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Artificial Intelligence for Socio-Ecological Resilience and Sustainable Resource Governance

Ayu Rimanda[1*], Prima Wira Nanda[2], Zakia Hary Nisa[3], Lilik Susilowati[4], Okky Merben[5]
[1,2,3,4,5]Department of Midwifery, Universitas Bhakti Pertiwi Indonesia, Indonesia
[1]rimandaayu6@gmail.com , [2]primawirananda30@gmail.com , [3]zakia.11tugas@gmail.com , [4]liliksusilowati31@gmail.com , [5]okkymerben@gmail.com
***Corresponding Author**

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ABSTRACT

Climate change, biodiversity loss, resource depletion, and increasingly volatile **environmental** conditions require governance systems that can move beyond retrospective monitoring toward anticipatory and adaptive action. Artificial intelligence (AI) offers relevant capabilities, but current environmental applications remain fragmented across sensing, prediction, **optimization**, and decision support. This study develops the AI-Enabled Socio-Ecological Resilience Framework (AI SERF) through a systematic literature review and qualitative conceptual synthesis of peer-reviewed studies published between January 2022 and June 2026. The reported review process screened 412 records and retained 73 studies for thematic synthesis. The revised **framework** links four functional pillars, namely Autonomous Eco Monitoring, Predictive Resource Optimization, Adaptive Algorithmic Governance, and Eco Resilient Feedback Loops, to absorptive, adaptive, and transformative resilience capacities. Its novelty lies not in proposing another isolated AI architecture, but in connecting data acquisition, predictive intelligence, human-supervised **governance**, ecological intervention, and learning within a single resilience-oriented cycle. The framework is operationalized through candidate data sources, AI models, governance actors, performance indicators, and responsible AI safeguards. Particular attention is given to explainability, energy and carbon efficiency, algorithmic bias, cyber-physical security, **institutional** capacity, and data limitations in tropical and archipelagic settings. The study provides a theoretically grounded and implementation-oriented basis for future empirical validation of **AI-enabled** environmental governance and clarifies its contribution to SDGs 9, 11, 13, 14, and 15.

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1. INTRODUCTION

Socio-ecological systems are increasingly exposed to interacting climatic, ecological, technological, and institutional disturbances. Resilience scholarship treats these systems as complex adaptive systems whose capacity to persist depends not only on the ability to absorb shocks but also on the ability to adapt and, where existing structures become untenable, transform [1]. Conventional environmental management remains indispensable, yet it is often constrained by intermittent field observations, fragmented databases, delayed reporting, and institutional decision cycles that can be slower than the dynamics of environmental change. These challenges directly relate to global sustainability priorities outlined in the Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land), which emphasize the need for improved climate adaptation, ecosystem protection, biodiversity conservation, and sustainable resource management. Furthermore, strengthening digital infrastructure and innovation capabilities through SDG 9 (Industry, Innovation and Infrastructure) and improving resilient urban and community systems through SDG 11 (Sustainable Cities and Communities) require advanced technological approaches that can support evidence-based environmental governance [2].

At the same time, AI, Internet of Things (IoT), edge computing, remote sensing, and digital twin technologies have expanded the technical possibilities for continuous environmental observation, high dimensional pattern recognition, forecasting, and scenario analysis. Recent reviews show rapidly growing AI adoption in environmental disciplines and sustainability research, ranging from air quality modelling and ecosystem monitoring to water, energy, waste, and urban systems [3]. AI-enabled urban and environmental systems increasingly combine sensing, analytics, and digital representations of physical systems, but their integration into governance processes remains uneven [4, 5].

This technological expansion does not automatically create resilience. AI can improve speed, scale, and predictive capability while simultaneously introducing opacity, computational energy demand, model bias, infrastructure dependency, and new cyber-physical risks. Sustainability therefore requires evaluation of both AI for sustainability and the sustainability of AI itself. Green AI research emphasizes computational efficiency and transparent reporting of resource use, while responsible AI scholarship stresses governance, accountability, and impact assessment [6–8].

1.1. Research Gap and Novelty

The literature can be organized into three partially overlapping streams. First, environmental AI studies demonstrate technical performance in sensing, classification, forecasting, and optimization. Second, sustainability and smart city research increasingly integrates AI, AIoT, and digital twins into data-driven planning. Third, responsible AI and Green AI research addresses transparency, fairness, energy use, and governance [9]. These streams are valuable, but they do not consistently explain how AI capabilities translate into distinct socio - ecological resilience capacities and then into accountable environmental action.

AI SERF addresses this gap through a resilience-oriented governance architecture. Its central theoretical contribution is a mapping between four functional AI governance stages and three resilience capacities: monitoring and rapid detection primarily strengthen absorptive capacity; prediction and resource optimization primarily strengthen adaptive capacity; and governance redesign, institutional learning [10], and feedback supported reconfiguration can enable transformative capacity. The framework also treats human oversight, ecological constraints, and responsible AI safeguards as cross-cutting design requirements rather than optional add ons. This differentiates AI SERF from technology-centric environmental AI models that end at prediction, from digital twin models that may not include accountable governance, and from responsible AI frameworks that are not tailored to socio -ecological system dynamics [11].

1.2. Research Questions and Objectives

- **RQ1.** How can AI capabilities be organized into a resilience-oriented conceptual architecture for sustainable resource governance?
- **RQ2.** How do the four AI-SERF pillars contribute to absorptive, adaptive, and transformative socio-ecological resilience?
- **RQ3.** Which technical, institutional, ethical, and environmental safeguards are required for responsible implementation, particularly in tropical and archipelagic contexts?

Accordingly, the study aims to develop and theoretically position AI-SERF, operationalize its four pillars into measurable implementation components, compare AI-enabled and conventional environmental management configurations using evidence-based criteria, and specify practical governance, SDG, and responsible-AI implications. Furthermore, this study seeks to establish a comprehensive conceptual foundation that explains how AI-driven environmental systems can integrate technical intelligence, adaptive governance, and resilience-oriented mechanisms to support sustainable decision-making [12]. The proposed framework also provides a structured pathway for evaluating AI implementation beyond computational performance by considering transparency, accountability, ecological effectiveness, and long-term sustainability outcomes.

2. THEORETICAL FOUNDATION AND LITERATURE SYNTHESIS

2.1. Socio-Ecological Resilience as the Theoretical Anchor

Socio-ecological resilience concerns the capacity of linked human and ecological systems to maintain essential functions while responding to disturbance and change. For this study, resilience is operationalized through three capacities [13]. Absorptive capacity refers to sustaining critical functions and limiting immediate damage during shocks. Adaptive capacity concerns incremental adjustment of practices, allocation rules, and system behavior in response to changing conditions. Transformative capacity refers to more fundamental reconfiguration of institutions, infrastructures, or resource-use patterns when existing arrangements are no longer viable. AI-SERF uses these capacities as theoretical outcomes rather than treating resilience as a generic synonym for [14].

2.2. AI Capabilities in Environmental Governance

AI contributes to environmental governance through a chain of capabilities rather than a single model class. Computer vision and spatial AI can extract environmental signals from satellite, drone, and field imagery. Time series and machine-learning models can forecast hazards, demand, and ecosystem conditions [15]. Optimization and decision-support models can compare interventions under multiple constraints. Digital twins can integrate observations with dynamic models to support scenario exploration and, in more mature deployments, bidirectional interaction with physical systems [16]. The practical value of these capabilities depends on data quality, interoperability, local ecological knowledge, institutional readiness, and the availability of qualified human decision-makers.

2.3. Positioning AI-SERF Against Existing Approaches

To position the proposed AI-Enabled Socio-Ecological Resilience Framework (AI-SERF), this study compares it with existing approaches, including Environmental AI, AIoT-based frameworks, digital twin models, and green and responsible AI frameworks. The comparison highlights their main contributions, limitations, and how AI-SERF extends previous approaches by integrating AI capabilities, governance mechanisms, and socio-ecological resilience principles [17].

Table 1. Theoretical positioning and novelty.

Approach	**Primary focus**	**Established strength**	**Remaining limitation**	**AI-SERF contribution**
Environmental AI application reviews	AI models for prediction, classification, and optimization	Strong technical breadth	Limited linkage between AI outputs, governance, and resilience capacities	Adds resilience mapping and governance cycle
AIoT and smart eco-city frameworks	Integrated sensing, connectivity, and analytics	System integration and urban sustainability	Often technology-centric, while ecological governance remains implicit	Adds socio-ecological and cross-scale governance logic
Digital-twin environmental models	Dynamic virtual representations and scenario analysis	Real-time integration and system simulation	Many implementations remain predictive rather than decision-to-action closed loops	Defines feedback and authorized intervention as a distinct pillar
Green and responsible AI frameworks	Efficiency, transparency, accountability, and impact assessment	Strong safeguards for AI design and deployment	Not commonly structured around environmental resilience mechanisms	Embeds safeguards across four environmental-governance pillars
AI-SERF	Monitoring $\rightarrow$ prediction $\rightarrow$ governance $\rightarrow$ intervention $\rightarrow$ learning	Resilience-oriented closed-loop architecture	Conceptual framework requiring empirical validation	Links AI functions, human oversight, resilience capacity, and measurable implementation components

Table 1 presents that existing approaches provide valuable contributions in AI-based prediction, sensing, simulation, and responsible AI practices. However, most approaches remain limited in connecting AI outputs with governance processes and resilience development. AI-SERF addresses this gap by integrating monitoring, prediction, governance, intervention, and learning into a closed-loop framework. This framework further combines technical AI capabilities with human oversight, ecological considerations, and responsible AI safeguards to support sustainable environmental governance [18].

3. METHODOLOGY

This study employs qualitative conceptual research supported by a Systematic Literature Review (SLR) to develop a theoretically grounded framework for AI-enabled socio-ecological resilience. The purpose of this research is theory building and conceptual integration rather than testing a specific algorithm or collecting primary field data. The SLR approach was applied to systematically identify, evaluate, and synthesize relevant peer-reviewed studies related to artificial intelligence, sustainable resource governance, environmental resilience, and responsible AI implementation. The literature selection process involved database searching, screening, quality assessment, and thematic synthesis, resulting in a final corpus of 73 relevant studies from an initial set of 412 records. The selected studies were analyzed through conceptual coding to identify key relationships among AI capabilities, environmental governance functions, resilience capacities, and implementation challenges. The synthesis process was used to transform fragmented research findings into the proposed AI-Enabled Socio-Ecological Resilience Framework (AI-SERF), which integrates environmental monitoring, predictive optimization, algorithmic governance, and feedback learning mechanisms. This methodological approach enables the study to establish a comprehensive conceptual foundation that connects technological capabilities with socio-ecological resilience outcomes while incorporating responsible AI considerations, including explainability, energy efficiency, cybersecurity, and human oversight [19].

3.1. Search and Screening Protocol

The source manuscript reports searches in Scopus and Web of Science covering January 2022 to June 2026 using the Boolean structure: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Sustainable Resource Management" OR "Environmental Resilience") AND ("Framework" OR "Governance"). The initial search yielded 412 records. Title and abstract screening excluded 215 records that lacked an environmental context or treated sustainability only as a corporate finance outcome [20]. Full text assessment of 197 records then excluded 124 studies that did not meet the stated conceptual relevance or publication quality criteria, leaving a final synthesis corpus of 73 studies.

Because the underlying article level extraction sheet was not included in the submitted manuscript, this revision does not invent study level coding data. Instead, it clarifies the coding logic that should be applied to the reported 73 study corpus and presents transparent categories that can be populated from the authors' review database during final submission [21, 22].

3.2. Coding and Thematic Synthesis

Each retained study is conceptually coded across four dimensions: (1) environmental data source and sensing modality; (2) AI functional role, such as detection, prediction, optimization, decision support, or automated control; (3) governance function, including information provision, policy choice, resource allocation, intervention, or evaluation; and (4) resilience contribution, classified as absorptive, adaptive, transformative, or mixed. A fifth crosscutting code records implementation risks and safeguards, including explainability, energy use, bias, cybersecurity, interoperability, institutional capacity, and human oversight [23].

The framework is then derived through a staged thematic synthesis. Open codes describing similar AI functions are consolidated into functional categories. Categories are compared for sequencing and dependence, producing a process structure from environmental observation to analysis, governance, intervention, and learning. The four recurrent functions are labelled Autonomous Eco Monitoring, Predictive Resource Optimization, Adaptive Algorithmic Governance, and Eco-Resilient Feedback Loops [24, 25]. The resulting architecture is then checked against the three resilience capacities to ensure that each pillar has a theoretically interpretable contribution rather than functioning as a purely technical layer [26].

3.3. Comparative Analysis Criteria

The comparison between conventional and AI-enabled environmental management is treated as a conceptual benchmark, not as an empirical performance test [27, 28]. Criteria are limited to dimensions supported by the literature: observation latency, data integration, spatial and temporal scalability, decision support capability, failure modes, and computational or organizational dependencies [29, 30]. Claims are therefore expressed conditionally for example, AI-enabled systems can reduce monitoring latency when continuous sensing and reliable connectivity are available rather than as universal performance guarantees [31].

4. RESULTS AND DISCUSSION

The revised SLR and conceptual synthesis pipeline used to develop the AI-Enabled Socio-Ecological Resilience Framework (AI-SERF). The process begins with literature identification from Scopus and Web of Science, followed by screening, quality assessment, and conceptual coding of relevant studies. The selected studies were then analyzed through thematic synthesis to identify key AI functions, governance mechanisms, and resilience contributions, resulting in the construction of the proposed AI-SERF framework.

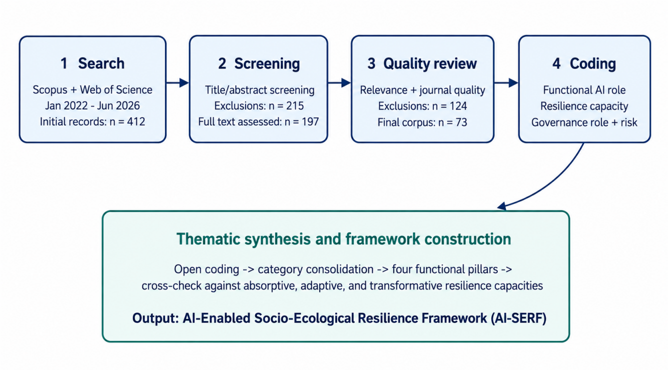

Figure 1. SLR and pipeline for AI-SERF development.

As shown in Figure 1 the pipeline demonstrates how the reviewed literature was systematically transformed from individual research findings into integrated conceptual components. Through this process, the study identified four main functional pillars of AI-SERF: Autonomous Eco-Monitoring, Predictive Resource Optimization, Adaptive Algorithmic Governance, and Eco-Resilient Feedback Loops, which collectively support absorptive, adaptive, and transformative resilience capacities.

4.1. Revised AI-SERF Architecture

AI-SERF is organized as a closed-loop socio-technical governance cycle. Environmental observations enter the system through heterogeneous sensing infrastructures. AI models transform these observations into estimates, forecasts, risk maps, and scenarios. Governance actors interpret and validate these outputs, select interventions under ecological and social constraints, and authorize actions. Outcomes are subsequently observed, compared with expected effects, and used to update models, policies, and intervention rules. Human oversight is therefore present at the governance and intervention stages and can also constrain data collection, model use, and automated actuation.

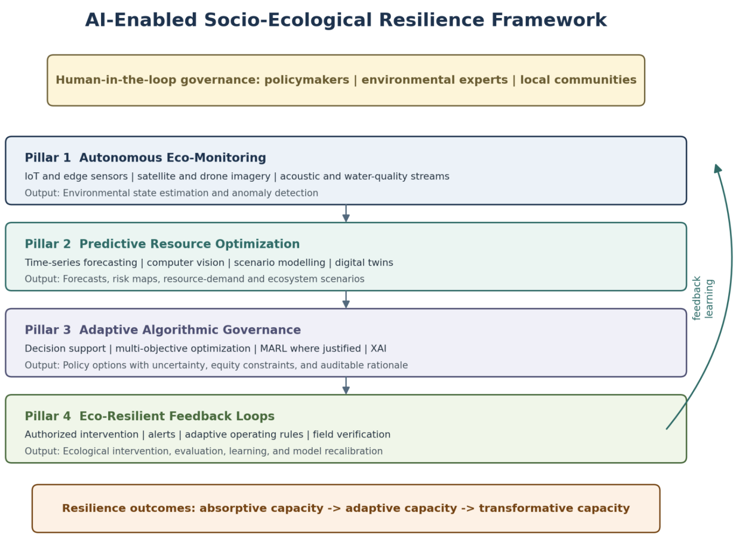

Figure 2. AI-SERF information flow.

As shown in Figure 2 the information flow of the AI-Enabled Socio-Ecological Resilience Framework (AI-SERF), illustrating how environmental data are transformed into governance decisions, ecological interventions, and continuous learning processes. The framework begins with Pillar 1 Autonomous Eco-Monitoring, where IoT and edge sensors, satellite observations, drone imagery, and environmental monitoring systems collect real-time ecological information for state estimation and anomaly detection. These observations are processed in Pillar 2 Predictive Resource Optimization, where time-series forecasting, computer vision, scenario modelling, and digital twin approaches generate forecasts, risk maps, and resource management scenarios. The outputs are then integrated into Pillar 3 Adaptive Algorithmic Governance, where decision-support mechanisms, multi-objective optimization, explainable AI (XAI), and human oversight support the selection of policy options while considering ecological, legal, and social constraints. Finally, Pillar 4 Eco-Resilient Feedback Loops enables authorized interventions, field verification, adaptive rule adjustment, and model recalibration by incorporating outcomes back into the system. Through this closed-loop process, AI-SERF connects technological capabilities with governance actions and strengthens absorptive, adaptive, and transformative socio-ecological resilience capacities.

Table 2. Technical and governance operationalization.

Pillar	Data Infrastructure	AI and Analytics Approach	Operational Outcome	Evaluation Indicators	Resilience Role
Autonomous Eco-Monitoring	IoT sensors, satellite imagery, drones, acoustic monitoring, and water-quality observation systems	Computer vision models, anomaly detection, and edge inference methods	Real-time ecosystem estimation, environmental alerts, and anomaly visualization	Detection delay, false alarm rate, coverage area, and sensor availability	Absorptive
Predictive Resource Optimization	Historical and streaming ecological, climate, hydrological, energy, and land-use datasets	Machine learning forecasting, deep learning models, digital twins, and optimization techniques	Prediction results, scenario analysis, and resource allocation recommendations	Forecast accuracy, uncertainty estimation, resource efficiency, and decision lead time	Absorptive and Adaptive
Adaptive Algorithmic Governance	Model outputs combined with regulations, ecological constraints, budget limitations, and stakeholder requirements	Multi-objective optimization, explainable AI, and reinforcement learning when applicable	Prioritized policy alternatives with uncertainty analysis and decision justification	Decision transparency, constraint compliance, fairness evaluation, and expert validation	Adaptive and Transformative
Eco-Resilient Feedback Loops	Authorized intervention records with continuous post-action environmental monitoring	Adaptive control mechanisms, causal evaluation, rule adjustment, and model updating	Operational alerts, intervention strategies, and continuously improved AI models	Recovery time, ecosystem response, unintended impacts, and learning effectiveness	Absorptive, Adaptive, and Transformative

Table 2 presents the technical and governance operationalization of the proposed AI-Enabled Socio-Ecological Resilience Framework (AI-SERF). The technical and governance operationalization of the proposed Green Artificial Intelligence framework by describing the integration between data infrastructure, AI and analytics capabilities, operational outcomes, evaluation indicators, and resilience contributions across four main pillars. The Autonomous Eco-Monitoring pillar enables real-time environmental observation through IoT sensors, satellite imagery, drones, and ecological monitoring systems supported by AI-based detection and inference methods to improve early anomaly identification and ecosystem awareness. The Predictive Resource Optimization pillar utilizes historical and streaming ecological datasets combined with machine learning, deep learning, and digital twin approaches to generate predictive insights, optimize resource allocation, and enhance adaptive decision-making. The Adaptive Algorithmic Governance pillar ensures that AI-driven decisions remain transparent, explainable, and aligned with ecological constraints through optimization techniques, explainable AI, and reinforcement learning mechanisms. Meanwhile, the Eco-Resilient Feedback Loops pillar establishes continuous learning and system improvement by incorporating intervention records, adaptive control strategies, causal evaluation, and model updating processes. Collectively, these pillars demonstrate how Green AI can strengthen ecological resilience by improving the ability to absorb disturbances, adapt to changing conditions, and transform operational strategies through intelligent, sustainable, and governance-aware decision-making.

4.2. Interaction Mechanisms Among the Pillars

The pillars are interdependent rather than modular in isolation, forming an integrated cyber-physical governance architecture in which each component continuously supports and reinforces the others. Pillar 1 establishes the foundational observational layer by collecting, processing, and validating environmental information to determine whether ecological changes can be detected with sufficient spatial coverage, temporal resolution, and measurement reliability. The effectiveness of subsequent pillars depends strongly on the quality, consistency, and accessibility of these observations, as incomplete or biased sensing may propagate uncertainty throughout the decision process. Pillar 2 transforms multi-source observations into anticipatory knowledge through predictive analytics, forecasting mechanisms, and scenario exploration. However, its outputs must explicitly communicate uncertainty levels, data limitations, model assumptions, and potential prediction errors to prevent overreliance on algorithmic recommendations. Pillar 3 functions as the institutional decision interface where analytical insights are translated into actionable governance strategies. Rather than replacing human authority, this pillar integrates predictive outputs with legal mandates, ecological thresholds, financial constraints, ethical considerations, equity requirements, and stakeholder knowledge to ensure that decisions remain contextually appropriate and socially accountable. Pillar 4 represents the operational execution layer, where only authorized interventions are implemented and continuously evaluated based on their ecological, social, and operational consequences. The outcomes generated from these interventions are not treated as final results but as additional learning resources that improve future system performance. Feedback from Pillar 4 is therefore returned to Pillars 1 and 2 through updated observations, improved datasets, and model recalibration, while also informing Pillar 3 through policy evaluation and governance refinement. This continuous interaction creates an adaptive learning loop that enables the AI-SERF framework to evolve dynamically in response to changing environmental conditions, emerging risks, and long-term sustainability objectives.

Table 3. Comparison of Conventional and AI-Driven Environmental Systems

Comparative Metric	Conventional Management	AI-Driven Framework (AI-SERF)	Resilience Impact
Operational Latency	High (Weeks to Months): Relies on manual field sampling, laboratory processing, and retrospective bureaucratic review.	Low (Real-Time to Hours): Employs edge computing, automated satellite telemetry processing, and continuous stream ingestion.	Rapid detection prevents minor ecological disturbances from cascading into irreversible systemic collapses.
Data Integration & Synthesis	Fragmented & Linear: Relies on siloed spreadsheet structures, isolated GIS layers, and historical statistical averages.	Holistic & Multi-Modal: Synthesizes heterogeneous, high-velocity data including IoT data, unstructured images, and audio.	Captures non-linear feedback loops and complex cross-boundary dependencies across ecosystems.
Scalability & Spatial Granularity	Localized & Macro-Scale:Confined to localized pilot regions or overly generalized macro-national metrics.	Hyper-Local to Global: Scalable across vast geographic biomes while maintaining high pixel-level granularity.	Enables simultaneous macro-governance and precision micro-interventions across diverse territories.
Systemic Failure Vulnerability	Bureaucratic Inertia: Prone to human communication failure, political delays, and analytical blind spots.	Technological Fragility: Susceptible to sensory degradation, adversarial data corruption, and network blackouts.	Requires hybrid, human-in-the-loop fail-safes to mitigate physical security and software vulnerabilities.
Resource Dependency Profile	High Labor, Low Energy:Dependent on extensive field personnel, physical travel, and manual infrastructure.	High Compute, High Energy:Dependent on specialized hardware, rare-earth metals, and continuous data center power.	Introduces the “carbon-irony” paradox, necessitating green computing architectures to ensure net sustainability.

Table 3 presents a comparison between conventional and AI-driven environmental systems. This interaction resolves a major ambiguity in the original framework: AI-SERF does not equate algorithmic governance with autonomous government. Instead, the framework positions AI as an analytical and decision-support infrastructure that enhances evidence-based environmental governance without replacing human authority and institutional accountability. Algorithmic systems organize complex environmental data, identify patterns, generate predictive insights, evaluate scenarios, and support decision alternatives, while accountable human institutions retain responsibility for decisions involving legal requirements, distributive impacts, safety concerns, ethical considerations, and ecological consequences. Automation may be appropriate for bounded operational controls with clearly defined objectives and risk levels, such as environmental monitoring, anomaly detection, and resource optimization; however, escalation thresholds, audit mechanisms, and override procedures must remain explicitly established to ensure responsible deployment. By balancing computational intelligence with human-centered governance, AI-SERF enables organizations to leverage AI capabilities while preserving transparency, accountability, and adaptive decision-making in complex environmental systems.

4.3. Conventional and AI-Enabled Environmental Management

The comparison between conventional and AI-enabled environmental management configurations highlights the differences in operational characteristics, data processing capabilities, decision mechanisms, and resource requirements. Rather than assuming that AI-based systems universally outperform conventional approaches, this comparison considers the contextual conditions that influence system effectiveness, including sensing availability, data quality, institutional capacity, and technological maturity. The evaluation focuses on several critical criteria, including observation latency, data integration, scenario capability, decision processes, failure profiles, and resource dependency, to provide a balanced understanding of the potential benefits and limitations of AI-enabled environmental management.

Table 4. Comparison of Environmental Management Approaches

Criterion	Conventional Configuration	AI-Enabled Configuration	Evidence Basis
Observation latency	Often periodic because field sampling and reporting are scheduled	Can approach near-real-time when continuous sensing, edge processing, and connectivity are available	[3,4]
Data integration	May depend on separate databases, GIS layers, and institutional reporting chains	Can fuse heterogeneous sensor, image, text, and model data, but interoperability remains a major constraint	[5,6]
Scenario capability	Frequently uses static or periodic modelling and expert review	Can support continuously updated forecasts and digital-twin scenarios where models and data are mature	[6,12]
Decision process	Human-led and institutionally accountable, but potentially slow and information-limited	AI can accelerate analysis and option generation; accountability still requires human governance	[8,11]
Failure profile	Vulnerable to sampling gaps, organizational silos, and delayed coordination	Adds sensor drift, model error, cyber risk, connectivity failure, and automation dependence	[6,8]
Resource dependency	Higher dependence on field labor and administrative coordination	Higher dependence on compute, energy, hardware, data infrastructure, and specialized skills	[7,9]

Table 4 presents above demonstrates that AI-enabled environmental management provides enhanced capabilities in real-time observation, heterogeneous data integration, predictive scenario analysis, and accelerated decision support. However, these advantages are accompanied by new dependencies on computational resources, data infrastructure, connectivity reliability, and governance mechanisms. Conventional approaches remain valuable due to their interpretability, institutional familiarity, and lower technological complexity, although they may face limitations in scalability and responsiveness. Therefore, the integration of AI should not be viewed as a complete replacement for conventional environmental management but as an augmentation strategy that combines advanced analytics with human expertise, institutional oversight, and adaptive governance to strengthen long-term environmental resilience.

5. RESPONSIBLE AI AND REAL WORLD IMPLEMENTATION

5.1. Explainability Human Oversight and Accountability

Environmental decisions can redistribute access to critical resources, including water, land, energy, conservation areas, and other public environmental assets, thereby creating potential social, economic, and ecological consequences across different stakeholder groups. For this reason, predictive accuracy alone is insufficient as the primary measure of AI system effectiveness. AI-SERF requires decision-level transparency through interpretable or explainable outputs, comprehensive documentation of model assumptions and limitations, explicit uncertainty reporting, auditable decision trails, and clearly assigned institutional responsibility to ensure accountable governance. Human-in-the-loop governance should involve not only technical experts but also domain specialists, policymakers, local communities, and relevant public actors, particularly when AI-supported decisions influence livelihoods, customary resource practices, vulnerable populations, or issues related to environmental justice. Furthermore, AI impact assessment provides a practical governance mechanism for systematically evaluating anticipated benefits, potential risks, affected stakeholder groups, mitigation strategies, ethical considerations, and post-deployment monitoring requirements. Through these mechanisms, AI-SERF ensures that algorithmic capabilities are integrated within a responsible governance structure that balances technological innovation with fairness, accountability, and long-term ecological sustainability.

5.2. Green AI and Net Sustainability

AI can create a sustainability paradox if the computational, storage, cooling, and hardware requirements associated with developing and operating intelligent systems generate environmental impacts that exceed the ecological benefits achieved through improved monitoring, prediction, and resource management. Therefore, Green AI principles become an essential design criterion within AI-SERF to ensure that technological advancement remains aligned with sustainability objectives rather than introducing additional environmental burdens. The implementation of Green AI requires consideration of the entire AI lifecycle, including model development, deployment, maintenance, infrastructure utilization, and eventual system replacement. Relevant mitigation strategies include right-sizing model complexity according to operational needs, applying edge processing when it can reduce unnecessary data transmission and cloud dependency, adopting sparse or compressed models to minimize computational demands, implementing energy-aware scheduling mechanisms, reporting energy consumption and carbon emissions, conducting lifecycle assessments, and prioritizing lower-carbon computing infrastructure whenever technically and economically feasible. In addition, AI-SERF evaluation should incorporate both ecological performance indicators, such as resource efficiency, emission reduction, and ecosystem improvement, and computational sustainability indicators, including energy consumption, processing efficiency, hardware utilization, and carbon footprint. By adopting a balanced evaluation approach, AI systems can maximize environmental benefits while minimizing their own operational impacts, ensuring that AI-driven environmental management contributes to genuine long-term sustainability rather than creating new forms of resource dependency.

5.3. Bias Data Sovereignty and Cyber-Physical Security

Environmental AI can reproduce spatial and institutional inequality when models are trained on data-rich regions and transferred to under-monitored ecosystems. Local calibration, uncertainty-aware transfer learning, physics-informed modelling, and incorporation of validated local ecological knowledge can reduce but not eliminate this risk. Data-governance rules should clarify ownership, access, retention, community rights, and cross-agency sharing. For cyber-physical systems, defense-in-depth is required: authenticated sensors, network segmentation, anomaly detection, secure update mechanisms, manual fallback procedures, and explicit human override for consequential actuators.

Table 5. Responsible-AI and implementation safeguards integrated into the framework.

Risk domain	Why it matters	Practical mitigation within AI-SERF
Black-box decisions	Opaque model rationale can undermine trust and accountability	Use interpretable models where feasible; XAI; uncertainty reporting; audit logs; human approval
Compute and carbon burden	Training/inference may increase energy and lifecycle impacts	Model efficiency metrics; edge/efficient inference; workload scheduling; lower-carbon infrastructure; lifecycle accounting
Bias and spatial data inequality	Data-rich regions may dominate model performance	Local validation; transfer learning with uncertainty; community and expert review; minimum-data quality thresholds
Cyber-physical vulnerability	Compromised sensors or controls can create physical harm	Zero-trust principles; sensor authentication; segmentation; fail-safe states; manual override; incident response
Institutional capacity	Agencies may lack skills, maintenance budgets, and procurement capacity	Phased adoption; interdisciplinary teams; capacity building; service-level and maintenance planning
Interoperability	Fragmented formats and agencies can prevent end-to-end integration	Open standards; shared metadata; API governance; common geospatial and temporal identifiers

Table 5 presents that responsible AI implementation within AI-SERF requires a comprehensive governance approach addressing technical performance, ethical considerations, operational challenges, and institutional risks. The identified safeguards highlight that transparency, accountability, and security must be embedded throughout the AI lifecycle, from data acquisition and model development to deployment and continuous monitoring. While explainable models, uncertainty reporting, and audit mechanisms strengthen decision accountability, measures such as local validation, community involvement, and bias-aware data practices are necessary to prevent unequal environmental outcomes. Furthermore, cyber-physical security measures, including authenticated sensing, network protection, secure update mechanisms, and human override capabilities, are essential to maintain system reliability under adverse conditions. The framework emphasizes that responsible AI is achieved not only through algorithmic improvement but also through technical safeguards, institutional capacity, stakeholder participation, and adaptive governance to enhance environmental intelligence while maintaining trust, resilience, fairness, and sustainability.

5.4. Tropical and Archipelagic Application Contexts

Tropical and archipelagic regions provide a demanding but strategically important context for AI-SERF. High biodiversity, rapid land-use change, intense rainfall variability, coastal exposure, coral and mangrove ecosystems, dispersed islands, and uneven connectivity create both monitoring needs and implementation constraints. In these settings, Pillar 1 may combine satellite observation with low-power edge sensing and targeted drone surveys to reduce dependence on dense terrestrial networks. Pillar 2 can support flood, drought, wildfire, coastal, fisheries, and ecosystem-risk forecasting, but models require local calibration because imported training data may not capture tropical phenology or island-scale microclimates. Pillar 3 should integrate national and local governance, scientific expertise, and community knowledge, while Pillar 4 should prioritize reversible or supervised interventions where communication links are intermittent.

The framework is therefore particularly relevant to archipelagic governance because it supports distributed sensing and multi-scale decision support without assuming uniform infrastructure. However, implementation should begin with bounded use cases for example mangrove change detection, watershed early warning, coastal water quality monitoring, or urban heat risk mapping before progressing toward automated cyber-physical intervention.

6. MANAGERIAL IMPLICATIONS

For environmental agencies and resource managers, AI-SERF provides a staged adoption pathway. Organizations can begin with monitored decision support rather than immediate automation: establish reliable environmental data flows, validate forecasting models, create interpretable decision interfaces, and only then consider bounded feedback automation. This progression reduces institutional risk and creates evidence for whether additional automation adds resilience rather than merely technical complexity. Policy frameworks should define minimum requirements for data quality, model documentation, uncertainty communication, accountability, cybersecurity, environmental footprint reporting, and human override. Regulatory sandboxes can be useful for testing high-impact AI applications under controlled conditions. Shared environmental-data infrastructures and open standards can reduce duplication across agencies, but access rules must protect sensitive ecological, community, and infrastructure information. For tropical and archipelagic countries, investment priorities should emphasize robust low-power sensing, satellite integration, interoperable geospatial infrastructure, local model validation, and workforce capability. A high-compute digital twin is not necessarily the most appropriate first step; a smaller, auditable model with reliable data and clear institutional ownership may deliver greater net resilience.

7. CONCLUSION

This study reframes AI-enabled environmental management as a socio-ecological governance challenge rather than merely a technological problem focused on isolated algorithms. Through systematic literature synthesis, the study developed the AI-Enabled Socio-Ecological Resilience Framework (AI-SERF), which integrates four interconnected pillars: Autonomous Eco-Monitoring, Predictive Resource Optimization, Adaptive Algorithmic Governance, and Eco-Resilient Feedback Loops. These pillars establish a continuous information-to-action cycle connecting environmental sensing, predictive intelligence, institutional decision-making, ecological intervention, and adaptive learning. The main theoretical contribution of AI-SERF lies in explicitly linking AI capabilities with absorptive, adaptive, and transformative resilience capacities, thereby extending existing environmental AI approaches that often emphasize technical performance without fully addressing governance and resilience mechanisms.

AI-SERF further establishes a governance-oriented implementation logic in which AI functions as a decision-support capability rather than an autonomous decision-maker. Each pillar can be operationalized through appropriate data infrastructures, AI and analytical approaches, operational outputs, and measurable indicators, while responsible-AI safeguards are incorporated across the system. The framework emphasizes explainability, uncertainty management, cybersecurity, fairness, human oversight, and institutional accountability as essential conditions for responsible environmental AI deployment. Green AI is also positioned as a design criterion to address computational energy, infrastructure, and lifecycle impacts, ensuring that improvements in environmental management do not generate disproportionate technological burdens. This perspective is particularly relevant to complex tropical and archipelagic environments, where heterogeneous ecosystems, uneven data availability, geographic dispersion, and diverse governance arrangements require locally adaptive implementation strategies.

From a practical perspective, AI-SERF provides policymakers, environmental agencies, and resource managers with a structured basis for progressively developing AI-enabled environmental systems, beginning with reliable data infrastructures and validated predictive capabilities before advancing toward transparent decision interfaces and controlled feedback mechanisms. The framework also clarifies that AI adoption should complement rather than replace conventional environmental management, with the appropriate configuration depending on sensing availability, data quality, institutional capacity, and technological maturity. Nevertheless, the study remains conceptual and requires empirical validation through real-world deployments, comparative case studies, and quantitative assessment of resilience outcomes. Future research should therefore examine the performance of AI-SERF across different ecological contexts, governance structures, and levels of technological maturity, while evaluating whether its integrated approach can produce measurable improvements in environmental resilience, responsible resource governance, and long-term ecological sustainability.

8. DECLARATIONS

8.1. About Authors

Ayu Rimanda (AR) https://orcid.org/0009-0004-5747-8379

Prima Wira Nanda (PN) https://orcid.org/0009-0005-0583-8034

Zakia Hary Nisa (ZN) https://orcid.org/0009-0003-2625-0518

Lilik Susilowati (LS) https://orcid.org/0009-0005-1081-7596

Okky Merben (OM) https://orcid.org/0009-0003-7936-5810

8.2. Author Contributions

Conceptualization: AR and PN; Methodology: AR and LS; Software: OM; Validation: PN and ZN; Formal Analysis: AR and ZN; Investigation: PN and LS; Resources: OM; Data Curation: ZN and OM; Writing–Original Draft Preparation: AR and ZN; Writing–Review and Editing: PN, LS, and OM; Visualization: LS and OM. All authors have read and agreed to the published version of the manuscript.

8.3. Data Availability Statement

The study is based on secondary literature. The article-level review database and coding matrix should be made available as supplementary material or from the corresponding author upon reasonable request.

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8.5. Declaration of Conflicting Interest

The authors declare that there are no competing interests, financial conflicts, or personal relationships that could have influenced the research, interpretation, or reporting of the findings presented in this manuscript.

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