Research Landscape of Google Earth Engine: A Comprehensive Review of Domestic and International Studies

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Abstract： Google Earth Engine (GEE), a cloud-based geospatial processing platform, has transformed large-scale environmental monitoring by integrating petabytes of satellite data with high-performance computing. This review synthesizes cutting-edge applications across agriculture, hydrology, and ecology, drawing on 76 peer-reviewed studies (2020–2025) from China and globally. In China, research prioritizes agricultural monitoring (e.g., cropland extraction in Liaoning with >85% accuracy) and water resource management (e.g., Yellow River morphology analysis). Internationally, studies focus on wildfire impact assessment and precision farming (e.g., FAO's global drought monitoring). Despite advancements, challenges persist in data resolution, algorithm complexity, and validation. Future directions include integrating edge computing and pre-trained AI models to democratize access. This analysis underscores GEE's role in achieving sustainable development goals through planetary-scale geospatial analytics.

Keywords: Google Earth Engine；Big date；Cloud computing；Remote sensing

DOI:10.69979/3041-0843.25.02.042

1 Introduction

Launched in 2010, Google Earth Engine (GEE) hosts over 70 petabytes of satellite imagery (e.g., Landsat, Sentinel) and enables parallel processing for continental-scale analyses. By eliminating data storage bottlenecks and reducing computation time from months to hours, GEE supports long-term environmental tracking and real-time decision-making. This review examines technological innovations, regional research priorities, and emerging challenges, highlighting how GEE reshapes geospatial sciences in the era of big data.

2 Domestic Research Progress in China

2.1 Agricultural Monitoring and Management

Chinese researchers leverage GEE for high-precision crop mapping and irrigation optimization. Key advances include: Cropland Extraction: Wang Ruifeng et al. utilized Landsat 8 OLI and random forests on GEE to map Liaoning's cropland (2015), achieving >85% accuracy through spectral-temporal feature engineering. In Heilongjiang, Sentinel-2-based deep learning models improved rice mapping precision to 92.3% by integrating phenological metrics . Irrigation Area Monitoring: Xu Chao's team combined random forests with the Water-Adjusted Greenness Index (WGI) on GEE to track irrigation patterns in Shaanxi's Baojixia Irrigation District (2010–2020). The WGI index amplified sensitivity to water stress, achieving 95.35% accuracy in distinguishing irrigated/rainfed crops .

2.2 Water Resource Dynamics

GEE facilitates long-term hydrological studies through efficient time-series processing: River Morphology: Jin Xin's group analyzed Yellow River changes (1999–2023) using pan-sharpened Landsat imagery and the Automated Water Extraction Index (AWEIsh). They detected lateral channel migration (4.67–10.18 m/year) linked to hydropower dams, with extraction precision reaching Kappa = 0.985. Surface Water Change: In the Beijing-Tianjin-Hebei region, multi-index water detection rules revealed a net increase of 1,788.95 km² in seasonal water bodies (1985–2021), driven by inter-basin water transfers. Permanent water bodies declined in Baiyangdian Lake due to agricultural water withdrawal .

2.3 Urban Expansion and Ecological Assessment

Land Use Evolution: A Jinan study (2010–2020) using Landsat time-series and random forests showed urbanization-driven land conversion: construction land increased by 10.52%, while farmland decreased by 6.47%. Transfer matrices quantified transitions from cropland to built-up areas.

Ecological Quality: MODIS-based Remote Sensing Ecological Index (RSEI) modeling for Western Sichuan Plateau (2001–2023) indicated 56.82% of the region experienced ecological improvement, attributed to rising vegetation greenness and humidity .

Table 1: Representative Domestic Studies Using GEE

Application Area	Region	Method	Key Findings
Cropland Mapping	Liaoning	Landsat 8 + Random Forest	>85% accuracy; effective feature engineering
Irrigation Monitoring	Baojixia, Shaanxi	Sentinel-2 + WGI Index	95.35% accuracy; enhanced water stress detection
River Morphology	Yellow River	Pan-sharpening + AWEIsh	Kappa=0.985; detected dam-induced channel shifts
Ecological Assessment	Western Sichuan	MODIS RSEI	56.82% area improved; greenness/humidity dominant drivers

3 International Research Trends

3.1 Crop Mapping and Food Security

Global Farmland Monitoring: FAO employs GEE to fuse Sentinel-1 SAR and Sentinel-2 optical data for drought impact assessment, reducing crop yield prediction errors by 15%–30% compared to ground surveys . Genotype-Environment Interaction: In India, GGE biplot analysis identified disease-resistant mung bean genotypes, with environmental factors explaining 67.4% of yield variation .

3.2 Climate Change and Disaster Response

Desertification Drivers: Central Asian studies (2001–2020) linked reference evapotranspiration to desertification gradients (south-north decline, west-east increase), projecting future hotspots in northwest regions . Wildfire Recovery: In Italy's Bosco Difesa Grande forest, dNBR from Sentinel-2 showed vegetation recovery in single-burn areas was 80% within 12 months, versus <50% in repeat-burn zones .

3.3 Technical Innovations

Multi-Sensor Fusion: US studies integrated Landsat with MODIS for multi-resolution crop mapping, enhancing temporal consistency in cloud-prone areas . Automated Water Extraction: The Dual-Polarized First-Principal-Component Water Index (DFWI) improved Sentinel-1-based flood mapping, achieving F1-scores of 97.83% in Turkey's Hatay region during floods .

Table 2: Methodological Innovations in International Studies

Domain	Innovative Method	Advantage	Application
Agriculture	SAR-optical fusion	Reduced cloud interference; all-weather data	Global drought monitoring
Hydrology	DFWI Index	Resolved radar-shadow confusion	Flood emergency response

Domain	Innovative Method	Advantage	Application
Disaster Management	dNBR-dNDVI synergy	Quantified post-fire recovery rates	Burn severity assessment

4 Technological Innovations and Workflow Optimization

4.1 Cloud Computing Architecture

GEE's distributed processing engine enables continental-scale analyses previously infeasible on desktops: Data Catalog: 20000+ public datasets, including Landsat (1972–present), Sentinel-1/2 (2014–present), and climate reanalysis products . Algorithm Portability: JavaScript/Python APIs support machine learning (e.g., Random Forests, CNN) and time-series methods (e.g., change detection, phenology tracking) .

4.2 Algorithm Integration

Machine Learning: Random forests dominate land cover classification due to high accuracy (>80% OA) and resistance to overfitting. Index Development: Custom indices like WGI (Water-Adjusted Greenness Index) enhance irrigation detection by combining soil moisture (NDWI) and vegetation vigor (GCVI).

4.3 Multi-Source Data Fusion

Temporal Gap Filling: Harmonic regression models reconstruct cloud-contaminated NDVI time-series in tropical regions.Topographic Integration: SRTM DEM data improves terrain-dependent classification in fragmented landscapes like China's Loess Plateau .

5 Challenges and Future Directions

5.1 Persistent Limitations

Data Constraints: High-resolution imagery (e.g., WorldView) remains scarce; cloud cover in tropics reduces usable observations. Algorithm Complexity: Implementing U-Net or Transformer models requires Python/JavaScript proficiency, limiting non-expert adoption.Validation Bottlenecks: Ground truth scarcity in remote areas (e.g., Tibetan Plateau) introduces uncertainty .

5.2 Emerging Opportunities

Edge Computing Synergy: Deploying lightweight models on mobile devices for real-time field validation (e.g., crop disease scouting). Pre-trained AI Models: No-code interfaces like Earth Engine Apps could democratize access to deep learning for land cover segmentation. Commercial Data Integration: Incorporating Planet Labs (3–5 m resolution) to support urban-scale monitoring.

Table 3: Future Research Priorities

Challenge	Proposed Solution	Expected Impact
Low-resolution urban maps	Integrate SkySat/Planet Labs imagery	Enable 3–5 m resolution impervious surface mapping
Algorithm accessibility	Pre-trained U-Net for land cover segmentation	Allow non-programmers to run complex analyses
Ground truth scarcity	IoT soil sensors + GEE fusion	Improve crop stress validation in remote areas

6 Conclusion

GEE has emerged as a transformative platform for geospatial analysis, enabling unprecedented scales of environmental monitoring. Chinese research excels in agricultural optimization (e.g., phenology-guided crop mapping) and hydrological engineering(e.g., river morphology quantification), while international studies lead in climate adaptation (e.g., desertification forecasting) and disaster resilience (e.g., burn severity mapping). The convergence of cloud computing, open-data policies,and AI will further empower GEE to support sustainable development goals. Future advancements hinge on democratizing algorithm access, enhancing data resolution, and fostering cross-border collaborations to translate insights into policy.

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