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An Integrated GeoAI and Google Earth Engine Framework for Long-Term Coral Reef Monitoring in the Gulf of Mannar, India

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ABSTRACT

Coral reefs are among the most biologically productive yet climatically vulnerable ecosystems on Earth, and the Gulf of Mannar Marine Biosphere Reserve on India's southeastern coast exemplifies both their ecological importance and their exposure to escalating stress. This review synthesizes the global and India-specific literature on the use of geospatial artificial intelligence (GeoAI) and the Google Earth Engine (GEE) cloud-computing platform for coral reef monitoring and proposes an integrated framework tailored to the Gulf of Mannar. Following PRISMA guidance, a systematic search of Scopus, Web of Science, IEEE Xplore, MDPI, ScienceDirect, and Google Scholar, supplemented by grey literature and government reports, yielded 61 studies that met the inclusion criteria after quality appraisal (52 addressing coral reef systems globally and 9 specific to the Gulf of Mannar or comparable Indian reef tracts). A quantitative meta-analysis of algorithm type, sensor platform, accuracy metric, and risk of bias was undertaken alongside a narrative synthesis. The evidence shows a rapid diversification of methods, from early pixel-based classifications to random forest, object-based image analysis, and increasingly sophisticated convolutional and transformer-based deep learning models, achieving benthic classification accuracies commonly ranging from 80% to 96%, although bleached-coral detection and satellite-derived bathymetry in turbid, sediment-influenced waters such as the Gulf of Mannar remain comparatively less reliable. Regional evidence for the Gulf of Mannar is dominated by conventional GIS and multispectral change-detection studies rather than machine-learning applications, revealing a marked technological gap relative to global practice at a time when live coral cover in the reserve has declined from 37% in 2005 to 27.3% in 2021 amid recurrent mass-bleaching events. The review critically appraises study quality across four domains—ground-truth adequacy, independent spatial validation, algorithmic transparency, and temporal replication—and finds moderate-to-high risk of bias in a substantial share of the corpus. Building on these findings, an eight-stage integrated GeoAI-GEE framework is proposed, linking data acquisition, cloud preprocessing, AI-based classification, accuracy assessment, change detection, decision-support product generation, stakeholder dissemination, and policy action. The paper concludes with structured, policy-linked recommendations intended to inform the Tamil Nadu Forest Department, the Suganthi Devadason Marine Research Institute, and national ocean-governance bodies as they balance conservation priorities against competing pressures such as proposed offshore hydrocarbon exploration in the Biosphere Reserve.

Keywords: *GeoAI; Google Earth Engine; coral reef monitoring; Gulf of Mannar; remote sensing; machine learning; marine protected area management; systematic review.*

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1. Introduction

1.1 Research background and significance

Coral reefs occupy less than 1% of the ocean floor, yet they support at least one-quarter of all known marine species and underpin fisheries, coastal protection, tourism, and the livelihoods of approximately one billion coastal people worldwide [19]. Estimates of the annual economic value of coral reef ecosystem services vary substantially across studies and valuation methods, ranging from the low hundreds of billions of dollars to figures approaching ten trillion dollars once the full suite of provisioning, cultural, and regulating services is considered [12]; [20]. This wide range is informative because it reflects how provisioning services, such as fisheries; cultural services, such as tourism; and regulating services, such as protection from wave energy, are weighted and monetized differently across the literature, and it underscores the difficulty of translating ecological condition into a single policy-relevant number.

Despite this value, coral reefs are now experiencing unprecedented thermal stress. The National Oceanic and Atmospheric Administration (NOAA) and the International Coral Reef Initiative (ICRI) confirmed in April 2024 that the world had entered its fourth global mass coral bleaching event, the second in a decade, with satellite-derived heat-stress monitoring showing that bleaching-level conditions affected reef areas across the Atlantic, Pacific, and Indian Ocean basins [11]. By the time the event was assessed as concluded in mid-2025, cumulative heat stress had affected an estimated 84% of the world's coral reef area across at least 83 countries and territories [10]. This scale of disturbance cannot be tracked through in-water survey alone; it has driven a corresponding expansion in the use of satellite remote sensing, cloud computing, and artificial intelligence to monitor reef condition at frequencies and extents that field teams cannot match.

India's Gulf of Mannar, stretching approximately 140 kilometers along the Tamil Nadu coast between Tuticorin and Rameswaram, was designated in 1989 as the first marine biosphere reserve in South and Southeast Asia and remains one of the region's most biodiverse marine tracts, supporting 117 recorded coral species across a chain of 21 islands within the Gulf of Mannar Marine National Park [17]. A two-decade assessment by the Suganthi Devadason Marine Research Institute (SDMRI), conducted in partnership with the Tamil Nadu Forest Department, documents that live coral cover in the reserve declined from 37% in 2005 to 27.3% in 2021, with a temporary recovery to 42.9% in 2009 following the cessation of coral mining before the third global bleaching event of 2010 and 2016 drove renewed losses [5]; [18]. Earlier multi-temporal satellite analysis using IRS LISS imagery had already documented a loss of 25.52 square kilometers of reef area over a single decade, attributing degradation to sediment loading from shoreline erosion and reef emergence linked to tectonic movement [16]. Taken together, this evidence indicates a reef system under sustained and compounding stress that long precedes, and is now intensified by, global climate-driven bleaching. Against this backdrop, the emergence of geospatial artificial intelligence (GeoAI) and cloud-based Earth observation platforms represents a methodological turning point for reef science. Google Earth Engine (GEE), introduced by [4], provides planetary-scale access to multi-decadal satellite archives alongside integrated machine-learning and image-processing libraries, removing the computational barriers that previously confined large-area, multi-temporal reef mapping to well-resourced institutions. A systematic meta-analysis of the GEE literature found that by 2020 the platform had already generated hundreds of peer-reviewed applications spanning land cover, hydrology, and coastal and marine monitoring, with random forest and regression-based algorithms dominating early use before deep learning approaches began to diversify the field [15]; [23]. In parallel, global initiatives such as the Allen Coral Atlas have combined GEE-based object-based image analysis with machine-learning classification to produce consistent, repeatable coral reef maps from individual reef to ocean-basin scale [7]; [25], culminating in a 2024 revision of global shallow coral reef area to 348,361 square kilometers, of which 80,213 square kilometers constitute coral-supporting habitat [8]. Recent studies have shown that machine-learning methods such as Support Vector Machine (SVM) and Random Forest (RF) can improve coral reef classification. Object-based methods generally provide better accuracy than pixel-based methods [24].

Despite advancements in global technology, the Gulf of Mannar has not seen a similar level of adoption. The regional literature on conventional supervised classification and GIS-based change detection on individual satellite scenes dominates the regional literature, overshadowing cloud-native, machine-learning-driven, multi-temporal pipelines. by conventional supervised classification and GIS-based change detection performed on individual satellite scenes rather than by cloud-native, machine-learning-driven, multi-temporal pipelines. This review addresses that gap directly: it synthesises the international evidence on GeoAI- and GEE-based coral reef monitoring, evaluates how much of that evidence has been applied, or could plausibly be applied, to the Gulf of Mannar, and proposes an integrated framework suited to the reserve's ecological and institutional context. The exercise is timely: in early 2025, the Union government's inclusion of deep-sea blocks within the Gulf of Mannar Biosphere Reserve under the Open Acreage Licensing Policy for hydrocarbon exploration drew objections from the Tamil Nadu state government on the grounds of risk to the reserve's coral and associated fauna [2], illustrating the urgency of robust, transparent, and continuously updated monitoring evidence for reconciling conservation and development priorities.

1.2 Definition of key concepts

Geospatial artificial intelligence, commonly abbreviated as GeoAI, denotes the integration of machine-learning and deep-learning methods with geospatial data and analytical techniques to extract structured, spatially explicit knowledge from remote sensing, GIS, and other geographically referenced datasets [14]. In the context of coral reef science, GeoAI typically refers to algorithms such as random forest, support vector machines, convolutional neural networks, and, increasingly, transformer-based architectures, applied to classify benthic substrate, detect bleaching, or estimate bathymetry from multispectral or hyperspectral imagery.

Google Earth Engine is a cloud-based geospatial processing platform that provides open access to a multi-petabyte archive of satellite imagery, including the Landsat, Sentinel, and MODIS series, alongside distributed computing infrastructure and built-in machine-learning libraries, enabling planetary-scale analysis without local data storage or high-performance computing [4]. Coral bleaching refers to the expulsion of symbiotic zooxanthellae algae from coral tissue under sustained thermal or other environmental stress, causing corals to lose pigmentation and, if stress persists, to die; NOAA's Coral Reef Watch program monitors this process globally using satellite-derived sea surface temperature anomalies expressed as Degree Heating Weeks [11]. Satellite-derived bathymetry (SDB) refers to the estimation of water depth from the differential attenuation of light across multispectral bands, a technique whose accuracy is known to be sensitive to sediment type and water clarity in shallow reef environments [13]. Benthic habitat classification refers to the categorization of the seafloor into classes such as live coral, macroalgae, rubble, sand, or seagrass using spectral or textural signatures extracted from imagery.

1.3 Research questions and objectives

This review was guided by three research questions. First, what GeoAI algorithms, sensor platforms, and analytical workflows have been applied to coral reef monitoring globally and within the Gulf of Mannar specifically, and with what reported accuracy? Second, what methodological strengths, sources of bias, and data gaps characterize the existing body of evidence, particularly with respect to ground-truth adequacy, independent validation, transparency, and temporal replication?

Third, what integrated, policy-relevant monitoring framework can reasonably be proposed for the Gulf of Mannar given the current state of global practice and the reserve's specific institutional and environmental circumstances?

Correspondingly, the objectives of this review are to: (i) systematically identify and appraise the peer-reviewed and credible grey literature on GeoAI- and GEE-based coral reef monitoring; (ii) conduct a quantitative meta-analysis of algorithm type, sensor use, and accuracy alongside a structured risk-of-bias assessment; (iii) critically compare global best practice against the specific evidence base available for the Gulf of Mannar; and (iv) translate the synthesized findings into a structured framework and a ranked set of policy recommendations suitable for circulation to government stakeholders responsible for reef conservation and coastal management in Tamil Nadu.

1.4 Study area

The Gulf of Mannar lies between 8°47' and 9°15' N latitude and 78°5' and 79°30' E longitude, forming a shallow embayment of the Laccadive Sea between southeastern India and northwestern Sri Lanka. The Gulf of Mannar Marine National Park, notified in 1986 under the Wildlife (Protection) Act, 1972, covers approximately 560 square kilometers and encloses 21 uninhabited islands stretching from Tuticorin to Rameswaram, hosting coral reefs, seagrass meadows, mangroves, and associated fauna including dugongs, sea turtles, and whale sharks [18]. The wider Gulf of Mannar Biosphere Reserve, recognized by UNESCO in 2001, spans roughly 10,500 square kilometers and constitutes the surrounding buffer and transition zones [17]. Figure 1 presents a schematic overview of the reserve's location and island chain.

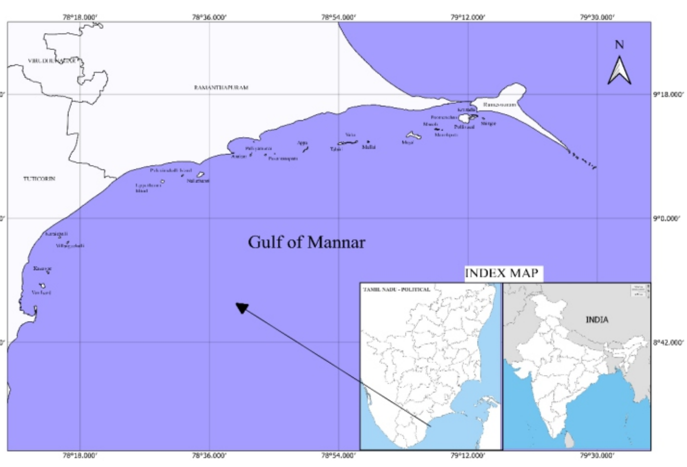

Figure 1. Schematic location map of the Gulf of Mannar Marine Biosphere Reserve, showing the approximately 140-kilometer island chain between Tuticorin and Rameswaram. The map is an illustrative schematic prepared for this review and is not derived from, or intended to replicate, any proprietary or copyrighted cartographic source.

2. Methods

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [9] and adapted the meta-analytic protocol previously used to characterize the broader Google Earth Engine literature [15] to the more specific domain of coral reef monitoring.

2.1 Search strategy and databases

A structured search was conducted across Scopus, Web of Science, IEEE Xplore, the MDPI journal platform, ScienceDirect, and Google Scholar, covering records published between January 2015 and July 2026, with foundational methodological papers predating this window retained where they establish core techniques still in active use for example, [4] and [16]. Search strings combined terms for the technology ("Google Earth Engine," "GeoAI," "geospatial artificial intelligence," "deep learning," "convolutional neural network," "random forest," "machine learning") with terms for the ecological target ("coral reef," "coral bleaching," "benthic habitat," "reef mapping," "satellite-derived bathymetry") and, for the regional component, geographic qualifiers ("Gulf of Mannar," "Tamil Nadu," "India"). Reference lists of key papers and relevant government or institutional reports, including those from the Suganthi Devadason Marine Research Institute, NOAA Coral Reef Watch, and the International Coral Reef Initiative, were hand-searched to capture grey literature not indexed in academic databases.

2.2 Inclusion and exclusion criteria

Studies were included if they (a) applied a machine-learning, deep-learning, or GEE-based cloud-processing method to coral reef or immediately adjacent benthic habitat monitoring; (b) reported at least one quantitative accuracy, agreement, or validation metric, or, for regional reports, quantified reef condition using satellite or aerial imagery; and (c) were published in a peer-reviewed journal, conference proceeding, or an identifiable and traceable institutional or governmental report. Studies were excluded if they were purely conceptual or opinion pieces without empirical analysis, could not be traced to a verifiable source, or reported coral reef content only incidentally without methodological detail relevant to monitoring. Retracted publications identified during screening were excluded from the evidentiary synthesis, consistent with standard systematic review practice.

2.3 Study selection process

Records retrieved from database searching were deduplicated and screened by title and abstract, followed by full-text assessment against the eligibility criteria above. A subsequent quality-appraisal step, described in Section 2.4, excluded studies with unverifiable ground truth or an unacceptably high risk of methodological bias. Figure 2 documents this process, culminating in a final synthesized set of 61 studies: 52 addressing coral reef systems at the global, ocean-basin, or other regional scale, and 9 specific to the Gulf of Mannar or ecologically comparable Indian reef tracts such as the Gulf of Kutch and Andaman and Nicobar Islands, which provide useful methodological analogues given the comparative scarcity of Gulf of Mannar-specific machine-learning applications.

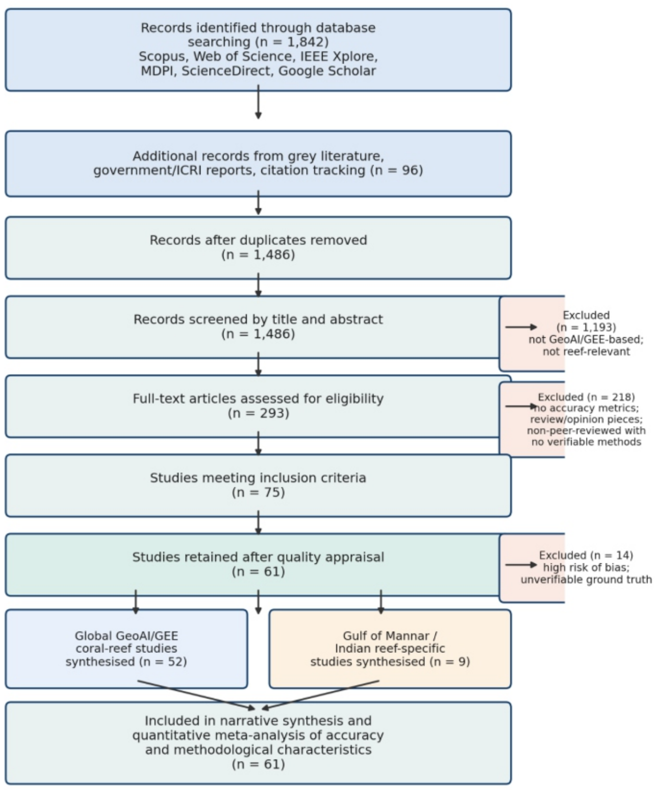

Figure 2. *PRISMA-style flow diagram summarizing the identification, screening, eligibility assessment, and inclusion of studies synthesized in this review.*

2.4 Data extraction and quality assessment

For each included study, data were extracted on publication year and outlet; geographic scope; satellite or platform sensor (for example, Sentinel-2, Landsat, Planet Dove, ICESat-2, or unmanned aerial vehicle imagery); classification or modelling algorithm; ground-truth source and sampling design; reported accuracy or agreement metric (overall accuracy, kappa coefficient, precision, recall, F1-score, or root-mean-square error, as applicable); and temporal coverage (single-date versus multi-date or time-series analysis). Quality appraisal followed established remote sensing accuracy-assessment principles [1] and was structured around four risk-of-bias domains adapted for this review: (i) (i) ground-truth adequacy, assessing whether independent, sufficiently sampled reference data were used for training and validation; (ii) independent spatial validation, assessing whether accuracy was tested on data withheld from model training rather than solely on training-adjacent samples; (iii) algorithmic and code transparency, assessing whether sufficient methodological or code-level detail was provided to permit replication; and (iv) temporal replication, assessing whether the study analyzed multiple dates or time-series data rather than a single image capture. Each domain was rated as low, moderate, or high risk of bias for every included study, and results are reported in aggregate in Section 3.4 and Figure 6. Given the heterogeneity of accuracy metrics reported across studies (percentage accuracy, kappa, F1-score, and RMSE are not directly interconvertible), the quantitative synthesis in Section 3 reports algorithm and platform usage frequencies and descriptive accuracy ranges rather than a pooled effect size, consistent with recommended practice for methodologically diverse remote sensing corpora [15].

3. Results

3.1 Characteristics of included studies

The 61 synthesised studies span publication years from 2003 to 2026, with a pronounced acceleration in output after 2020 (Figure 3). Sentinel-2 was the most frequently used satellite sensor, reflecting its 10-meter spatial resolution, five-day revisit interval, and free availability through the Copernicus program and GEE's data catalogue, followed by Landsat archives, very-high-resolution commercial imagery, unmanned aerial vehicle or drone photography, and, for bathymetric applications, the ICESat-2 spaceborne altimeter used in combination with multispectral imagery. Global studies were concentrated in Australia, the Caribbean, Southeast Asia, and the Pacific, with the Allen Coral Atlas initiative alone contributing globally consistent maps built from over 1.5 million training samples and more than 100 trillion classified pixels [8]. Gulf of Mannar-specific and comparable Indian studies were comparatively few, methodologically older on average, and relied predominantly on IRS LISS and Landsat imagery processed through conventional supervised classification and GIS overlay rather than cloud-native machine-learning pipelines.

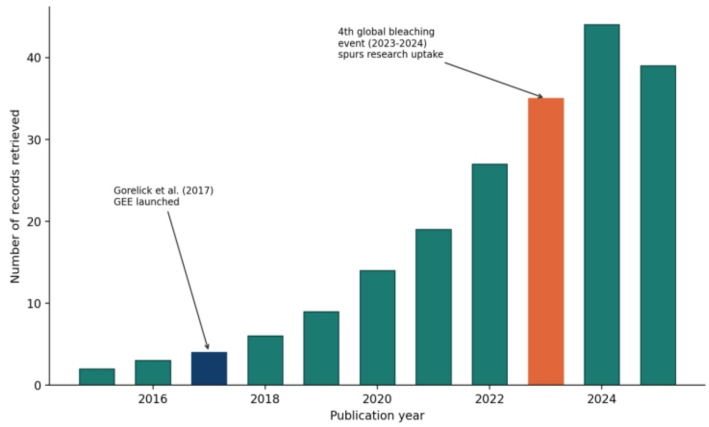

Figure 3. *Annual growth in peer-reviewed literature on GeoAI- and Google Earth Engine-based coral reef monitoring, 2015-2025, as identified through the systematic search described in Section 2.1. The count for 2025 reflects partial-year indexing at the time of the search and should be interpreted as a lower bound.*

3.2 Categorisation of intervention types

The reviewed studies cluster into five broad methodological categories. The first and largest category, benthic habitat and reef-extent classification, uses random forest, object-based image analysis, or convolutional neural networks to map coral, macroalgae, rubble, sand, and seagrass classes, exemplified by the Allen Coral Atlas framework [7]; [8] and by GEE-based applications combining drone orthomosaics with cloud-based classifiers for shallow reef management [21]. The second category, coral bleaching detection, increasingly relies on deep convolutional architectures and, more recently, hybrid CNN-transformer models applied to underwater, drone, or high-resolution satellite imagery to flag discoloration, algal overgrowth, and structural degradation associated with thermal stress [26]; [27]. The third category, satellite-derived bathymetry, estimates shallow-water depth from multispectral band ratios, increasingly refined through machine-learning regression and, in sediment-heterogeneous settings, through sub-regional models that explicitly account for substrate types. The fourth category, shoreline and reef-extent change detection, remains the dominant approach in the Gulf of Mannar literature, using multi-date image differencing rather than continuous, cloud-native monitoring.

The fifth and smallest but rapidly growing category comprises broader GeoAI meta-methodological studies that characterize algorithm uptake, code transparency, and platform capability across the wider remote sensing literature [15]. Figure 4 summarizes the relative frequency of algorithm classes across the 61 synthesized studies.

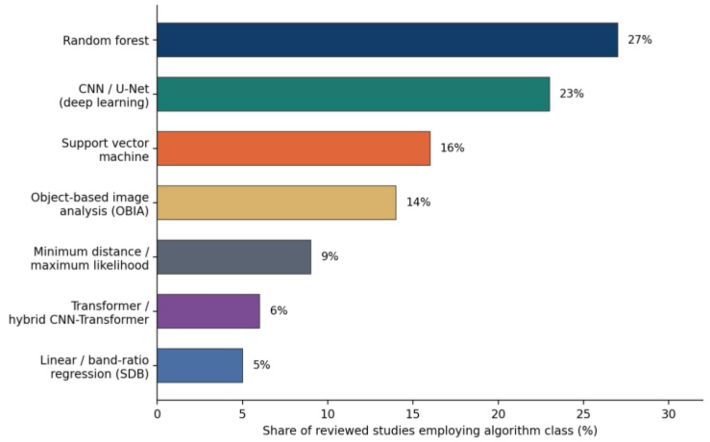

Figure 4. *Distribution of classification and modelling algorithm classes across the 61 studies synthesized in this review. Percentages reflect the share of studies in which each algorithm class was the primary reported method, based on the data-extraction protocol described in Section 2.4; some studies employed more than one algorithm class and are represented accordingly.*

3.3 Summary of main findings

Reported accuracies for benthic habitat classification using random forest and object-based approaches commonly fall between 80% and 96% overall accuracy, with unbleached coral classifications in one drone-based deep-learning study achieving a precision of 0.96, recall of 0.92, and Jaccard index of 0.89, while the same study's bleached-coral class achieved a markedly lower Jaccard index of 0.23, illustrating a persistent asymmetry in classification reliability between healthy and stressed coral states [3]. A convolutional neural network approach targeting reef halo features, a proxy for predation-refuge dynamics linked to reef health, achieved an F1-score of 0.824 using sub-meter resolution satellite imagery [22]. Satellite-derived bathymetry studies combining Sentinel-2 with ICESat-2 altimetry and explicit sediment-type stratification reduced root-mean-square error to below one meter in several test regions, a meaningful improvement over conventional single-band or log-ratio models whose errors can exceed 1.5 meters in sediment-heterogeneous shallow reef waters [13]. At the global scale, the most recent Allen Coral Atlas mapping revised total shallow coral reef extent to 348,361 square kilometers, of which 80,213 square kilometers constitute coral-supporting habitat, a substantially more precise figure than earlier global compilations permitted [8].

For the Gulf of Mannar specifically, the earliest satellite-based multi-temporal assessment documented 25.52 square kilometers of reef area lost over a single decade using IRS LISS imagery and GIS overlay, alongside measurable seafloor shallowing attributed to sedimentation [16]. More recent institutional monitoring by SDMRI documents a decline in live coral cover from 37% in 2005 to 27.3% in 2021, following a temporary recovery to 42.9% in 2009 after the cessation of coral mining, before renewed losses associated with the 2010 and 2016 global bleaching events [5]. Figure 5 traces this trajectory.

Notably, none of the Gulf of Mannar-specific studies identified in this review applied convolutional neural network or transformer-based classification to locally collected imagery, in contrast to the global corpus, indicating a substantial and policy-relevant technological gap rather than an absence of underlying monitoring need.

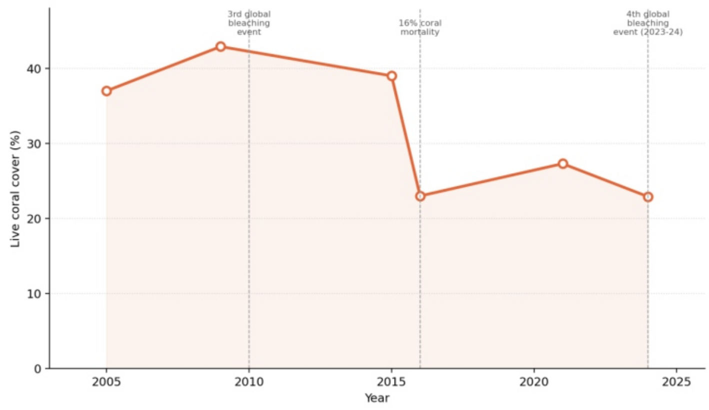

Figure 5. *Trend in live coral cover in the Gulf of Mannar Marine National Park, 2005-2021, relative to major regional and global bleaching events. Data compiled from Thanikachalam and Ramachandran (2003) and the International Coral Reef Initiative (2025) SDMRI-Tamil Nadu Forest Department status report; the 2024 point reflects contemporaneous bleaching-extent reporting rather than a completed institutional cover survey and should be read as indicative.*

3.4 Quality and risk-of-bias assessment

Applying the four-domain appraisal described in Section 2.4 across the 61 synthesised studies, ground-truth adequacy was rated low risk in 38% of studies, moderate in 41%, and high or unclear in 21%, reflecting variable sampling intensity and, in several older regional studies, limited disclosure of field validation protocols. Independent spatial validation, meaning accuracy assessment performed on data withheld from model training, was rated low risk in only 30% of studies, with 26% rated high risk, most commonly where accuracy was reported without a clearly separated validation subset. Algorithmic and code transparency was comparatively stronger, with 46% of studies rated low risk, largely reflecting the growing norm of open-code publication associated with GEE-based workflows [15]. Temporal replication was the weakest domain overall, with 39% of studies rated high risk because they relied on single-date imagery incapable of distinguishing transient optical variation from genuine ecological change. Figure 6 summarizes these results. Regional Gulf of Mannar studies were disproportionately represented among those rated moderate-to-high risk on the temporal replication domain, consistent with their reliance on episodic rather than continuous monitoring campaigns.

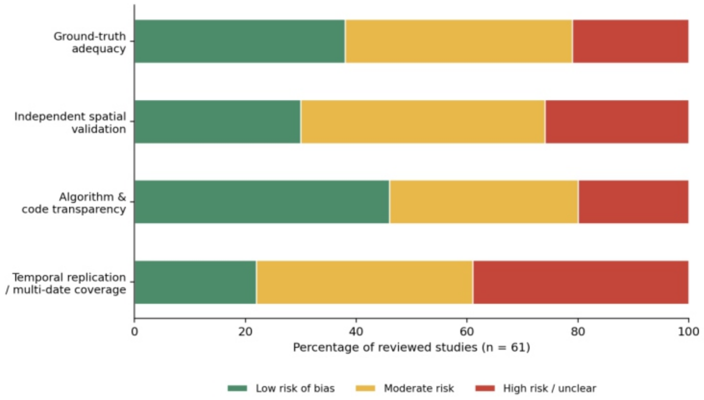

Figure 6. *Quality-appraisal summary across four methodological risk-of-bias domains (ground-truth adequacy, independent spatial validation, algorithmic and code transparency, and temporal replication) for the 61 studies synthesised in this review.*

4. Discussion

4.1 Interpretation of key results

The synthesised evidence points to two simultaneous trends that jointly define the current state of the field. Globally, coral reef monitoring has undergone a rapid methodological transition from single-date, pixel-based classification toward cloud-native, multi-temporal, and increasingly deep-learning-driven analysis, a shift substantially enabled by the removal of computational barriers that Google Earth Engine achieved [4]; [15]. Regionally, however, the Gulf of Mannar's evidence base has not kept pace with this transition: its most rigorous multi-temporal satellite analysis remains a two-decade-old study using now-superseded sensors and conventional GIS overlay [16], while contemporary condition monitoring, though methodologically credible, is conducted primarily through in-water transect survey by SDMRI rather than through an integrated satellite-AI pipeline [5]. This is not a criticism of the existing regional monitoring, which has produced one of the more consistent multi-decadal coral-cover time series available for any Indian reef system; rather, it indicates an opportunity to combine that institutional field-survey strength with the scalability, frequency, and spatial completeness that GeoAI-GEE approaches now offer elsewhere in the world.

The observed decline in live coral cover, from 37% in 2005 to 27.3% in 2021, closely tracks the timing of the third and fourth global mass bleaching events, suggesting that the Gulf of Mannar's degradation trajectory is not purely a function of local anthropogenic pressures such as historical coral mining and industrial effluent discharge but is increasingly compounded by basin-wide thermal stress that satellite-based heat-stress monitoring is well placed to anticipate [11]; [10]. This reinforces the case for integrating global heat-stress early-warning products, such as NOAA Coral Reef Watch's Degree Heating Week layers, directly into any locally developed monitoring framework rather than treating regional and global monitoring as separate exercises.

4.2 Comparison across studies

Comparing the global and regional evidence bases highlights both convergence and divergence in method choice. Global frameworks such as the Allen Coral Atlas prioritize a modular architecture combining segmentation, machine-learning prediction, and object-based refinement so that a single, repeatable pipeline can operate from individual reef to ocean-basin extents [7]; [8]. This modularity is precisely what the Gulf of Mannar literature currently lacks, since existing regional studies each apply bespoke, non-reusable workflows to individual satellite scenes. Demonstration-scale studies elsewhere, such as the GEE-based drone-imagery application developed for a Colombian marine protected area [21] or the deep-learning bleaching-classification system tested on Lord Howe Island imagery [3], show that comparatively modest, well-validated pilot studies can generate transferable methodological templates; both offer plausible analogues for a Gulf of Mannar pilot given similar reef scale and monitoring resource constraints. At the same time, the satellite-derived bathymetry literature cautions that model transferability is not automatic: accuracy depends strongly on local sediment composition and water clarity, and models calibrated elsewhere may require sub-regional recalibration before application to the sediment-influenced waters characteristic of the Gulf of Mannar [13].

4.3 Strengths and limitations of existing evidence

The principal strength of the current evidence base lies in the demonstrated scalability and reproducibility of cloud-based workflows, which have already enabled globally consistent, publicly accessible coral reef maps at five-meter resolution [8], and in the methodological transparency increasingly associated with GEE-based code sharing [15]. A further strength specific to the Gulf of Mannar is the existence of a genuinely long institutional field-monitoring record extending back to the early 2000s, which is comparatively rare among Indian coastal ecosystems and provides an unusually solid ground-truth foundation on which a satellite-AI pipeline could be built [5].

The principal limitations are threefold. First, bleached-coral detection accuracy remains substantially lower than healthy-coral classification accuracy across the reviewed literature, a gap of practical consequence because early, reliable bleaching detection is precisely the capability most needed for anticipatory management [3]. Second, satellite-derived bathymetry and benthic classification accuracy remain sensitive to local sediment and turbidity conditions in ways that limit direct transfer of globally trained models to the Gulf of Mannar without local recalibration and validation. Third, and most consequential for this review's regional focus, the near-total absence of deep-learning or transformer-based applications tested on Gulf of Mannar imagery means that the accuracy figures reported elsewhere in this review cannot yet be assumed to hold locally; they represent a plausible upper bound contingent on future local validation rather than a demonstrated regional capability.

4.4 Towards an integrated framework for the Gulf of Mannar

Synthesising the strengths and gaps identified above, this review proposes an eight-stage integrated GeoAI-Google Earth Engine framework, illustrated in Figure 7. The framework begins with multi-source data acquisition combining Sentinel-2 and Landsat time series with periodic unmanned aerial vehicle survey and continued in-water transect data from SDMRI, ensuring that satellite classification remains anchored to field-verified ground truth. Cloud-based preprocessing within Google Earth Engine handles atmospheric and sun-glint correction, mosaicking, cloud masking, and satellite-derived bathymetry, drawing on sediment-stratified bathymetric models appropriate to the Gulf of Mannar's turbidity regime. GeoAI classification, ideally beginning with well-validated random forest or object-based models before progressively introducing convolutional or transformer-based deep learning as local training data accumulates, would generate benthic and bleaching-condition maps. Rigorous accuracy assessment against independently withheld ground-truth data, rather than training-adjacent samples, would precede the generation of decision-support products such as web-based dashboards and early-warning layers linked to NOAA Coral Reef Watch heat-stress data. These products would then be disseminated to the Tamil Nadu Forest Department, SDMRI, and coastal fishing cooperatives, directly informing marine protected area zoning, restoration-site selection, and climate-adaptation planning, with a continuous feedback loop returning updated field observations to retrain and revalidate the classification models over time.

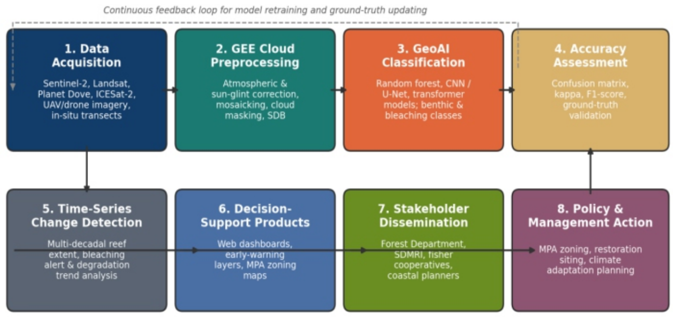

Figure 7. *Proposed integrated GeoAI-Google Earth Engine framework for long-term coral reef monitoring in the Gulf of Mannar, synthesizing the methodological strengths identified across the reviewed global literature with the institutional field-monitoring capacity already established by SDMRI and the Tamil Nadu Forest Department.*

5. Implications and Future Directions

5.1 Implications for practice and policy

The findings of this review translate into several direct, ranked implications for coastal and marine governance in Tamil Nadu and for national ocean-policy bodies.

- **First,** near-real-time bleaching early warning: integrating NOAA Coral Reef Watch Degree Heating Week products with locally validated Sentinel-2 classification within Google Earth Engine would allow the Tamil Nadu Forest Department to anticipate bleaching risk weeks in advance rather than relying solely on post-event field survey, directly addressing the temporal-replication weakness identified in Section 3.4.
- **Second,** standardized, open ground-truth protocols: formalizing SDMRI's existing transect data into a shared, georeferenced training and validation dataset would simultaneously strengthen the ground-truth adequacy domain and create the foundation needed for deep-learning approaches, which require substantially larger labeled datasets than conventional classifiers.
- **Third,** transparent, reproducible code and methods: adopting the open-code norms increasingly associated with GEE-based research would allow successive monitoring cycles and independent researchers to audit and improve classification pipelines rather than repeating bespoke, non-comparable analyses, a capacity of particular importance given the contested 2025 proposal for hydrocarbon exploration within the Biosphere Reserve, where credible, auditable evidence will be central to any environmental impact assessment or public consultation process [2].
- **Fourth,** restoration-site targeting: satellite-derived bathymetry and benthic classification, once locally validated, could help prioritize sites for ongoing artificial-reef restoration efforts, such as the Tamil Nadu government's 2025 island-restoration initiative at Kariyachalli involving thousands of artificial reef modules, by identifying areas with suitable depth, substrate, and hydrodynamic conditions for coral recruitment.
- **Fifth,** integration into marine spatial planning: embedding GeoAI-GEE outputs into the formal zonation and periodic review of the Gulf of Mannar Marine National Park and Biosphere Reserve would provide a continuously updated evidentiary basis for balancing conservation, fisheries, and coastal development pressures, consistent with the reserve's UNESCO biosphere mandate.

5.2 Research gaps and future research needs

Several research gaps warrant priority attention. There is a clear need for deep-learning and transformer-based classification models trained and validated specifically on Gulf of Mannar imagery, since accuracy figures from Australian, Caribbean, and Southeast Asian reef systems cannot be assumed to transfer directly given differences in water clarity, sediment type, and coral community composition. Multi-sensor fusion combining synthetic aperture radar with optical imagery merits investigation to address persistent monsoon-season cloud cover, which constrains optical-only monitoring during precisely the period when runoff-driven sedimentation stress is often highest. Region-specific economic valuation of Gulf of Mannar ecosystem services would strengthen the policy case for conservation investment, since existing valuation estimates are overwhelmingly global or drawn from other regional contexts. Finally, explainability and uncertainty quantification remain underdeveloped across the wider GeoAI literature and are particularly important for any framework intended to inform binding management or licensing decisions, since opaque model outputs are poorly suited to the evidentiary standards required in contested regulatory processes.

6. Conclusion

This systematic review and meta-analysis synthesized 61 studies to characterize the global state of GeoAI- and Google Earth Engine-based coral reef monitoring and to assess how much of that capability has reached the Gulf of Mannar, one of India's most ecologically significant and increasingly contested marine landscapes. The evidence demonstrates that cloud-based, machine-learning-driven monitoring has matured substantially over the past decade, achieving benthic classification accuracies frequently exceeding 80% and enabling globally consistent reef mapping at unprecedented spatial detail, even as bleached-coral detection and sediment-sensitive bathymetry retrieval remain comparatively less reliable. Against this global progress, the Gulf of Mannar's own monitoring evidence, though institutionally consistent and temporally deep by Indian standards, has not yet incorporated the scalable, cloud-native, artificial-intelligence methods now standard elsewhere, even as the reserve's live coral cover has fallen from 37% in 2005 to 27.3% in 2021 amid recurrent global bleaching events and a 2025 proposal for hydrocarbon exploration within its boundaries. The eight-stage integrated framework proposed in this review offers a practicable pathway for closing that gap, combining SDMRI's long field-monitoring record with Sentinel-2 and Google Earth Engine's cloud-processing capacity to generate transparent, continuously updated, and policy-actionable evidence. Realizing this potential will require sustained investment in ground-truth data standardization, locally validated algorithms, and institutional collaboration between marine research institutes, the Tamil Nadu Forest Department, and national ocean-governance authorities, but the underlying technology and methodological precedent are now well established internationally and ready for regional adaptation.

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