.791
Mounds (Test)	0.874	0.778	0.839	0.823
Pools (Validation)	0.997	0.890	0.942	0.946
Pools (Test)	0.955	0.886	0.919	0.933

Table 1. Detection performance metrics of YOLOv26m models on validation and test datasets.

Figures 3 and 4 demonstrate that the models can detect target objects of varying size and context. However, when applied to independent areas not included in the training process, the model exhibits a higher rate of false positive detections. This behavior highlights the challenges related to generalization across different geographic regions and data characteristics.

Figure 3. Examples of predicted mounds on test area using sliding-window approach.

Figure 4. Examples of predicted pools on test area using sliding-window approach.

The observed discrepancy is likely related to differences between the training and independent datasets, including the presence of visually similar non-target features and the limited diversity of the prototype training data. Despite this limitation, the workflow remains effective for large-scale screening, where false positives can be further reduced through post-processing or manual validation.

Acknowledgements

This research was funded by the Slovak Research and Development Agency under Contract No. APVV-22-0151 and by grant No. VEGA 1/0626/25 of the Scientific Grant Agency of the Ministry of Education, Science, Research, and Sport of the Slovak Republic and the Slovak Academy of Sciences.

References

Bundzel, M., Jaščur, M., Kováč, M., Lieskovský, T., Sinčák, P. and Tkáčik, T., 2020. Semantic Segmentation of Airborne LiDAR Data in Maya Archaeology. In: *Remote Sensing 2020*, Vol 12(22), 3685. https://doi.org/10.3390/rs12223685

Lieskovský, J., Lieskovský, T., Hladíková, K., Štefunková, D. and Hurajtová, N., 2022. Potential of airborne LiDAR data in detecting cultural landscape features in Slovakia. In: *Landscape Research 2022*, Vol 47(5), pp. 539–558. https://doi.org/10.1080/01426397.2022.2045923

https://doi.org/10.5194/ica-abs-12-134-2026