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GeoAI for climate monitoring – A mini review

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ABSTRACT

GeoAI, the integration of advanced machine learning techniques with geospatial data, has rapidly emerged as a critical tool in climate monitoring and environmental decision-making. Recent developments demonstrate a shift from isolated analytical models toward integrated, multimodal systems capable of processing multispectral, temporal, and sensor-based data for near-real-time applications. Key advancements include spatio-temporal data fusion, self-supervised learning (SSL) for low-label environments, operational deployment of monitoring systems, and the emergence of large geospatial foundation models. These innovations have enabled impactful applications such as methane emission detection, deforestation monitoring, wildfire prediction, and flood mapping. Despite this progress, challenges remain in benchmarking, generalization across heterogeneous data sources, uncertainty quantification, and equitable access to computational resources. Addressing these gaps is essential to ensuring reliable, scalable GeoAI solutions in climate science. To systematically analyze recent advancements in GeoAI for climate monitoring while identifying key methodological and operational gaps, with a focus on improving benchmarking standards and ensuring reproducibility in real-world applications. This review is constrained by the lack of standardized benchmarks and consistent evaluation frameworks across studies, which limits the comparability, reproducibility, and operational validation of GeoAI models.

KEY WORDS

GeoAI; Climate monitoring; Spatio-temporal data fusion; Self-supervised learning; Remote sensing

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Introduction

GeoAI, the application of modern machine learning methods to geospatial data, has rapidly become central to climate science and operational climate monitoring. Over the past few years, the field has shifted from isolated, task-specific models (e.g., building extraction or crop classification) toward integrated systems that fuse multispectral and temporal imagery, sensor networks, and domain knowledge to produce near-real-time, decision-ready insights for mitigation and adaptation [1]. Recent reviews and technical initiatives document this acceleration and the emergence of production systems that materially influence climate policy and enforcement.

Major Technical Advances and Themes

Multimodal data fusion and spatio-temporal modeling

Climate monitoring problems require fusing data across spectral bands, platforms, and timescales (e.g., optical & thermal satellite imagery, hyperspectral imagery, SAR imagery, air/ground sensors). Advances in spatio-temporal fusion algorithms and architectures enable models to combine irregularly sampled observations into coherent, temporally consistent outputs for phenomena such as wildfire progression, flood extent, or plume evolution. Recent methodological work emphasizes explicit modeling of modality-specific uncertainties (sensor noise, cloud gaps) and proposes filters and fusion layers tailored for multiresolution geospatial grids. These techniques improve robustness when sensors disagree or when inputs are sparse [2].

Self-supervised pretraining and few-shot adaptation

Label scarcity is a persistent challenge in environmental monitoring. High-quality ground truth is expensive, rare, and geographically biased. SSL approaches pretrain models on large unlabeled earth-observation corpora and then fine-tune for downstream tasks with far fewer labels. The remote-sensing community has adapted contrastive and reconstruction-style SSL objectives to multispectral imagery, showing large gains in sample efficiency and geographic transferability. These approaches are a foundational step toward building "foundation" models for climate tasks [3].

Near-real-time detection and operationalization

GeoAI is moving from offline experiments to operational monitoring: commercial platforms now detect methane plumes, flag deforestation, and monitor active fires with sub-daily cadence. Industry systems combine automated detection with human analyst review and geospatial analytics to produce alerts that are actionable for regulators and responders [4]. This operationalization requires careful pipeline engineering (tiling, change detection thresholds, latency optimization) as much as algorithmic sophistication. Real-world deployments have exposed critical engineering requirements and failure modes not visible in static benchmarks [5].

Large, foundation-style geospatial models (emerging)

Inspired by foundation models in language and vision, the geospatial community and industry players are developing large geospatial models (LGMs) trained on massive multimodal location datasets [6]. These models aim to learn transferable spatial representations that can be adapted to a wide range of downstream climate tasks (e.g., land-cover change, infrastructure risk, ecological mapping). Industry announcements indicate practical interest and early R&D

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investment; academic work is beginning to explore architectures and pretraining signals suitable for spatial reasoning. LGMs raise both opportunity (transfer learning, few-shot learning) and governance questions (data provenance, compute costs) [5].

Uncertainty quantification, validation and trustworthy outputs

Because climate decisions can have large social and economic impacts, research on calibrated uncertainty, interpretable model outputs, and reproducible evaluation is accelerating. Papers propose improved probabilistic output models, spatial calibration techniques, and evaluation frameworks that measure not only accuracy but operational utility (e.g., downstream decision cost, false-negative risk in disaster alerts). Standardized benchmarks and leaderboards are still nascent but repeatedly called for in the literature [7].

Representative applications in climate monitoring

Methane and greenhouse gas emissions

Satellite-enabled methane detection combined with ML analytics has become a flagship GeoAI climate application. Commercial services and research groups use hyperspectral/thermal sensors, along with automated plume detection, to identify major point-source emitters and estimate emission rates. These systems have already uncovered long-duration leaks and drawn regulatory attention; they also illustrate the interplay of algorithmic detection, atmospheric transport modeling, and ground-truthing [8].

Deforestation, land-use change, and carbon accounting

Time-series analysis of optical and radar imagery with GeoAI enables near-real-time deforestation alerts, land-use classification for carbon stock estimation, and tracking of restoration efforts. Automated change detection reduces lag between events and responses and can feed jurisdictional carbon accounting systems, but it requires careful bias mitigation to avoid systematic under- or overestimation in certain geographies [9].

Wildfire detection and fire-risk forecasting

ML models that combine thermal anomalies, vegetation indices, and weather forecasts produce probabilistic fire-risk maps and early alerts. The combination of rapid satellite revisit, airborne sensors, and on-the-ground observations allows GeoAI systems to both detect ignitions and forecast smoke transport, improving situational awareness for emergency services. Operationalization again highlights latency, data gaps (cloud), and calibration issues [10].

Hydrological extremes: Floods and coastal inundation

High-resolution, near-real-time flood mapping integrates SAR (cloud-penetrating) data, hydraulic models, and learned segmentation networks to estimate inundation extent and depth. GeoAI methods support rapid damage assessment and inform adaptive infrastructure decisions, especially in data-poor regions when paired with transfer-learning techniques [11].

Key Challenges and Open Research Directions

Benchmarking and reproducibility

Existing task datasets are fragmented, and evaluation metrics often fail to capture operational relevance . Community standards and curated benchmarks for climate-related tasks are urgently needed.

Sensor heterogeneity and domain shift

Models must generalize across sensors, seasons, and regions; methods that explicitly model sensor-specific noise and spatio-temporal covariates are a pressing research need.

Uncertainty propagation into decisions

Moving from pixelwise predictions to decision-support requires principled propagation of model uncertainty into policy actions and economic cost models.

Compute, equity and governance

Training large models and maintaining operational monitoring systems requires substantial resources; research into efficient architectures, federated approaches, and equitable data access can reduce the concentration of capacity.

Integration with domain science

Better coupling of data-driven GeoAI with physical process models (e.g., atmospheric transport and hydrology) will improve interpretability and credibility in science and policy contexts [12].

Conclusion

GeoAI is now mission-critical for climate monitoring: it delivers novel detection capabilities (e.g., methane leak detection), improves situational awareness (e.g., fire and flood), and supports long-term climate accounting (e.g., deforestation and coastal change). The most impactful near-term research will combine (a) robust multimodal pretraining and domain adaptation, (b) rigorous uncertainty quantification tied to decision-relevant metrics, and (c) reproducible benchmarks that reflect operational utility. Simultaneously, governance research data provenance, privacy, and equitable access to infrastructure must keep pace with technical advances.

Disclosure Statement

The Authors declare that there is no conflict of interest.

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