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Utilizing Google Earth Engine for Spatiotemporal Land Cover Mapping and Environmental Impact Assessment Compliance Monitoring: A Case Study of the Pac Ma Hydropower Project (2016–2022)

Do Thi Phuong Thao[1], Duong Anh Quan[1]*,
1. GMA research group, Faculty of Geomatics and Land administration,
Hanoi University of Mining and Geology,
Hanoi, Vietnam.

Thi-Mai-Chinh Duong [3]
3 Thanh Hoa Branch, Hanoi Univ. of Natural Resources and Environ.

Van-Sy Mai [2]
2 Coastal Region Investment, Design & Consulting JSC, Vietnam;

Ngoc-Nam Nguyen [4]
4 National Remote Sensing Dept. (NRSD), MONRE, Hanoi, Vietnam

Abstract—**Monitoring compliance with Environmental Impact Assessment (EIA) commitments during the construction and operational phases of hydropower projects has conventionally relied on in situ field measurements and periodic self-reporting by project developers. However, in rugged and inaccessible mountainous regions, these traditional methods are labor-intensive, hazardous, economically prohibitive, and lack continuous large-scale spatial coverage. This study establishes a robust cloud-native geospatial framework leveraging the Google Earth Engine (GEE) platform and the Random Forest (RF) machine learning algorithm to track spatiotemporal land cover dynamics at the Pac Ma hydropower project (Lai Chau Province, Northwestern Vietnam) across the 2016–2022 development cycle. Cloud-free dry-season surface reflectance mosaics derived from Landsat 8 OLI and Sentinel-2 MSI were integrated with multi-spectral indices, including the Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Built-Up Index (NDBI). The classification model achieved exceptional performance, yielding an overall accuracy of 95.8% and a Cohen's Kappa coefficient exceeding 94.6%. Post-classification cross-tabulation change detection illuminated two distinct engineering and ecological phases: (1) The initial construction phase (2016–2017) was dominated by intensive valley-floor infrastructure expansion, featuring the direct conversion of 29.41 ha of agricultural land and 5.24 ha of alluvial sandbars into built-up ground; (2) The subsequent impoundment and operational stabilization phase (2017–2022) revealed the spatial consequences of reservoir filling (16.16 ha of forested and hilly land permanently inundated) and subsequent livelihood relocation, evidenced by the clearing of 91.53 ha of upland slopes for agricultural cultivation. The quantitative spatial datasets generated herein provide an objective, auditable foundation to cross-examine on-the-ground developments against legally approved EIA commitments, demonstrating the indispensable utility of cloud geocomputation for environmental governance and post-EIA compliance auditing.**

Keywords—Google Earth Engine; Environmental Impact Assessment (EIA); Land use and land cover change (LULCC); Random Forest classification; Spectral indices; Pac Ma hydropower plant; Environmental compliance auditing.

I. INTRODUCTION

The development of hydroelectric infrastructure plays a pivotal role in securing national energy supplies and catalyzing regional socioeconomic growth, particularly as the global community navigates the transition toward low-carbon and sustainable renewable energy sources [1]. Nevertheless, large-scale dam construction invariably involves profound socio-ecological trade-offs, including irreversible alterations to natural hydrological regimes, aquatic habitat fragmentation, extensive deforestation, and severe landscape degradation [2]. In Vietnam, hydropower constitutes a vital pillar of the national energy portfolio, capitalizing on the country's favorable geography characterized by an extensive river network and steep mountainous topography [3]. In particular, the Da River basin hosts a strategic cascade of mega-hydropower facilities that generates a substantial proportion of national electricity output. However, the cumulative development of this cascade has raised pressing environmental concerns regarding natural forest degradation, heightened susceptibility to rainfall-triggered landslides, and the displacement of indigenous upland livelihoods [4].

To mitigate and regulate these deleterious impacts, Environmental Impact Assessment (EIA) has been established as an indispensable legal and scientific instrument. Mandated prior to project approval, the EIA report serves to forecast potential adverse impacts, stipulate environmental management plans, and legally bind project proponents to stringent environmental protection and ecological restoration commitments [5]. Despite the foundational importance of the approved EIA, post-licensing verification and compliance monitoring remain substantial administrative and technical bottlenecks in environmental governance. Historically, compliance auditing has relied heavily on periodic self-reported dossiers submitted by project owners, supplemented

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by infrequent, scheduled on-site inspections conducted by regulatory agencies [6]. Such conventional monitoring practices are not only resource-intensive, logistically demanding, and costly, but they fundamentally lack spatial synopticity and temporal continuity. Crucially, in the remote, rugged, and disaster-prone mountainous terrain of Northwestern Vietnam, accurately quantifying forest canopy loss from land clearance, delineating the true spatial extent of reservoir inundation, and tracking post-construction ecological rehabilitation using terrestrial surveying techniques represent formidable logistical and safety challenges [7]. Consequently, there is an urgent imperative for an objective, automated, and continuous Earth observation approach capable of regional-scale auditing.

In this context, satellite remote sensing coupled with Geographic Information Systems (GIS) has emerged as an authoritative tool for macro-scale environmental and natural resource monitoring [8]. More recently, the advent of planetary-scale cloud geocomputing platforms—foremost among them Google Earth Engine (GEE)—has revolutionized geospatial data analytics. By integrating multi-petabyte archives of open-access Earth observation imagery (e.g., Landsat and Sentinel constellations) with massively parallel high-performance computing clusters, GEE allows researchers to execute complex, multi-temporal time-series analyses seamlessly without requiring local high-end workstation infrastructure [9]. Globally, GEE has been deployed extensively to quantify the footprint of mega-dams, track seasonal reservoir water surface dynamics, and assess watershed vegetation degradation [10, 11]. In Vietnam, machine learning algorithms implemented on GEE have begun to see successful adoption in surface land cover classification, coastal wetland mapping, salinity intrusion tracking, and flood disaster assessment [12, 13]. Nonetheless, developing a tailored remote sensing methodology specifically engineered to benchmark spatiotemporal landscape transformations directly against the legal commitments specified in approved EIA dossiers remains an underexplored frontier in environmental management.

The Pac Ma Hydropower Project, situated in Lai Chau Province, broke ground in 2016 and reached completion in recent years. The dramatic metamorphosis of the riparian landscape—from pristine mountainous valleys to active civil engineering construction zones, followed by reservoir filling and water level rise—provides an ideal real-world testbed to evaluate the spatial dynamics of hydropower infrastructure [14, 15]. Addressing the aforementioned practical demands and methodological gaps, this research pursues two primary objectives: (1) To harness the computational capabilities of Google Earth Engine to construct high-accuracy multi-temporal land cover and surface water maps for the Pac Ma hydropower project area across the 2016–2022 lifecycle; and (2) To deploy these quantitative spatial datasets to rigorously cross-examine, audit, and benchmark observed ground transformations against the statutory commitments specified in the project's legally approved EIA dossier. Ultimately, this study aims to deliver both an objective scientific account of the Pac Ma project's environmental trajectory and a standardized, replicable remote sensing protocol to empower regulatory authorities in modernizing post-EIA environmental auditing.

II. STUDY AREA AND DATASETS

A. Study Area

The Pac Ma Hydropower Project is a major run-of-river energy infrastructure facility constructed on the upper reaches of the Da River in Muong Te District, Lai Chau Province, Northwestern Vietnam. The main dam axis is situated at approximately 22°34' N latitude and 102°32' E longitude. Pac Ma represents the fourth consecutive cascade step on the mainstream of the Da River system, designed with an installed capacity of 140 MW. The surrounding terrain is representative of the Northern Indochina tectonic zone, characterized by extreme topographic dissection, steep mountain slopes exceeding 30–45°, and narrow, deeply incised V-shaped river valleys. Climatologically, the study area falls within the tropical mountain monsoon zone, characterized by two sharply contrasting seasons: an intense rainy season spanning May to October (concentrating 80% to 85% of total annual precipitation) and a protracted dry season extending from November to the following April [14].

Prior to civil construction in 2016, the riparian corridor along both banks of the Da River was predominantly covered by watershed protection forests and commercial production forests (consisting of mixed broadleaf-bamboo stands and secondary regrowth), complemented by narrow strips of alluvial sandbars and subsistence agriculture along the valley floor. Between 2016 and 2022, intensive civil engineering activities were executed, encompassing massive earthwork excavation, slope cutting, cofferdam construction, aggregate quarrying, spoil disposal dump formation, temporary camp erection, and ultimate reservoir impoundment [15]. Consequently, the analytical boundary for this investigation was defined as a spatial buffer zone encompassing the entire reservoir catchment corridor, the primary dam and powerhouse site, and all auxiliary construction yards as officially delineated in the project's approved EIA dossier (Fig. 1).

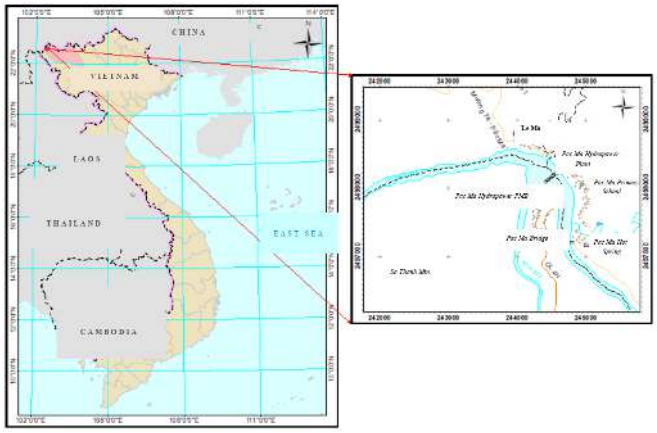

Fig. 1. Geographic location of the study area: (left) National overview of Vietnam; (right) Detailed layout of the Pac Ma hydropower project area along the upper Da River, Lai Chau Province.

B. Datasets Used

Multi-spectral optical satellite imagery archives cataloged within Google Earth Engine served as the primary data source for long-term spatiotemporal monitoring (TABLE I). Surface Reflectance (SR) products from the Landsat 8 Operational Land Imager (OLI) and the Sentinel-2 Multi-Spectral

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Instrument (MSI) were extracted for the target temporal benchmarks. To circumvent persistent, heavy cloud cover and atmospheric haze that severely obscure the mountainous terrain of Northern Vietnam during the monsoon, image collections were filtered exclusively across the dry season (November through April of the subsequent year) for the observation epochs 2015–2016, 2016–2017, and 2021–2022.

TABLE I. TABLE I. DETAILED SPECIFICATIONS OF SATELLITE REMOTE SENSING DATA UTILIZED IN THIS STUDY

Data Source	Sensor	Spatial Resolution	GEE Dataset ID	Acquisition Period
Landsat 8	OLI	30 m	LANDSAT/LC08/C02/T1_L2	November 2015 – April 2016
Landsat 8	OLI	30 m	LANDSAT/LC08/C02/T1_L2	November 2016 – April 2017
Sentinel-2	MSI	10 m	COPERNICUS/S2_SR	November 2021 – April 2022

In addition to public medium-resolution imagery, high-resolution commercial and national satellite datasets were incorporated for visual photo-interpretation and fine-scale validation. These included VNREDSat-1 imagery (2.5 m pan-sharpened spatial resolution, 3-day revisit capability) and SPOT 6 imagery (1.5 m spatial resolution, 12-day revisit cycle). Furthermore, the approved Environmental Impact Assessment (EIA) dossier of the Pac Ma Hydropower Project provided authoritative legal baselines, including official cadastral coordinates of the site acquisition boundary, statutory quotas for planned forest and agricultural land conversion, normal water level (NWL) reservoir storage contours, and designated locations for spoil disposal sites, worker campsites, and material quarries.

1) Training and Validation Sampling:

Representative ground-truth samples were established across five major thematic land cover categories: (1) Water surface, (2) Built-up/construction land, (3) Agricultural land, (4) Alluvial land/sandbars, and (5) Forest and hilly land. Reference polygons were digitized manually via expert visual interpretation supported by multi-temporal ultra-high-resolution imagery available in Google Earth Pro historical archives, corroborated against VNREDSat-1 and SPOT 6 acquisitions for 2016, 2017, and 2022.

III. RESEARCH METHODOLOGY

The end-to-end processing pipeline was executed natively on the Google Earth Engine cloud computing environment utilizing the JavaScript API. The methodological workflow comprised four systematic stages: (1) Satellite imagery ingestion, atmospheric screening, and seasonal composite generation; (2) Extraction of multi-spectral biophysical indices (NDVI, MNDWI, and NDBI); (3) Supervised machine learning classification via the Random Forest (RF) algorithm accompanied by rigorous cross-validation; and (4) Post-classification spatiotemporal transition matrix analysis and benchmarking against approved EIA commitments.

A. Atmospheric Screening and Seasonal Compositing

Surface reflectance datasets from Landsat 8 and Sentinel-2 are provided with standard geometric and atmospheric corrections. To mitigate persistent cloud and shadow contamination, the automated CFmask algorithm (for Landsat) and the QA60 cloud-masking band (for Sentinel-2) were applied. Pixel-wise median compositing was executed across all valid, cloud-free observations within each dry-season window (November to April), producing seamless, artifact-free surface reflectance mosaics covering the entire project watershed.

B. Spectral Feature Engineering

To maximize spectral separability among highly spectrally confusable terrestrial classes in steep mountain terrain (such as deep water bodies, topographic shadows, barren rock, excavated soil, and degraded shrubland), three diagnostic remote sensing indices were computed:

1) Normalized Difference Vegetation Index (NDVI):

NDVI is widely utilized to quantify aboveground biomass, chlorophyll absorption, and canopy density. It serves as a primary metric for monitoring forest loss caused by access road construction, camp leveling, and reservoir biomass clearance. NDVI is formulated as:

$$N\Delta\varsigma I = (\rangle_NIP - \rangle_P\varepsilon\delta) / (\langle_NIP + \rangle_P\varepsilon\delta) \quad (1)$$

where ρ_NIR and ρ_Red denote surface reflectance values in the near-infrared and red bands, respectively. NDVI values range from -1.0 to +1.0. Negative values correspond to water bodies; values between 0.0 and ~0.1 represent non-vegetated surfaces (e.g., bare rock, sandbars, compacted earth, or civil structures); values from 0.2 to 0.5 indicate sparse vegetation, shrubs, and secondary grasslands; while values approaching 1.0 characterize dense, healthy forest canopies.

2) Modified Normalized Difference Water Index (MNDWI):

In rugged mountain terrain, deep topographic shadows cast by steep ridges frequently exhibit spectral characteristics very similar to open water when using conventional water indices. The MNDWI overcomes this limitation by substituting the near-infrared band with the shortwave infrared (SWIR1) band, substantially suppressing terrain noise and sharply delineating the evolving reservoir boundary. MNDWI is calculated as:

$$MN\Delta\Omega I = (\rangle_\Gamma\rho\varepsilon\varepsilon\nu - \rangle_\Sigma\Omega IP1) / (\langle_\Gamma\rho\varepsilon\varepsilon\nu + \rangle_\Sigma\Omega IP1) \quad (2)$$

where ρ_Green represents green band reflectance and ρ_SWIR1 corresponds to shortwave infrared band 1 reflectance. MNDWI produces values between -1.0 and +1.0, with positive values (> 0) demarcating water bodies (river reaches, backwaters, and reservoirs), whereas negative or near-zero values correspond to terrestrial surfaces.

3) Normalized Difference Built-Up Index (NDBI):

NDBI is employed to identify and extract artificial impervious surfaces, compacted earth, and structural concrete associated with dam infrastructure. NDBI is expressed as:

$$N\Delta BI = (\rangle_\Sigma\Omega IP1 - \rangle_NIP) / (\langle_\Sigma\Omega IP1 + \rangle_NIP) \quad (3)$$

where ρ_SWIR1 and ρ_NIR denote reflectance in the shortwave infrared and near-infrared spectra. Built-up surfaces, quarry excavations, and barren roads exhibit positive NDBI values, with higher values reflecting greater degree of artificial

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compaction or concrete construction, whereas vegetated areas and open water yield negative values.

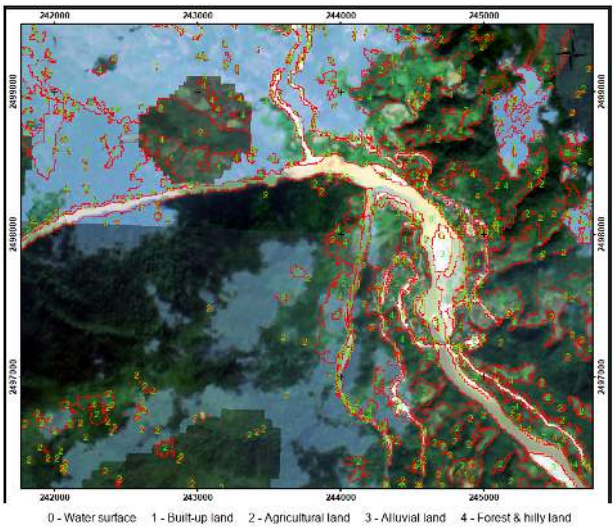
C. *Machine Learning Classification and Accuracy Assessment*

Supervised classification was performed using the Random Forest (RF) classifier implemented in the GEE machine learning library. Random Forest is an ensemble learning method that constructs a multitude of decorrelated decision trees during training and outputs the majority class vote. It is exceptionally well-suited for high-dimensional remote sensing applications due to its high tolerance to spectral noise, robust resistance to overfitting, and inherent parallel processing scalability on cloud architectures. In this study, the input feature space comprised all original spectral reflectance bands along with the derived indices (NDVI, MNDWI, NDBI). The ground-truth reference dataset was randomly partitioned into a 70% training subset and a 30% independent validation subset. Only when the Overall Accuracy (OA) and Cohen's Kappa coefficient exceeded the accepted scientific benchmark threshold (>85%) were the classified rasters accepted for cartographic production and post-classification transition modeling.

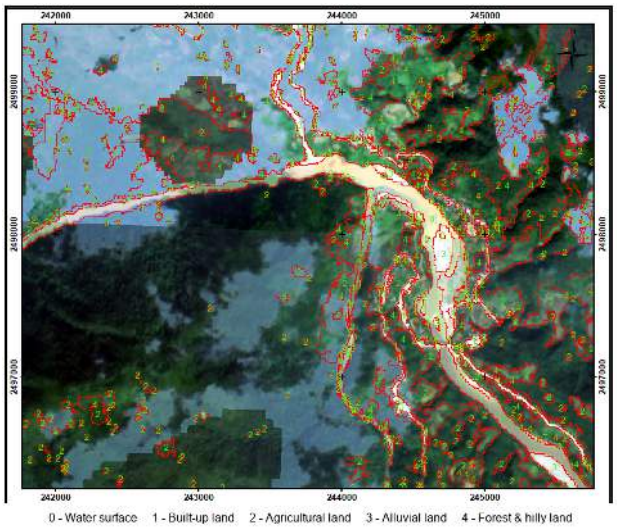
IV. RESULTS AND DISCUSSION

A. *Land Cover Extraction at the Pac Ma Hydropower Plant Area*

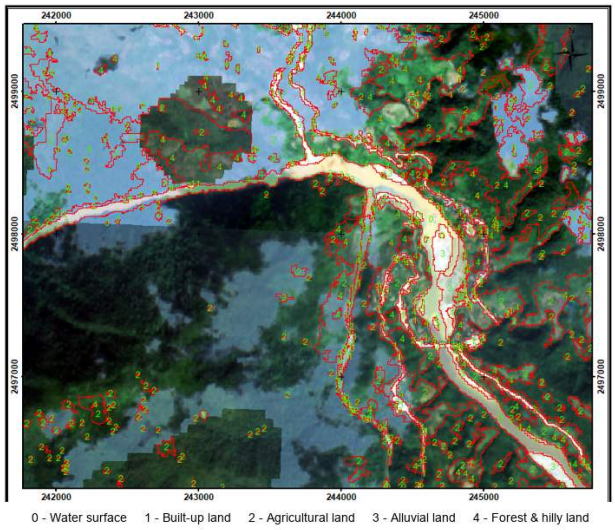
Automated land cover classification across the five designated classes was conducted for the benchmark years 2016, 2017, and 2022 using the calibrated Random Forest model on Google Earth Engine (Fig. 2). Accuracy assessment using independent validation samples demonstrated an Overall Accuracy of 95.8% and a Cohen's Kappa coefficient of 94.6%. These metrics confirm the high predictive fidelity of the model and validate the effectiveness of integrating multi-spectral indices with multi-seasonal cloud-free satellite imagery in complex, shadow-prone mountainous environments.



(a) 2016 Pre-construction Baseline



(b) 2017 Construction Commencement



(c) 2022 Operational Stabilization

Fig. 2. Automated land cover classification results using the Random Forest machine learning algorithm on Google Earth Engine: (a) 2016 pre-construction baseline; (b) 2017 construction commencement; and (c) 2022 operational stabilization. Classes: 0 - Water surface, 1 - Built-up land, 2 - Agricultural land, 3 - Alluvial land, 4 - Forest & hilly land.

B. *Development of Thematic Maps to Support EIA Compliance Monitoring*

The validated classification rasters were compiled into standardized thematic land cover baseline maps for the years 2016, 2017, and 2022 (Figs. 3, 4, and 5). Delineating the annual spatial distribution of landscape classes provides a comprehensive geographic inventory at each critical milestone of the hydropower project. To quantify transition trajectories, post-classification change detection was performed across two operational intervals: Phase 1 (2016–2017, corresponding to project inception and heavy civil construction) and Phase 2 (2017–2022, representing dam structural completion, reservoir filling, and operational stabilization). These transition maps (Figs. 6 and 7) provide critical empirical evidence illustrating the magnitude and spatial distribution of anthropogenic and hydrological impacts.

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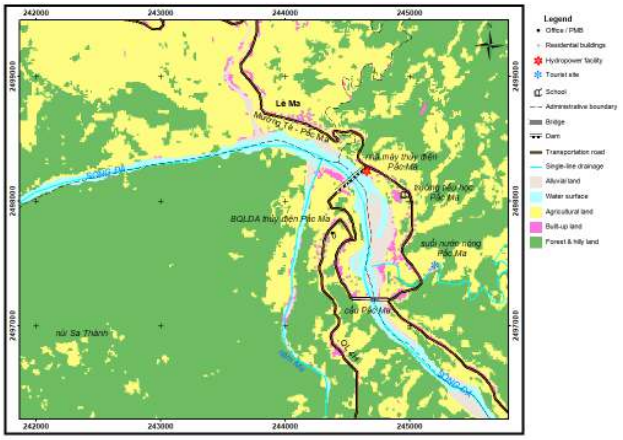

Fig. 3. Land cover classification map of the Pac Ma hydropower project area in 2016 (Pre-construction baseline).

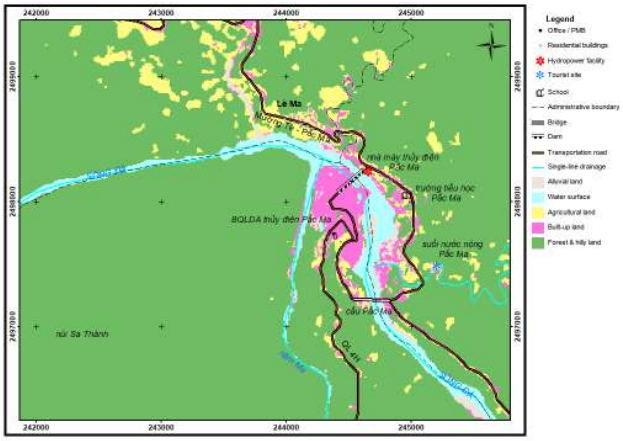

Fig. 4. Land cover classification map of the Pac Ma hydropower project area in 2017 (Active construction phase).

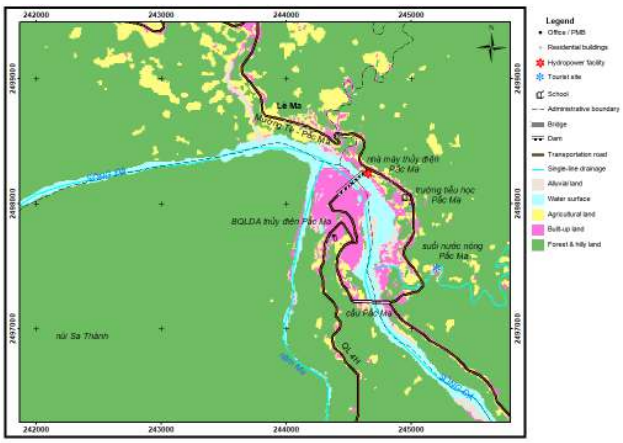

Fig. 5. Land cover classification map of the Pac Ma hydropower project area in 2022 (Reservoir impoundment and operational stabilization).

C. *Spatiotemporal Dynamics during Phase 1 (2016–2017: Construction Commencement)*

Quantitative transition dynamics between 2016 and 2017 are detailed in the cross-tabulation matrix in TABLE II and cartographically portrayed in Fig. 6. The initial phase was dominated by two primary trends: extensive site preparation on the valley floor and farmland fallowing. The most striking volumetric shift occurred from agricultural land to forest and hilly land (312.14 ha). This substantial transition within a single year reflects the socioeconomic realities of large infrastructure projects. Following formal announcements of land acquisition, compensation demarcations, and impending reservoir inundation, local farming households ceased active capital investment and abandoned cultivation plots located within the designated project acquisition boundary. Given the humid tropical mountain climate, abandoned agricultural terraces experienced rapid ecological colonization by pioneer shrubs and secondary bamboo within a single monsoon cycle, causing them to be classified as secondary hilly vegetation.

Simultaneously, the direct spatial footprint of civil engineering is underscored by the conversion of 29.41 ha of agricultural land and 5.24 ha of alluvial sandbars directly into built-up ground. This represents the rapid development of construction yards, worker barracks, concrete batching plants, access roads, and foundation excavations on former valley-floor farmland. Furthermore, 8.52 ha of alluvial land was submerged into water surface, capturing the initial impacts of river channel constriction, temporary cofferdam installation, and construction-phase flow diversion.

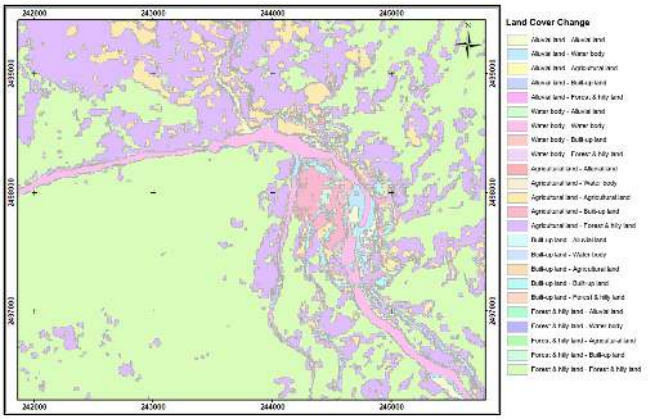

Fig. 6. Spatiotemporal land cover change detection map of the Pac Ma hydropower project area during the 2016–2017 construction phase.

TABLE II. TABLE II. LAND COVER CHANGE TRANSITION MATRIX AND AREA STATISTICS BETWEEN 2016 AND 2017 (HA)

2016 \ 2017	Water	Built-up	Agri.	Alluvial	Forest
Water surface	40.54	2.70	0.00	1.89	3.51
Built-up land	0.45	16.67	4.13	1.28	2.48
Agricultural land	0.53	29.41	67.74	2.00	312.14
Alluvial land	8.52	5.24	1.23	10.16	1.94
Forest & hilly	1.66	2.70	1.32	0.05	800.89
Total (2017)	**51.70**	**56.72**	**74.42**	**15.38**	**1120.96**

D. *Spatiotemporal Dynamics during Phase 2 (2017–2022: Impoundment and Operational Stabilization)*

Statistical transitions for the 2017–2022 period (TABLE III and Fig. 7) highlight the long-term ecological and spatial reconfiguration associated with permanent dam operation, reservoir filling, and community resettlement. Water impoundment caused water levels to rise steadily, submerging lower mountain slopes along both banks and resulting in the permanent loss of 16.16 ha of forest and hilly land to open water. Consequently, the total water surface area expanded

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significantly to 75.19 ha, a signature characteristic of reservoir-type hydropower schemes.

Furthermore, infrastructure expansion extended into higher elevation zones, as demonstrated by the conversion of 21.25 ha of forest and hilly land into built-up ground. This reflects the construction of high-clearance perimeter bypass roads, electrical transmission substations and pylon corridors, and new resettlement village housing situated above the designated flood margin. Crucially, the most profound socioeconomic finding is the massive conversion of 91.53 ha of forest and hilly land into agricultural cultivation. As fertile alluvial and valley-floor farmlands were permanently acquired for reservoir storage and power facilities (with 10.26 ha absorbed into built-up ground), displaced local households were compelled to relocate agricultural activities upslope. Farming communities cleared secondary forests and shrublands on steep hillsides to establish new upland swidden and terraced fields, seeking to secure replacement agricultural livelihoods.

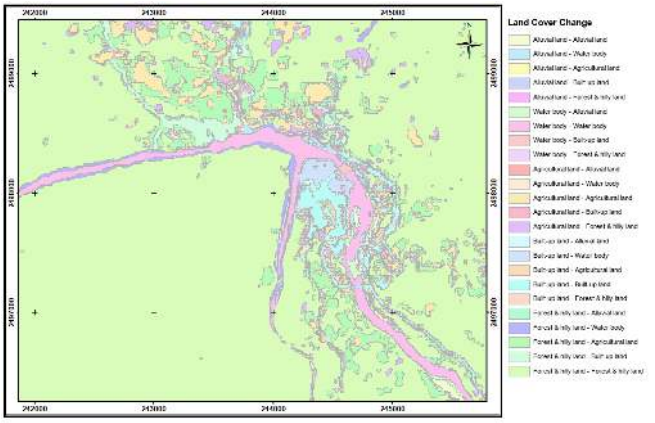

Fig. 7. Spatiotemporal land cover change detection map of the Pac Ma hydropower project area during the 2017–2022 impoundment and operational phase.

TABLE III. TABLE III. LAND COVER CHANGE TRANSITION MATRIX AND AREA STATISTICS BETWEEN 2017 AND 2022 (HA)

2017 \ 2022	Water	Built-up	Agri.	Alluvial	Forest
Water surface	45.23	1.33	0.06	4.32	0.76
Built-up land	8.92	31.64	9.50	4.01	2.65
Agricultural land	1.16	10.26	44.25	2.11	16.64
Alluvial land	4.32	3.84	0.61	6.36	0.25
Forest & hilly	16.16	21.25	91.53	3.07	988.95
Total (2022)	**75.79**	**68.32**	**145.95**	**19.87**	**1009.25**

E. Benchmarking Satellite Observations against Approved EIA Commitments

In synthesizing the two monitoring cycles, the multi-temporal satellite analysis faithfully reconstructs the actual engineering trajectory of the Pac Ma project. Phase 1 (2016–2017) captured the intense lateral expansion of civil infrastructure across the valley floor, whereas Phase 2 (2017–2022) revealed the dual pressures of hydrological impoundment and indirect land use shifts, characterized by the displacement of human settlements and cultivation onto steep upland slopes. Comparing these empirical observations directly with the approved EIA dossier provides vital regulatory insights. The observed water surface expansion (75.19 ha) conforms closely with the projected normal water level (NWL) backwater profile, confirming that dam impoundment remained within authorized design limits. However, the unexpected upslope agricultural encroachment (91.53 ha) highlights a critical indirect ecological impact frequently overlooked in initial EIA documentation. While the developer complied with statutory on-site engineering boundaries, the lack of sustainable replacement arable land prompted secondary deforestation on steep slopes, increasing regional soil erosion risks. This finding powerfully illustrates that satellite remote sensing not only verifies direct developer compliance but also detects broader unintended social-ecological feedback loops across the watershed.

V. CONCLUSIONS AND RECOMMENDATIONS

This study successfully demonstrated the practical efficacy and scientific rigor of integrating the Google Earth Engine (GEE) cloud computing platform with the Random Forest machine learning algorithm to monitor long-term land cover dynamics and evaluate EIA compliance at the Pac Ma Hydropower Project between 2016 and 2022. The automated classification workflow achieved high overall accuracy (95.8%) and a Cohen's Kappa coefficient exceeding 94.6%, affirming that combining seasonal cloud-free Landsat 8 and Sentinel-2 mosaics with specialized spectral indices (NDVI, MNDWI, NDBI) effectively overcomes severe cloud contamination and topographic shadow distortions in rugged mountain terrains.

Spatiotemporal change detection quantitatively revealed two distinct evolutionary phases: (1) The 2016–2017 construction inception phase, marked by intensive valley-floor infrastructure sprawling, including the direct conversion of 29.41 ha of agricultural land and 5.24 ha of alluvial sandbars into built-up ground; and (2) The 2017–2022 operational stabilization phase, characterized by permanent reservoir impoundment (inundating 16.16 ha of forest land) and an indirect displacement of local livelihoods, driving the clearance of 91.53 ha of upland mountain slopes for compensatory agriculture.

These derived spatial databases establish an objective, auditable benchmark to cross-examine on-the-ground developments against legally approved EIA commitments, land acquisition schedules, and ecological restoration targets. Based on these findings, it is strongly recommended that environmental governance agencies (e.g., the Ministry of Natural Resources and Environment - MONRE) mandate the integration of cloud-based satellite monitoring into the statutory post-EIA compliance auditing framework for all major infrastructure developments in Vietnam. Furthermore, future EIA planning must explicitly incorporate post-relocation livelihood support programs to mitigate secondary upland deforestation driven by displaced agricultural communities.

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