

Closing the Observation–Inference Gap in Southeast Asian Coastal Ecosystem Monitoring

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Abstract

This study develops a quantitative evidence architecture for interpreting remote-sensing and ecological data in Southeast Asian coastal ecosystems. A fixed corpus of 30 DOI-indexed studies published between 2007 and 2024 was coded by ecosystem, evidence mode, spatial scale, and primary ecological target, then analyzed using descriptive statistics, contingency analysis, and a 20,000-permutation test. The corpus was dominated by mangrove (40.0%) and coral (33.3%) research, while seagrass represented only 10.0%; 70.0% of studies were published from 2018 onward. Evidence mode differed substantially among ecosystems ($\chi^2 = 24.62$; permutation $p = 0.016$; Cramer's $V = 0.523$), with coral studies dominated by multi-source quantitative designs and seagrass studies concentrated in synthesis and mapping. Numeric benchmarks showed that high map accuracy or broad spatial coverage did not remove uncertainty in below-ground carbon, functional recovery, or biological response to thermal stress. The study introduces an Observation–Inference Gap framework in which stronger ecological and management claims require proportionally stronger field calibration, temporal continuity, cross-sensor validation, and uncertainty propagation. The framework provides a practical basis for interoperable coastal monitoring without treating all spatial products as equivalent ecological evidence.

Keywords : remote sensing, ecological inference, coastal ecosystems, evidence integration, Southeast Asia.



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INTRODUCTION

Coastal ecosystems sit at the intersection of biodiversity conservation, climate regulation, fisheries production, and hazard protection, but their condition is difficult to observe consistently because the ecological processes of interest operate across different spatial and temporal scales. Satellite, airborne, and uncrewed sensing platforms solve part of this problem by making repeated observation possible, yet the meaning of a mapped signal depends on whether the signal corresponds to habitat extent, ecological state, ecosystem function, or only a proxy. Blue-carbon and coastal-vegetation syntheses show that mangroves, seagrasses, and other vegetated coastal habitats store substantial carbon and buffer physical disturbance, while their degradation converts ecological loss into climate and livelihood risk (Duarte et al., 2013; Howard et al., 2017; Macreadie et al., 2021). Southeast Asia is particularly important because it combines globally significant mangrove and seagrass resources with high exposure to land conversion, coastal development, and climate extremes (Fortes et al., 2018; Unsworth et al., 2019). The central monitoring problem is therefore not whether more imagery can be obtained, but whether spatial observations are sufficiently calibrated to support ecological inference and management decisions.

Mangrove monitoring illustrates both the strength and the limitation of contemporary Earth observation. Global Mangrove Watch v2.5 mapped approximately 140,260 km² of mangroves for 2010 and reported an overall accuracy of 95.1% from 50,750 reference points, demonstrating that habitat extent can be observed with high spatial consistency when classification and validation are explicit (Bunting et al., 2022). Longitudinal analyses further show that remote sensing can identify both rates and proximate drivers of loss: Southeast Asian mangroves declined at an average of 0.18% per year during 2000–2012, with aquaculture accounting for about 30% of observed conversion, while later global work estimated that 62% of mangrove loss during 2000–2016 was associated with land-use

change (Richards & Friess, 2016; Goldberg et al., 2020). Reviews of global mangrove condition nonetheless emphasize that spatial persistence does not guarantee functional integrity because hydrology, sediment dynamics, regeneration, and carbon pools respond differently to disturbance and recovery (Friess et al., 2019). This difference between reliable observation and uncertain ecological interpretation is the first component of what this study terms the observation–inference gap.

Seagrass monitoring presents a more difficult observability problem because water depth, turbidity, bottom type, sunglint, seasonal phenology, and mixed pixels can alter the relationship between spectral response and meadow condition. Regional synthesis identified 21 seagrass species in Southeast Asia and about 36,762.6 km² of known meadows, while also documenting pronounced geographic gaps and uneven national mapping capacity (Fortes et al., 2018). The global distribution literature likewise demonstrates that the mapped extent of seagrass remains less complete than mangrove coverage, even though seagrass meadows are widely distributed and ecologically important (McKenzie et al., 2020). Conservation analyses therefore stress that field observations of species composition, shoot density, water quality, and disturbance remain indispensable for interpreting spatial products and detecting degradation before complete habitat loss occurs (Unsworth et al., 2019). The resulting evidence asymmetry is important for regional monitoring because a low-visibility ecosystem can appear less threatened simply because it is less consistently observed.

Coral reefs reveal a different form of the same problem. Thermal exposure can be monitored repeatedly and consistently from sea-surface temperature products, but biological outcomes vary with the intensity and history of heat stress, taxonomic composition, local pressures, and recovery opportunity. Global and Indo-Pacific studies link recurrent warming to mass bleaching, assemblage transformation, altered ecosystem services, and differences in rebound potential, yet the ecological consequence of a thermal anomaly cannot be inferred from temperature alone (Hoegh-Guldberg et al., 2007; Graham et al., 2015; Hughes et al., 2017; Hughes et al., 2018; Sully et al., 2019). Multi-site analyses further show that local environmental and social conditions can amplify or moderate losses and that management strategies depend on both ecological status and exposure context (Cinner et al., 2016; Darling et al., 2019; Donovan et al., 2021). Projections of local thermal refugia and assessments of declining ecosystem-service capacity reinforce the need to distinguish physical exposure from ecological resilience and service delivery (Dixon et al., 2022; Eddy et al., 2021).

Blue-carbon research makes the observation–inference gap especially consequential because mapped area is frequently converted into estimates of biomass, soil carbon, avoided emissions, or mitigation potential. Indonesian mangroves have been estimated to contain about 3.14 PgC at a mean ecosystem carbon stock of $1,083 \pm 378$ MgC ha⁻¹, but such estimates depend on field sampling, soil depth, allometry, land-use history, and scaling assumptions that cannot be resolved from canopy mapping alone (Murdiyarso et al., 2015). Subsequent work has refined national emission factors, documented land-use effects on blue carbon, and quantified management potential while continuing to emphasize uncertainty in below-ground and converted carbon pools (Murdiyarso et al., 2023; Sasmito et al., 2019; Sidik et al., 2018; Rahman et al., 2024). Regional syntheses show substantial imbalance in both the quantity and methodological quality of blue-carbon evidence, with seagrass data particularly sparse and spatially biased (Stankovic et al., 2023). Remote-sensing reviews similarly identify strong progress in mangrove mapping but persistent limitations for below-ground carbon and economic valuation (Roy et al., 2024).

The difficulty is not solved by adding more datasets unless the datasets reduce different components of uncertainty. Predictive global analyses can estimate future mangrove carbon emissions by combining carbon stocks, distribution, deforestation rates, and land-use drivers, but their conclusions still depend on the transferability of input parameters (Adame et al., 2021). Local vulnerability studies can integrate exposure, sensitivity, adaptive capacity, biomass, and sediment carbon to strengthen ecological interpretation, yet such detailed designs are more demanding and less readily standardized across regions (Analuddin et al., 2024). At the global scale, estimates of emissions from coastal ecosystem conversion and the mitigation potential of protection and restoration illustrate the policy value of synthesis, but they also show how uncertainty accumulates as analysis moves from mapped extent to function and then to economic or management outcomes (Pendleton et al., 2012; Macreadie et al., 2021). A theoretically stronger monitoring architecture must therefore specify where observation ends, where model-based inference begins, and what validation is necessary at each transition.

This study operationalizes that problem through an Observation–Inference Gap framework. The framework treats monitoring as a four-level chain: direct observation of physical or structural variables; calibrated estimation of ecological state; inference about ecosystem function; and decision-level claims about resilience, restoration success, or management priority. The theoretical proposition is that evidentiary requirements should increase with inference distance: directly sensed variables may be defensible with sensor validation and classification accuracy, whereas functional and management claims require additional field calibration, temporal continuity, uncertainty propagation, and cross-context testing. Rather than assigning a universal quality score to heterogeneous studies, the framework asks whether the evidence mode is appropriate for the ecological claim being made. This shifts assessment from technological sophistication to measurement validity.

The study therefore had three objectives: to quantify the structure of a 30-study coastal evidence corpus by ecosystem, evidence mode, scale, and time; to extract numerical benchmarks that reveal differences in spatial coverage, validation intensity, carbon estimation, and climate-response thresholds; and to translate the resulting pattern into an interoperable monitoring architecture for Southeast Asia. The novelty lies in comparing mangrove, seagrass, and coral research within a single inference framework while statistically testing whether evidence modes are distributed differently among ecosystems. The approach preserves heterogeneity instead of forcing incomparable effect sizes into a meta-analysis and uses the heterogeneity itself as data about how coastal ecosystems are currently observed. This design is intended to produce a more defensible link between remote sensing, ecological process evidence, and management interpretation.

RESEARCH METHODS

The research used a quantitative evidence-mapping design combined with secondary-data synthesis. A fixed corpus of 30 peer-reviewed, DOI-indexed studies published from 2007 through 2024 was assembled to represent coastal monitoring questions involving mangroves, seagrass meadows, coral reefs, and cross-ecosystem blue-carbon or conservation processes. Sources were eligible when they contributed empirical, spatial, model-based, or synthesis evidence on habitat distribution, land-cover change, carbon storage and emissions, thermal exposure, ecological condition, ecosystem services, vulnerability, or management response. The design is intentionally an evidence map rather than a claim of exhaustive systematic coverage; the fixed corpus was retained in full so that every source contributed to the analytical dataset and remained traceable in the final bibliography.

Each study was coded on six variables: publication year, ecosystem focus, dominant evidence mode, spatial scale, primary ecological target, and the presence of directly extractable quantitative benchmarks. Ecosystem categories were mangrove, coral, seagrass, and cross-ecosystem. Dominant evidence mode was coded as review/synthesis, multi-source quantitative, remote/spatial, field/process, or model/scenario; the dominant-mode rule prevented a single study from being counted repeatedly even when it used several data streams. Spatial scale was coded as global, transnational regional, national Indonesia, or local. Primary targets were grouped around habitat extent and change, carbon and biogeochemistry, thermal stress and biological response, vulnerability or condition, and management or ecosystem services. Coding was based on the reported study design and principal analytical contribution rather than on journal discipline or publication prestige.

A second extraction stage recorded numerical anchors from studies that reported metrics directly relevant to observation, validation, ecological scale, or decision thresholds. These anchors included mapped area, map accuracy, reference-point counts, rates of habitat loss, carbon-stock estimates, sample sizes, temporal windows, thermal thresholds, and mitigation quantities. Values were retained in their published units because converting heterogeneous quantities into a common effect size would create false comparability. The numerical benchmark table therefore functions as a calibration layer: it demonstrates the magnitude and precision of what individual evidence systems can directly support while keeping extent, carbon, temperature, and ecosystem-service metrics analytically distinct.

Analysis was performed with descriptive frequencies, percentages, medians, and cross-tabulation. The association between ecosystem and dominant evidence mode was evaluated using a Pearson chi-square statistic for effect-size calculation and a 20,000-shuffle permutation test because several expected cell counts were small; association strength was summarized with Cramér's V. Statistical results describe the structure of this purposively defined evidence corpus and are not interpreted as population estimates for all coastal literature. A sensitivity check retained the same

conclusions when the four spatially oriented mangrove and seagrass studies were combined with the multi-source quantitative category, indicating that the main ecosystem asymmetry was not an artifact of a single coding boundary. No human participants, personal data, experimental animals, or new field samples were involved.

Table 1. Analytical Coding Framework For The Quantitative Evidence Map

Variable	Categories	Operational rule	Analytical purpose
Ecosystem	Mangrove; coral; seagrass; cross-ecosystem	Classified by primary habitat or explicit multi-habitat scope	Compare evidence structure among ecosystem types
Evidence mode	Review/synthesis; multi-source quantitative; remote/spatial; field/process; model/scenario	Single dominant mode based on principal analytical contribution	Measure methodological concentration and asymmetry
Spatial scale	Global; regional; Indonesia; local	Scale at which results were interpreted	Evaluate transferability and regional relevance
Primary target	Extent/change; carbon; thermal response; condition/vulnerability; management/services	Target receiving the main ecological inference	Locate where observation is converted into ecological claims
Numeric benchmark	Area, accuracy, sample size, rate, stock, threshold, or mitigation quantity	Extracted only when explicitly reported and interpretable	Anchor discussion in verifiable quantitative evidence

Table 1 makes the analysis reproducible by separating what a study observes from the ecological claim it ultimately supports. The coding architecture also prevents technological complexity from being treated automatically as higher evidentiary quality, because a review, model, field survey, or satellite product can each be appropriate when matched to the inference level being addressed.

RESULTS AND DISCUSSION

Structure and asymmetry of the evidence base

The 30-study corpus spans 18 years and is strongly weighted toward recent work. The median publication year was 2019, and 21 studies (70.0%) were published from 2018 through 2024. This concentration reflects rapid development in global Earth-observation products, blue-carbon accounting, and large multi-site coral datasets, but it also means that methodological standards changed substantially within the period. Earlier climate and blue-carbon studies established the conceptual importance of coastal ecosystems, while newer studies increasingly combined spatial products, field data, and decision-oriented modelling (Hoegh-Guldberg et al., 2007; Pendleton et al., 2012; Duarte et al., 2013; Macreadie et al., 2021). Figure 1 shows that the evidence base becomes denser after 2018, a period in which remote sensing and ecosystem-accounting applications were also becoming more operational.

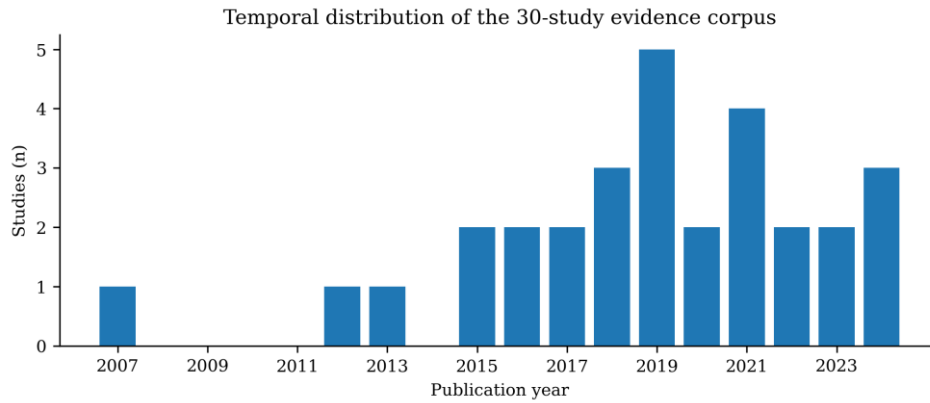


Figure 1. Temporal Distribution of The 30-Study Evidence Corpus

The temporal pattern matters because methodological comparability cannot be assumed across generations of sensors, validation strategies, and ecological models. Long-term monitoring systems should therefore archive processing rules and calibration data so that improved methods can be introduced without creating artificial ecological trends.

Mangrove studies were the largest component of the corpus (12 studies; 40.0%), followed by coral studies (10; 33.3%), cross-ecosystem studies (5; 16.7%), and seagrass studies (3; 10.0%). The distribution is not simply a reflection of ecological importance; it also mirrors observability and data infrastructure. Mangrove canopy and intertidal location are comparatively compatible with repeated optical and radar mapping, coral research has developed extensive temperature and multi-site field networks, and seagrass remains difficult to map consistently across variable water columns. Cross-ecosystem studies largely addressed blue-carbon or climate-mitigation questions and therefore depended on synthesized parameters from several habitat classes. Figure 2 makes the resulting monitoring imbalance explicit.

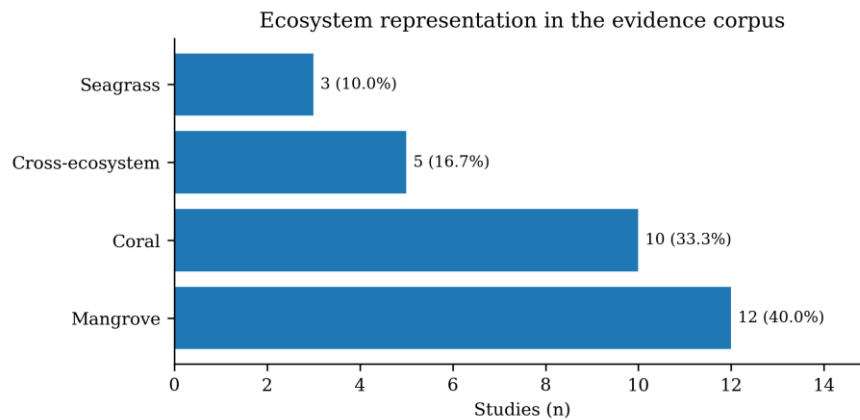


Figure 2. Ecosystem Representation in The 30-Study Evidence Corpus

The small seagrass share is particularly consequential because regional seagrass diversity and area are high, but the evidentiary base remains less spatially complete and more methodologically heterogeneous than for mangroves. This pattern is consistent with regional reviews that identify strong geographic gaps, uneven national mapping capacity, and substantially greater uncertainty in seagrass blue-carbon estimates (Fortes et al., 2018; McKenzie et al., 2020; Stankovic et al., 2023).

Evidence mode was also uneven. Review or synthesis papers accounted for 12 studies (40.0%), multi-source quantitative designs for 10 (33.3%), remote/spatial analyses for four (13.3%), and field/process and model/scenario studies for two each (6.7% each). This distribution becomes more informative when cross-tabulated by ecosystem: eight of ten coral studies were multi-source quantitative, whereas five of twelve mangrove studies were reviews and three were dominated by remote/spatial analysis; two of three seagrass studies were reviews. The ecosystem-by-mode association was substantial (chi-square = 24.62, df = 12; permutation p = 0.016; Cramer's V = 0.523). The result

should not be interpreted as a ranking of ecosystem research quality; it shows that different habitats are being known through different evidentiary architectures, which directly affects the type of management inference that can be made.

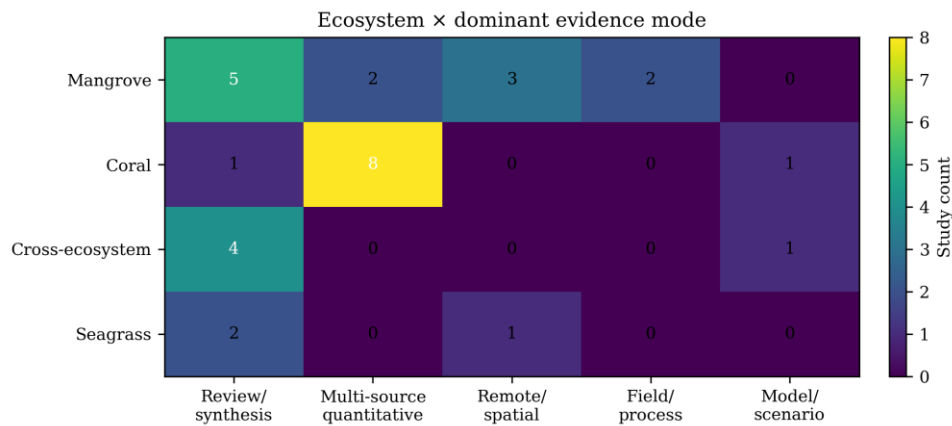


Figure 3. Ecosystem × Dominant Evidence Mode in The Coded Corpus

Figure 3 shows that coral evidence in this corpus is unusually concentrated in large quantitative datasets that combine thermal exposure, field observations, ecological condition, or socioeconomic drivers, while cross-ecosystem work is dominated by synthesis. Mangrove research occupies the broadest methodological range, reflecting both mature remote-sensing products and extensive carbon-process literature. The asymmetry supports the study’s core proposition that interoperability requires an explicit record of evidence mode, because a regional dashboard that treats all habitat indicators as methodologically equivalent would conceal fundamentally different inference pathways.

Table 2. Coded Profile of The 30-Study Coastal Evidence Corpus

Study	Year	Ecosystem	Evidence mode	Scale	Primary target
Adame et al.	2021	Mangrove	Multi-source quantitative	Global	Blue carbon / future emissions
Analuddin et al.	2024	Mangrove	Field/process	Local	Vulnerability / blue carbon
Bunting et al.	2022	Mangrove	Remote/spatial	Global	Habitat extent / map accuracy
Cinner et al.	2016	Coral	Multi-source quantitative	Global	Reef condition / management
Darling et al.	2019	Coral	Multi-source quantitative	Indo-Pacific	Reef condition / drivers
Dixon et al.	2022	Coral	Model/scenario	Global	Thermal refugia
Donovan et al.	2021	Coral	Multi-source quantitative	Global	Heatwave response
Duarte et al.	2013	Cross-ecosystem	Review/synthesis	Global	Mitigation / adaptation
Eddy et al.	2021	Coral	Multi-source quantitative	Global	Ecosystem services
Fortes et al.	2018	Seagrass	Review/synthesis	Southeast Asia	Distribution / conservation

Friess et al.	2019	Mangrove	Review/synthesis	Global	Status / change
Goldberg et al.	2020	Mangrove	Remote/spatial	Global	Loss drivers
Graham et al.	2015	Coral	Multi-source quantitative	Indo-Pacific	Recovery / regime shift
Hoegh-Guldberg et al.	2007	Coral	Review/synthesis	Global	Climate stress
Howard et al.	2017	Cross-ecosystem	Review/synthesis	Global	Climate mitigation
Hughes et al.	2017	Coral	Multi-source quantitative	Global	Mass bleaching
Hughes et al.	2018	Coral	Multi-source quantitative	Regional	Heat exposure / assemblage change
Macreadie et al.	2021	Cross-ecosystem	Review/synthesis	Global	Blue carbon / mitigation
McKenzie et al.	2020	Seagrass	Remote/spatial	Global	Global distribution
Murdiyarso et al.	2023	Mangrove	Review/synthesis	Indonesia	Emission factors
Murdiyarso et al.	2015	Mangrove	Field/process	Indonesia	Carbon stock / emissions
Pendleton et al.	2012	Cross-ecosystem	Model/scenario	Global	Blue-carbon emissions
Rahman et al.	2024	Mangrove	Multi-source quantitative	Indonesia	Blue-carbon potential
Richards & Friess	2016	Mangrove	Remote/spatial	Southeast Asia	Deforestation / land-use drivers
Roy et al.	2024	Mangrove	Review/synthesis	Asia-Pacific	Remote sensing / blue carbon
Sasmito et al.	2019	Mangrove	Review/synthesis	Global	Land-use change / blue carbon
Sidik et al.	2018	Mangrove	Review/synthesis	Indonesia	Conservation / mitigation
Stankovic et al.	2023	Cross-ecosystem	Review/synthesis	South & Southeast Asia	Blue-carbon evidence gaps
Sully et al.	2019	Coral	Multi-source quantitative	Global	Bleaching / thermal stress
Unsworth et al.	2019	Seagrass	Review/synthesis	Global	Conservation / pressures

Table 2 retains every source in the bibliography within the analytical dataset and shows why pooled meta-analysis was not appropriate: the corpus mixes mapped extent, field carbon, global reef observations, scenarios, and integrative reviews. Its value lies in making the heterogeneity explicit and then using that heterogeneity to design a monitoring system that preserves the evidentiary limits of each indicator.

Quantitative benchmarks and the observation–inference gap

The benchmark extraction demonstrates that high precision at one inference level does not guarantee precision at the next. Bunting et al. (2022) reported 95.1% overall accuracy for the 2010 Global Mangrove Watch baseline using 50,750 validation points, which is strong evidence for mapped extent. Richards and Friess (2016) then used remote sensing to estimate more than 100,000 ha of Southeast Asian mangrove removal during 2000–2012 and an average loss rate of 0.18% per year, while Goldberg et al. (2020) attributed 62% of global mangrove losses during 2000–2016 to land-use change. These studies establish a robust spatial foundation, but they do not by themselves quantify the full ecological consequences of conversion. Carbon, regeneration, biodiversity, and sediment processes require additional information that operates below the spatial signal.

Table 3. Quantitative Benchmarks Extracted From Key Studies in The Retained Corpus

Source	System / metric	Reported quantitative benchmark	Inference level
Bunting et al. (2022)	Mangrove mapping	140,260 km ² global 2010 extent; 95.1% overall accuracy; 50,750 reference points	Direct observation / validation
Richards & Friess (2016)	Mangrove change	>100,000 ha removed in Southeast Asia, 2000–2012; 0.18% yr ⁻¹ ; aquaculture ≈30% of loss	Direct change / driver inference
Goldberg et al. (2020)	Mangrove loss drivers	62% of global loss, 2000–2016, associated with land-use change	Driver inference
Murdiyarso et al. (2015)	Indonesia mangrove carbon	1,083 ± 378 MgC ha ⁻¹ ; 2.9 Mha scaled extent; ≈3.14 PgC national stock	Field-to-national functional inference
Rahman et al. (2024)	Indonesia blue carbon	3,267.87 MtC; 11,982.21 MtCO ₂ e potential; Papua 1,707.22 MtC	Secondary-data functional inference
Fortes et al. (2018)	Southeast Asian seagrass	21 species; ≈36,762.6 km ² known meadow extent	Regional synthesis / distribution
Stankovic et al. (2023)	Blue-carbon evidence	432 articles from 1967–2022 across 13 South and Southeast Asian countries	Evidence-base scale
Sully et al. (2019)	Coral bleaching	3,351 sites in 81 countries, 1998–2017	Field observation / thermal association
Darling et al. (2019)	Coral drivers	2,584 Indo-Pacific reefs; 21 climate, social, and environmental drivers	Multi-source ecological inference
Hughes et al. (2018)	Coral thermal response	Immediate mortality above ≈3–4 °C-weeks; assemblage shift at ≥6 °C-weeks; 29% of	Exposure-to-biological threshold

		3,863	reefs	
		transformed		
Macreadie et al. (2021)	Global blue carbon	>30,000 TgC	across	Global functional /
		≈185 million ha;		mitigation synthesis
		protection	≈304	
		TgCO ₂ e yr ⁻¹ avoided;		
		restoration	≈841	
		TgCO ₂ e yr ⁻¹ by 2030		

Table 3 shows that the corpus contains large and high-quality datasets, but the quantities are not commensurable and should not be collapsed into a single performance metric. Mapping accuracy, carbon density, thermal exposure, sample size, and mitigation potential answer different questions; the scientific problem is to specify the evidentiary bridge between them rather than to maximize any one value.

The mangrove carbon literature illustrates this bridge. Murdiyarso et al. (2015) estimated Indonesian mangrove ecosystem carbon at $1,083 \pm 378$ MgC ha⁻¹ and about 3.14 PgC nationally, values that required field measurements of biomass and sediments before national scaling. Later work derived Indonesian emission factors and demonstrated that land-use history materially changes blue-carbon outcomes, reinforcing the need for process-specific parameters rather than generic conversion factors (Murdiyarso et al., 2023; Sasmito et al., 2019). National secondary-data analysis estimated 3,267.87 MtC of mangrove blue carbon and 11,982.21 MtCO₂e of carbon-dioxide absorption potential, with Papua contributing the largest regional share, but such accounting inherits assumptions from the global or national average used for carbon density (Rahman et al., 2024). Management analyses further show that carbon conservation gains can conflict with socioeconomic objectives unless institutional and community dimensions are integrated (Sidik et al., 2018).

The same logic applies to projected future emissions. Adame et al. (2021) integrated global carbon stocks, mangrove distribution, deforestation rates, and land-use drivers to project emissions under continued loss. The study is analytically stronger than a simple area-to-carbon multiplication because it integrates multiple causal datasets, yet uncertainty still enters through carbon-stock surfaces, future loss assumptions, and land-use transitions. Roy et al. (2024) reached a similar conclusion from a remote-sensing perspective, finding that Asia-Pacific mangrove blue-carbon assessment remains skewed toward above-ground components and familiar sensors while below-ground carbon is less studied. Analuddin et al. (2024) demonstrates the complementary local solution: vulnerability, sediment carbon, biomass, exposure, sensitivity, and adaptive capacity can be assessed together, but the intensive design is harder to scale. The implication is not that local or global approaches are superior, but that inference distance and validation intensity must remain proportionate.

Seagrass evidence occupies a wider observation–inference gap because the spatial baseline itself is less certain. Fortes et al. (2018) estimated about 36,762.6 km² of known Southeast Asian seagrass meadows and documented 21 species, but also identified major regional gaps and inconsistent inventories. McKenzie et al. (2020) advanced global distribution knowledge but retained uncertainty associated with incomplete mapping and heterogeneous source data. Unsworth et al. (2019) argued that conservation requires attention to local pressures, ecological condition, and recovery capacity, variables that are only partly visible in remote imagery. Stankovic et al. (2023), reviewing 432 articles across South and Southeast Asia, found that seagrass blue-carbon evidence was both quantitatively and methodologically thinner than mangrove evidence. A regional monitoring system should therefore avoid interpreting missing or coarse seagrass data as ecological stability.

Coral evidence shows the opposite pattern: thermal exposure can be observed well, but biological response is nonlinear. Sully et al. (2019) synthesized 3,351 sites from 81 countries over 1998–2017 and showed that bleaching probability rose with the intensity and frequency of thermal-stress anomalies, while Donovan et al. (2021) demonstrated that local conditions magnify losses after marine heatwaves. Hughes et al. (2018) identified an immediate mortality response around 3–4 °C-weeks and major assemblage transformation above 6 °C-weeks, with 29% of 3,863 Great Barrier Reef reefs experiencing transformed ecological functioning after the 2016 event. These thresholds are powerful management indicators, but Graham et al. (2015) and Hughes et al. (2017) show that recovery potential and repeated bleaching cannot be inferred from exposure alone. Cinner et al. (2016) and Darling et al. (2019) further

demonstrate that social access, market exposure, local disturbance, and ecological status condition management outcomes, whereas Dixon et al. (2022) shows that the future availability of thermal refugia is itself climate-dependent.

Ecosystem-service inference represents a further step away from directly sensed variables. Eddy et al. (2021) documented a long-term global decline in the capacity of coral reefs to provide services, but service loss integrates habitat condition, biodiversity, fisheries, and human use rather than a single remote-sensing observable. Howard et al. (2017) similarly emphasized that coastal and marine climate-mitigation claims depend on defensible accounting boundaries and ecosystem-specific processes. Pendleton et al. (2012) quantified potentially large emissions from conversion of vegetated coastal ecosystems while explicitly identifying uncertainty in area, conversion rates, and the fate of carbon after disturbance. Macreadie et al. (2021) later estimated that conserving existing blue-carbon ecosystems could avoid roughly 304 TgCO₂e per year and that large-scale restoration could add about 841 TgCO₂e per year by 2030, but also highlighted uncertainty in habitat distribution and restoration feasibility. The observation–inference gap is therefore not a weakness unique to remote sensing; it is a general property of ecological scaling.

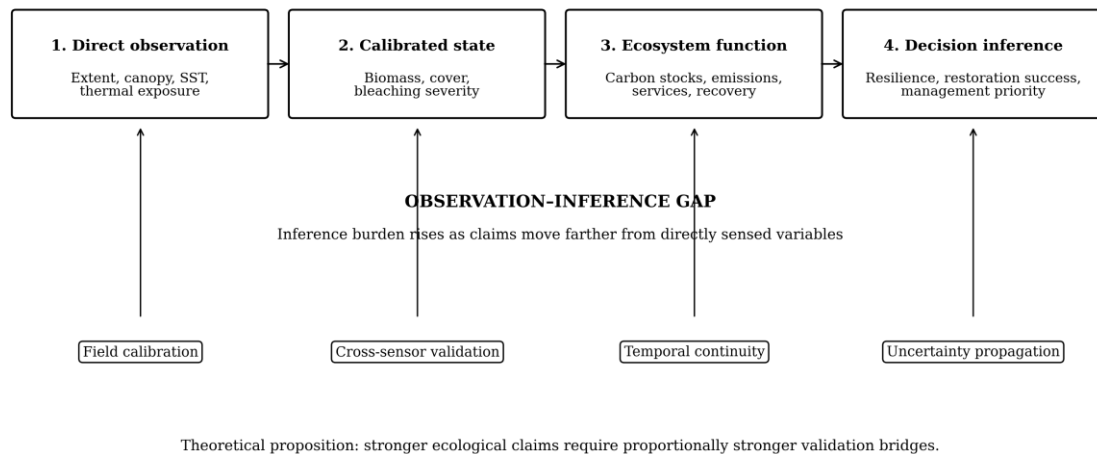


Figure 4. Observation–Inference Gap Framework for Coastal Ecosystem Monitoring

Figure 4 formalizes the theoretical contribution of the study. Directly observed variables require technical validation; calibrated ecological states require field linkage; ecosystem-function claims require temporal and process validation; and decision-level claims additionally require uncertainty propagation and explicit management thresholds. The framework is deliberately additive: more distant inferences are not prohibited, but they demand stronger evidentiary bridges.

An interoperable monitoring architecture for Southeast Asia

The evidence supports a monitoring architecture organized around inference level rather than sensor type. A sensor-first system tends to accumulate imagery and products, whereas an inference-first system begins with a management question and then selects the minimum combination of observations needed to answer it. For mangrove extent, high-quality remote sensing may be sufficient for screening and change detection; for blue-carbon accounting, the same map must be coupled to locally defensible biomass and soil parameters; for restoration verification, repeated field measures of hydrology, regeneration, and sediment processes are required. This logic directly addresses the concern that technically precise maps can create an appearance of ecological certainty when the variable of interest is only indirectly observed.

Table 4. Cross-Ecosystem Observability and Validation Requirements

Indicator	Remote observability	Field dependence	Main uncertainty	Minimum defensible evidence
Mangrove extent / canopy	High	Moderate	Cloud, tide, mixed boundaries, classification transfer	Optical/radar mapping + stable validation points
Mangrove biomass / soil carbon	Moderate to low	High	Allometry, soil depth, land-use history, below-ground pools	Remote structure + repeated field plots + sediment cores
Seagrass extent	Moderate	High	Depth, turbidity, substrate, seasonal phenology, mixed pixels	Standardized acquisition + water-column correction + in-water validation
Seagrass function / carbon	Low	Very high	Patchiness, productivity, sediment heterogeneity, sparse inventories	Field biomass/sediment sampling linked to mapped meadow boundaries
Coral thermal exposure	High	Moderate	SST resolution, local hydrodynamics, exposure duration	Thermal products + calibrated local exposure metrics
Coral biological condition	Moderate	High	Taxonomic response, delayed mortality, local stressors, recovery	In-water surveys + repeated post-event observations
Ecosystem services / resilience	Low as a direct observable	Very high	Social use, connectivity, recovery capacity, valuation assumptions	Multi-source ecological, social, temporal, and uncertainty data

Table 4 converts the literature into an operational rule: monitoring intensity should be allocated according to inference difficulty, not distributed evenly across habitats. This is especially important for seagrass and functional indicators, where another satellite image may add less information than a strategically designed validation campaign.

Temporal continuity is the second design principle. Ecological monitoring becomes decision-relevant only when repeated measurements distinguish persistent change from seasonal variability, short-lived disturbance, and methodological discontinuity. Coral bleaching studies demonstrate the value of repeated exposure and outcome observations across years and events, whereas mangrove studies show that canopy recovery can precede recovery of sediment processes or carbon stocks. Seagrass condition is similarly sensitive to seasonal water clarity and phenology. The monitoring unit should therefore be a versioned time series with documented sensor transitions, training data, calibration plots, and uncertainty estimates rather than a sequence of disconnected maps.

The third principle is explicit uncertainty propagation. Classification error should not disappear when mapped area is converted into biomass, carbon, avoided emissions, or restoration performance.

Each transformation should retain the uncertainty of the previous layer and add uncertainty from the new model or parameter. This is particularly important where national carbon values are derived from global averages or where restoration success is inferred from visible cover. The blue-carbon literature repeatedly demonstrates that soil depth, land-use history, and emission factors can dominate final estimates even when mapped boundaries are relatively accurate (Murdiyarso et al., 2015; Murdiyarso et al., 2023; Sasmito et al., 2019; Adame et al., 2021).

The fourth principle is cross-ecosystem interoperability without forced metric uniformity. A common regional platform can standardize metadata, time stamps, spatial reference, uncertainty fields, and evidence-level labels while allowing habitat-specific variables. Mangroves, seagrasses, and coral reefs should not be reduced to a single condition index because their observable processes differ; instead, they can share an evidence structure that records what was observed, how it was validated, what inference was made, and with what confidence. Such an architecture would allow managers to compare evidence strength across jurisdictions without pretending that canopy cover, seagrass meadow area, and degree-heating weeks are equivalent ecological quantities.

Table 5. Proposed Evidence Architecture For Decision-Oriented Coastal Monitoring

Monitoring tier	Core question	Typical indicators	Evidence requirement	Decision use
Screening	Where is change occurring?	Extent, cover, thermal anomaly	Repeatable spatial product with classification/measurement uncertainty	Trigger targeted validation
Diagnosis	What ecological process is changing?	Biomass, species composition, hydrology, bleaching severity	Field-calibrated state variables and process indicators	Identify mechanism and severity
Function	What does the change mean for carbon, services, or recovery?	Carbon pools, recruitment, productivity, service proxies	Temporal process data + model uncertainty + transferability test	Estimate ecological consequence
Decision	What action is justified?	Thresholds, vulnerability, restoration trajectory, connectivity	Integrated evidence with explicit confidence and alternative explanations	Prioritize protection, restoration, adaptation, or further data collection

Table 5 provides the final synthesis of the study: the monitoring system is tiered by question and inference burden. The structure is compatible with existing remote-sensing investments because it does not replace satellite products; it specifies when they are sufficient, when field evidence must be added, and when uncertainty should prevent a spatial product from being treated as a decision threshold.

Institutional design is the final condition for interoperability. Data continuity depends on agencies and research programs preserving metadata, calibration records, processing versions, and field-reference networks beyond individual projects. The evidence base shows that many of the strongest studies are possible precisely because large observations were maintained across space or time: thousands of reefs, tens of thousands of validation points, or multi-decadal habitat records. Southeast Asian monitoring would gain more from durable, distributed validation infrastructure than from repeatedly replacing methods before a comparable time series is established. This institutional perspective also makes uncertainty actionable: products with moderate confidence can be used for screening, while high-consequence carbon accounting, restoration verification, or regulatory decisions can be routed to stronger validation tiers.

Several limitations define the appropriate interpretation of the findings. The 30-study corpus was purposively fixed to preserve the validated bibliography and does not represent an exhaustive database search, so frequency results describe the corpus rather than the entire field. Dominant evidence mode is necessarily a simplification for studies that combine multiple approaches, although the permutation result remained qualitatively stable under a broader multi-source coding sensitivity check. Numeric benchmarks were not pooled because their units, scales, and inference targets are heterogeneous. These limitations are also informative: they demonstrate why coastal monitoring should preserve methodological provenance and why cross-ecosystem synthesis is more defensible when it compares evidence architecture rather than forcing incompatible ecological outcomes into a common effect size.

CONCLUSION

The analysis shows that the principal challenge in Southeast Asian coastal monitoring is not a shortage of spatial data but a mismatch between what is directly observed and what is inferred. The 30-study corpus was dominated by mangrove and coral research, contained relatively little seagrass evidence, and showed a substantial association between ecosystem type and dominant evidence mode. Quantitative benchmarks ranged from highly accurate global mangrove mapping and multi-thousand-site coral datasets to national carbon estimates and thermal thresholds, yet each supported a different level of ecological inference. The resulting Observation–Inference Gap framework clarifies that map accuracy, spatial coverage, or algorithmic sophistication cannot substitute for field calibration, temporal continuity, process evidence, and uncertainty propagation when conclusions move toward ecosystem function or management outcomes.

A stronger regional monitoring system should therefore be organized as a tiered evidence architecture: spatial products for screening, field-calibrated indicators for diagnosis, temporally validated models for functional inference, and integrated uncertainty for decision use. Mangrove programs can build on mature extent products while strengthening below-ground and restoration-process validation; seagrass programs require disproportionate investment in baseline mapping and in-water calibration; coral programs should preserve the separation between thermal exposure and biological response. The framework allows these ecosystems to remain methodologically distinct while becoming operationally interoperable through common metadata, evidence-level labels, and decision rules. This approach provides a defensible path from remote observation to ecological management without overstating what any single dataset can establish.

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