

GeoAI for Land Use Observations, Analysis, and Forecasting

Wenfeng Zheng ^{1,*} , Kenan Li ²  and Xuan Liu ³ ¹ School of Automation, University of Electronic Science and Technology of China, Chengdu 610054, China² Department of Epidemiology and Biostatistics, Saint Louis University, St. Louis, MO 63103, USA; kenan.li@slu.edu³ School of Public Affairs and Administration, University of Electronic Science and Technology of China, Chengdu 610054, China; liuxuan@uestc.edu.cn

* Correspondence: winfirms@ieee.org

Geographic artificial intelligence (GeoAI) is reshaping how we observe, understand, and govern land systems [1,2]. By coupling Earth observation with modern learning—from classical machine learning to deep networks—it moves the field from static mapping to dynamic, predictive, and decision-support paradigms across agriculture, environmental stewardship, urban development, and disaster risk management [3–5]. This Special Issue showcases advances that span the full GeoAI pipeline: novel data acquisition; representation learning for classification, change detection, and object/scene understanding; and application-oriented decision frameworks. Together, these works illuminate a common arc: data to models, models to insights, and insights to action.

At the sensing frontier, mobile laser scanning now delivers dense, centimeter-level 3D reconstructions [6]. Using a ZEB-HORIZON handheld LiDAR, Liu et al. conduct a scientific investigation and faithful replication of a karst cave in the Yunshui Village heritage area, building a full workflow from acquisition and calibration to registration, semantic mapping, and visualization (List of Contributions 1). Their paper details practical bottlenecks—octree sampling, point cleaning, route planning—and shows how an integrated pipeline can transform billions of points into a navigable, analyzable model usable by conservation and tourism stakeholders.

At the landscape scale, land-cover and land-use (LULC) mapping has matured into decision-oriented scenario modeling. Bol and Randhir analyze Myanmar's Chindwin River Basin with Landsat time series and classification, then forecast land change trajectories under multiple policy and development assumptions (List of Contributions 2). Their results quantify sharp shifts among forest, agriculture, grass/shrub, and water, and explicitly link these shifts to drivers such as population growth and development corridors, yielding tractable scenarios for basin governance.

In another contribution, Rodrigues et al. propose an operational change framework for Amazonian deforestation that pairs anomaly detection with neural networks in Google Earth Engine and deploys it across Indigenous land Kayapó (32,000 km²) and adjacent protected and non-protected areas (List of Contributions 3). They highlight a persistent gap: much monitoring focuses on protected areas, leaving other critical lands under-observed, and they demonstrate how dual-mode detection helps close that gap.

Several contributions emphasize not only accuracy but also computational efficiency—vital for edge deployment.

In precision agriculture, Hu et al. introduce SkipResNet, an attention-enhanced residual model tailored for crop-weed recognition (List of Contributions 4). On the Plant Seedlings and a corn/weed dataset, SkipResNet achieves high accuracy, while reducing



Received: 18 August 2025

Accepted: 11 October 2025

Published: 15 October 2025

Citation: Zheng, W.; Li, K.; Liu, X. GeoAI for Land Use Observations, Analysis, and Forecasting. *Land* **2025**, *14*, 2058. <https://doi.org/10.3390/land14102058>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

parameter count and inference time compared with heavier baseline evidence that careful architectural pruning and attention design can yield both speed and robustness in field conditions.

For scene classification, Hu et al. propose a multi-path reconfigurable residual network (MR-ResNet) (List of Contributions 5). Rather than committing to a fixed backbone, they cut and reassemble pre-trained networks into task-specific subgraphs, combining modular “block-split/block-merge” with transfer learning to reduce trial-and-error cost. On NWPU-RESISC45, RSSCN7, and SIRI-WHU, MR-ResNet surpasses classical ResNet with fewer parameters, illustrating a promising paradigm: architect the search space once, then “route” data through optimal paths for each scenario.

At the object-detection frontier, two papers target lightweight yet high-fidelity detectors for overhead imagery and remote sensing targets.

CGBi_YOLO integrates CSPGhostNet bottlenecks to slim down YOLO while preserving discriminative capacity; by interleaving mobile-friendly convolutions and tailored training, the authors report competitive performance on DOTA with materially fewer parameters (List of Contributions 6). They further explore two-stage transfer strategies to stabilize convergence in small-sample regimes typical of aerial datasets.

YOLOv5s-CACSD fuses coordinate attention (CA), CARAFE upsampling, and shape-aware IoU loss to boost small-object recall without inflating computation; the design uses depthwise separable convolutions to keep FLOPs/params near YOLOv5s while lifting AP, underscoring the payoff from plug-in “modular” improvements (List of Contributions 7).

Two contributions exemplify how GeoAI supports risk analysis and resource management.

Vasconcelos et al. present a comprehensive review of deep learning for wildfire detection across terrestrial, aerial, and satellite modalities (1990–2023) (List of Contributions 8). Their bibliometric and systematic synthesis charts the field’s rapid growth since the 2010s, identifies leading venues and countries, and distills model families and data pipelines that have proven durable, from optical smoke/flame detection to the segmentation of burned areas and SAR-based mapping. The review emphasizes sensor fusion, robust training data, and international collaboration as levers to improve early detection and response at scale.

Turning to drought, Zhou et al. designed a case-based reasoning (CBR) decision system for Yunnan Province, integrating hazard, exposure, vulnerability, and impact to produce actionable recommendations across prevention, preparedness, response, and recovery (List of Contributions 9). Their strategy library covers short-term emergency measures and long-term governance, and the 2019 case shows how corrective equations and evidential reasoning update recommendations as conditions evolve. The framework demonstrates how knowledge organization, not only learning accuracy, determines whether analytics translate into policy and field operations.

Cross-Cutting Themes and Outlook.

A recurrent message is the move from map-making to decision making. The Chindwin basin scenarios and Yunnan CBR system exemplify “analytics-to-action,” where classification is only a step toward policy-relevant recommendations.

MR-ResNet, CGBi_YOLO, YOLOv5s-CACSD, and SkipResNet converge on a principle: leverage modular design (attention, reconfigurable blocks, lightweight modules) to balance accuracy, speed, and portability—critical for edge devices, onboard processing, and rapid deployment in field operations.

The Amazon deforestation framework shows how cloud platforms (e.g., GEE) enable dual-mode pipelines from anomaly screening to be supervised confirmation across large regions and mixed jurisdictional mosaics.

From cave-scale centimeter models to continental fire monitoring, the issue emphasizes that actionable GeoAI must preserve fidelity where it matters—geometry in heritage conservation, temporal responsiveness in hazards, and class separability in agricultural plots.

Open challenges. Several gaps remain: (i) robust generalization across seasons, sensors, and domains; (ii) uncertainty quantification to accompany decisions; (iii) integration of physical constraints and knowledge bases with deep models; and (iv) governance workflows that absorb model outputs (alerts, scenarios, recommendations) into routine operations. The contributions here offer concrete building blocks toward these goals.

In sum, this Special Issue demonstrates a maturing GeoAI stack: high-fidelity sensing; efficient, modular learning; scalable change detection; and decision-centric systems. As the community advances, we expect three accelerants to dominate: foundation-model pretraining on multimodal geodata; reconfigurable architectures that “right-size” models for tasks and devices; and decision frameworks that pair data-driven inference with domain knowledge.

Author Contributions: Conceptualization, writing—original draft preparation, W.Z.; writing—review and editing, W.Z., K.L. and X.L.; All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

List of Contributions:

1. Liu, X.; Shan, Y.; Ai, G.; Du, Z.; Shen, A.; Lei, N. A Scientific Investigation of the Shangfang Mountain Yunshui Cave in Beijing Based on LiDAR Technology. *Land* **2024**, *13*, 895. <https://doi.org/10.3390/land13060895>.
2. Bol, T.T.; Randhir, T.O. Predicting Land Use and Land Cover Changes in the Chindwin River Watershed of Myanmar Using Multilayer Perceptron-Artificial Neural Networks. *Land* **2024**, *13*, 1160. <https://doi.org/10.3390/land13081160>.
3. Rodrigues, J.; Dias, M.A.; Negri, R.; Hussain, S.M.; Casaca, W. A Robust Dual-Mode Machine Learning Framework for Classifying Deforestation Patterns in Amazon Native Lands. *Land* **2024**, *13*, 1427. <https://doi.org/10.3390/land13091427>.
4. Hu, W.; Chen, T.; Lan, C.; Liu, S.; Yin, L. SkipResNet: Crop and Weed Recognition Based on the Improved ResNet. *Land* **2024**, *13*, 1585. <https://doi.org/10.3390/land13101585>.
5. Hu, W.; Lan, C.; Chen, T.; Liu, S.; Yin, L.; Wang, L. Scene Classification of Remote Sensing Image Based on Multi-Path Reconfigurable Neural Network. *Land* **2024**, *13*, 1718. <https://doi.org/10.3390/land13101718>.
6. Wang, R.; Lu, S.; Tian, J.; Yin, L.; Wang, L.; Chen, X.; Zheng, W. CGBi_YOLO: Lightweight Land Target Detection Network. *Land* **2024**, *13*, 2060. <https://doi.org/10.3390/land13122060>.
7. Hu, W.; Jiang, X.; Tian, J.; Ye, S.; Liu, S. Land Target Detection Algorithm in Remote Sensing Images Based on Deep Learning. *Land* **2025**, *14*, 1047. <https://doi.org/10.3390/land14051047>.
8. Vasconcelos, R.N.; Franca Rocha, W.J.S.; Costa, D.P.; Duverger, S.G.; Santana, M.M.M.d.; Cambui, E.C.B.; Ferreira-Ferreira, J.; Oliveira, M.; Barbosa, L.D.; Cordeiro, C.L. Fire Detection with Deep Learning: A Comprehensive Review. *Land* **2024**, *13*, 1696. <https://doi.org/10.3390/land13101696>.
9. He, L.; Lei, Y.; Yang, Y.; Liu, B.; Li, Y.; Zhao, Y.; Tang, D. Intelligent Recommendation of Multi-Scale Response Strategies for Land Drought Events. *Land* **2025**, *14*, 42. <https://doi.org/10.3390/land14010042>.

References

1. Janowicz, K.; Gao, S.; McKenzie, G.; Hu, Y.; Bhaduri, B. GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 625–636. [\[CrossRef\]](#)
2. Li, W.; Hsu, C.-Y. GeoAI for Large-Scale Image Analysis and Machine Vision: Recent Progress of Artificial Intelligence in Geography. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 385. [\[CrossRef\]](#)
3. Lavallin, A.; Downs, J.A. Machine learning in geography—Past, present, and future. *Geogr. Compass* **2021**, *15*, e12563. [\[CrossRef\]](#)

4. Khouya, A. L'intégration de l'intelligence artificielle en géographie: Nouvelles potentialités et défis persistants. *Géomatique Et Gest. Des Territ.* **2025**, *2*, 146–153. [[CrossRef](#)]
5. Senocak, A.A.; Guner Goren, H. Forecasting the biomass-based energy potential using artificial intelligence and geographic information systems: A case study. *Eng. Sci. Technol. Int. J.* **2022**, *26*, 100992. [[CrossRef](#)]
6. Di Stefano, F.; Chiappini, S.; Gorreja, A.; Balestra, M.; Pierdicca, R. Mobile 3D scan LiDAR: A literature review. *Geomat. Nat. Hazards Risk* **2021**, *12*, 2387–2429. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.