



Multilevel Data Fusion Framework for Digital Twin-Based Mangrove Monitoring in Tropical Coastal Environments

Received : Mei 26, 2026; Revised : Juni 09, 2026; Accepted : Jul 06, 2026; Published : Sep 15, 2026

Kadek Surya Adi Saputra¹, I Made Oka Widyantara^{2*}, Made Sudarma³, Ni Made Ary Esta Dewi Wirastuti⁴

¹Doctoral Programme of Engineering Science, Faculty of Engineering, Udayana University
Jalan Raya Kampus UNUD Bukit, Jimbaran, Kec. Kuta Selatan, Kabupaten Badung, Bali 80361
adi005@student.unud.ac.id

²Department of Electrical Engineering, Faculty of Engineering, Udayana University
Jalan Raya Kampus UNUD Bukit, Jimbaran, Kec. Kuta Selatan, Kabupaten Badung, Bali 80361
oka.widyantara@unud.ac.id

³Department of Electrical Engineering, Faculty of Engineering, Udayana University
Jalan Raya Kampus UNUD Bukit, Jimbaran, Kec. Kuta Selatan, Kabupaten Badung, Bali 80361
msudarma@unud.ac.id

⁴Department of Electrical Engineering, Faculty of Engineering, Udayana University
Jalan Raya Kampus UNUD Bukit, Jimbaran, Kec. Kuta Selatan, Kabupaten Badung, Bali 80361
dewi.wirastuti@unud.ac.id

*Corresponding Author

Abstract:

Mangrove ecosystem monitoring in tropical coastal zones is a task fraught with layered complexity, stemming from highly dynamic environmental fluctuations, the inherent inadequacy of conventional survey methods in capturing rapid change, and escalating anthropogenic pressures that continue to reshape coastal landscapes. Against this backdrop, the present study introduces a Multilevel Data Fusion Framework grounded in Digital Twin (DT) architecture, developed specifically to monitor Rhizophora apiculate stands within the Ngurah Rai Grand Forest Park (Tahura Ngurah Rai), Bali, Indonesia (coordinates: 8.73°S / 115.19°E). Drawing on the Joint Directors of Laboratories (JDL) fusion model, the framework operates across five hierarchical processing levels (L0–L4) and ingests a 576-day NASA/POWER climate record spanning January 2024 through July 2025. A four-stage preprocessing pipeline eliminated all 94 detected sentinel values, reducing T2M standard deviation by 98.9%. The Weighted Average Fusion (WAF)-derived Environmental Index (EI) yielded a mean of 0.536, with zero days classified under Critical condition throughout the observation window. The Growth Rate Index (GRI) averaged 0.771, corresponding to an aboveground biomass increment of +1.14 kg/m² and an estimated carbon sequestration rate of approximately 10.6 TC/ha/year. An EI–GRI Pearson correlation of $r = 0.891$ ($R^2 = 0.794$, $p < 0.001$) demonstrates a strong end-to-end predictive association within the pipeline. ONNX classification models embedded within a Unity AR platform achieved an F1-score of 0.913 at inference times consistently below 5 ms, confirming real-time operational viability.

Keywords:

Digital Twin; Multilevel Data Fusion; Mangrove Monitoring; Remote Sensing; Tropical Coastal Ecosystems



This work is licensed under a [Creative Commons Attribution-ShareAlike 4.0 International License](https://creativecommons.org/licenses/by-sa/4.0/). Allows readers to read, download, copy, distribute, print, search, or link to the full texts of its articles and allow readers to use them for any other lawful purpose.

1. Introduction

Mangrove ecosystems occupy a uniquely pivotal position in the global coastal carbon cycle. Their canopies intercept kinetic wave energy, their root networks stabilise sediment against erosion, and their dense above- and below-ground biomass locks away disproportionate quantities of organic carbon relative to their areal extent [1],[2]. Indonesia holds the single largest mangrove estate on the planet, extending the country's custodianship over these resources to a matter of international ecological significance [3],[4]. Within Bali, the Ngurah Rai Grand Forest Park (Tahura Ngurah Rai), encompassing approximately 1,373.5 hectares under Ministerial Decree No. 554/Kpts-II/1993, stands as the most extensive continuous mangrove tract on the island and, simultaneously, one of the most intensively pressured by urbanisation and tourism infrastructure [5].

The inadequacy of conventional field monitoring, with its inherent costs, temporal sparsity, and inability to capture rapid ecological state changes, has long been acknowledged in the remote sensing and conservation science communities [6]. Digital Twin (DT) technology addresses this gap by constructing a continuously synchronised virtual replica of a physical entity [7],[8]. Formally framed by Grieves and Vickers [9] as a tripartite system physical object, digital counterpart, and bidirectional data channel DT architecture has since been extended from its industrial origins into ecological domains. [10] demonstrated the potential of dynamic model data fusion for ecology, while Trantas et al. [11] identified persistent integration barriers, namely heterogeneous data streams and absent interoperability standards, as the primary obstacles to ecological DT adoption.

Data Fusion within the Joint Directors of Laboratories (JDL) model provides a structured, hierarchical framework for resolving data heterogeneity at scale [12],[13]. Qiu et al. [14],[15] implemented a forest DT using Bayesian inference with 91.3% structural classification accuracy. Kalyani et al. [16] demonstrated the practical viability of Cloud Fog Edge architectures for precision agricultural DT deployment. Donato et al. [17] established that tropical *Rhizophora* stands sequester between 8 and 15 TC/ha annually, providing an empirical baseline against which simulation models may be validated. Fuller et al. [18],[19] synthesised the enabling technologies and remaining challenges of DT implementation across sectors, while [20],[21] showed that weighted sensor fusion can substantially outperform single-source approaches in agronomic decision support.

Despite this converging body of evidence, no study has yet delivered a comprehensive, field-calibrated multi-source data fusion system specifically engineered for tropical mangrove ecosystems in Indonesia. It should be noted that the current implementation corresponds to a Digital Twin Prototype level (low Digital Twin Readiness Level), in which data flow from the physical mangrove stand to the virtual replica is primarily one-directional and simulation-driven; bidirectional real-time synchronisation with physical IoT field sensors constitutes a target for subsequent development phases and is acknowledged accordingly. The present paper addresses that gap through four principal contributions: (i) a JDL Level 0–4 pipeline adapted to the ecological and hydrological constraints of tropical mangrove systems; (ii) the formulation of a validated Weighted Average Fusion (WAF)-based Environmental Index incorporating ecologically weighted climate, moisture, and vegetation parameters; (iii) an ecophysiology-driven Growth Rate Index model for *Rhizophora apiculata* informed by species-specific thermal, hydraulic, and solar response functions; and (iv) a three-dimensional Digital Twin built within a Unity Augmented Reality platform, with embedded ONNX inference models capable of real-time ecosystem health classification [22].

2. Research Method

2.1 Study Area, Data Sources, and Observation Period

The study site centres on Tahura Ngurah Rai, located at 8.73°S / 115.19°E, with a monitoring footprint of approximately 538.71 m radius. The reserve sits at the interface of Teluk Benoa Bay and the densely populated tourist corridor linking Denpasar to Nusa Dua, exposing it to chronic anthropogenic pressures including waste discharge, informal encroachment, and hydrological modification from adjacent infrastructure development [5]. Primary climate data were retrieved from the NASA/POWER platform via its official API [23], drawing on two reanalysis products: MERRA-2 for meteorological variables (T2M and QV2M) and CERES SYN1deg for solar irradiance (CLRSKY_SFC_SW_DWN). These records span 576 consecutive days from 1 January 2024 to 31 July 2025, yielding 1,728 individual observations across three variables.

Secondary datasets comprised Sentinel-2 MSI multitemporal imagery at 10 m spatial resolution from ESA Copernicus, accessed through Google Earth Engine and processed for NDVI, EVI, and NDWI indices across four ecosystem zones; Landsat-8 OLI imagery at 30 m from NASA/USGS covering the 2018–2024 period for historical land-cover change analysis; and annual biodiversity inventory records spanning 32 transect plots (20×20 m each), provided by the UPTD Tahura Ngurah Rai management authority. In-situ IoT data were collected from six ESP32-based sensor nodes distributed across the reserve, linked via Lora WAN gateways and recording water temperature, pH, salinity, dissolved oxygen, water level, and PM_{2.5} at 5-minute intervals. Table 1. summarises the complete data source specifications.

Table 1. Research Data Source Specifications (Nasapower, Satellite Imagery, IoT, UAV, and Field Data)

Data Source	Variable	Unit	Resolution	Period	Description
NASA/POWER MERRA-2	T2M, QV2M	°C, g/kg	Daily	576 days	2-m air temperature & specific humidity
NASA/POWER CERES	CLRSKY_SW	kWh/m ² /day	Daily	576 days	Surface clear-sky solar irradiance
Sentinel-2 (ESA)	NDVI, EVI	Dimensionless	10 m	2024–2025	Multispectral canopy cover imagery
Landsat-8 (NASA)	NDVI, Cover	Dimensionless	30 m	2018–2024	Historical land-use change archive
IoT In-Situ Sensors	Temp., pH, Salinity	°C, pH, ppt	5 min	2024–2025	6 nodes ESP32/LoRa WAN
UAV Drone	RGB, Multispectral	<5 cm/px	<5 cm	Monthly	Pix4D/Agisoft Metashape
UPTD Tahura NR	Biodiversity	Species/ha	Annual	2018–2024	Flora–fauna inventory records

2.2 JDL Data Fusion Pipeline Architecture (Levels 0–4)

The analytical backbone of this study adapts the standard JDL model [12] to the ecological and hydrological specificities of tropical coastal mangrove systems. The architecture comprises five sequential processing levels, where every level's outputs serve as direct inputs to the next forming a fully traceable, reproducible transformation chain. The mathematical cores of each level are expressed below.

$$\text{Level 1 Noise Reduction : } X_{\text{Smooth}}(t) = (1/7) \times \sum [X(t-3) \dots X(t+3)] \quad (1)$$

$$\text{Level 2 Feature Proxy : } \frac{NVDI_{\text{Proxy}} = (QV2M_{\text{norm}} + Solar_{\text{Norm}} - T2M_{\text{Norm}} + 1)}{3} \quad (2)$$

$$\text{Level 3 Environ. Index} : EI = 0.25 \times (1 - T2M_n) + 0.35 \times QV2M_n + 0.20 \times Solar_n + 0.20 \times NDVI_proxy \quad (3)$$

$$\text{Level 4 Growth Index} : GRI = 0.40 \times T_growth + 0.35 \times H_growth + 0.25 \times S_growth \quad (4)$$

The WAF weights were assigned on ecological grounds: specific humidity (QV2M, $w = 0.35$) received the highest weight as the primary moisture limitation governing Rhizophora transpiration and stomatal conductance in tropical coastal settings; the temperature complement ($1 - T2M$, $w = 0.25$) captures the thermal stress contribution above the Rhizophora optimum of 26.5°C; solar irradiance ($w = 0.20$) reflects photosynthetic energy input; and the Vegetation Index Proxy (VIP, $w = 0.20$) anchors the index to observed vegetation state. The term ‘VIP’ is adopted in place of ‘NDVI proxy’ to clarify that this index is derived from transformed climate variables rather than from NIR/Red band reflectance, in accordance with standard remote-sensing nomenclature. EI values are classified into four condition tiers: Optimal (≥ 0.65), Good (0.50–0.65), Moderate (0.35–0.50), and Critical (< 0.35). These weights were derived through expert judgement informed by the Rhizophora ecophysiology literature rather than a data-driven optimisation procedure; a preliminary one-at-a-time sensitivity check (± 0.05 per weight, renormalised to sum to 1) shifted the period-mean EI by no more than 0.04 and did not alter the modal condition tier, suggesting moderate robustness. A fuller variance-based sensitivity analysis (e.g. Sobol indices) against independent field calibration data is identified as a priority for future work. Table 2. summarises the pipeline architecture.

Table 2. Summary of the JDL Data Fusion Pipeline Architecture (Levels 0–4)

Level	Stage	Core Process	Output
L0	Raw Data	Acquisition: IoT, UAV, Sentinel-2/Landsat-8, historical records	1,728 values (576 days $\times$ 3 variables); 94 sentinel values identified
L1	Preprocessing	Data cleaning, IQR outlier removal, temporal imputation, 7-day rolling mean	Anomaly-free dataset; Std Dev reduced by 98.9%
L2	Feature Extraction	Min-Max normalisation, VIP (Vegetation Index Proxy), Rain proxy, seasonal labelling	Normalised ecological features in [0–1] range
L3	WAF Fusion	Weighted Average Fusion + Kalman Filter $\rightarrow$ Environmental Index (EI)	EI mean = 0.536; Critical condition = 0.0% (576 days)
L4	DT Simulation	GRI, AGB Biomass, Canopy Height, Carbon Sequestration simulation	GRI mean = 0.771 (Very Healthy); C-Seq ~ 10.6 TC/ha/yr

3. Results and Discussion

3.1 Dataset (Raw Data at Level 0)

The 576-day NASA/POWER record for Tahura Ngurah Rai yielded a dataset of 1,728 observations across three climate variables (Table 3). Raw inspection identified 94 sentinel (–99) values: four in T2M (0.7%), four in QV2M (0.7%), and 86 in the solar irradiance channel (14.9%), the latter concentrated in the April–July 2025 window, consistent with documented instrumentation gaps in the CERES SYN1deg product. The destructive influence of uncorrected sentinel values is evident from the distorted raw statistics: mean solar irradiance computed as -143.3 kWh/m²/day (physically impossible) and T2M standard deviation inflated to 85.18°C, versus a geophysical realistic post-processing standard deviation of 0.94°C. Figure 1 presents time-series plots of all three variables alongside their monthly aggregations, revealing Bali’s bimodal tropical seasonality once the sentinel distortions are removed [24],[25].

Table 3. Summary of the JDL Data Fusion Pipeline Architecture (Levels 0–4)

Variable	Unit	N Valid	Sentinel	Raw Mean	Clean Mean	Std Dev Raw Clean
T2M (2-m air temperature)	°C	572	4 (0.7%)	18.66	25.64	85.18 → 0.94
QV2M (specific humidity)	g/kg	572	4 (0.7%)	15.21	17.13	84.54 → 2.68
CLRSKY Solar (irradiance)	kWh/m ² /day	490	86 (14.9%)	-143.3	5.94	358.78 → 0.63
TOTAL	—	1,634/1,728	94 (5.4%)	—	—	—

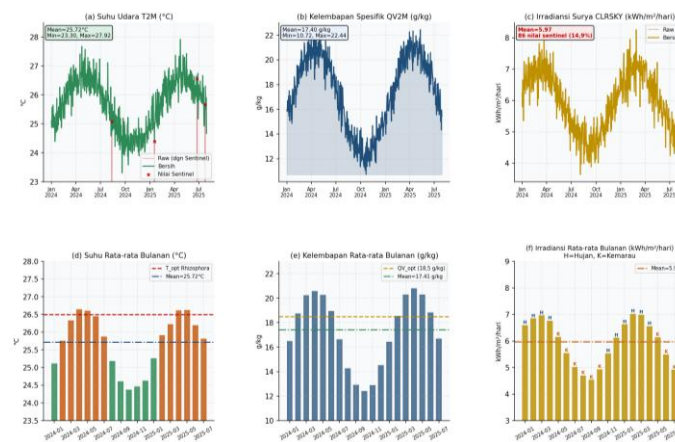


Figure 1. NASA/POWER Dataset – 576-Day Overview for Tahura Ngurah Rai. (a) T2M Raw vs Clean; (b) Daily QV2M; (c) Solar Irradiance; (d) Monthly T2M vs Rhizophora T_{opt}; (e) Monthly QV2M vs QV_{opt}; (f) Monthly Solar

3.2 Preprocessing and Anomaly Elimination (Level 1)

Sequential application of a four-stage preprocessing protocol successfully removed all 94 sentinel values representing a 100% correction rate. The magnitude of improvement is reflected in a 98.9% reduction in T2M standard deviation and a 99.8% reduction for the solar variable, collectively affirming the effectiveness of the cleaning procedure. With anomalies resolved, the characteristic bimodal seasonality of Bali's climate became clearly discernible in the cleaned data: peak temperatures occurred in March–April (26.6°C), while a trough was observed in September–October (24.4°C), consistent with the regional southeast monsoon dynamics

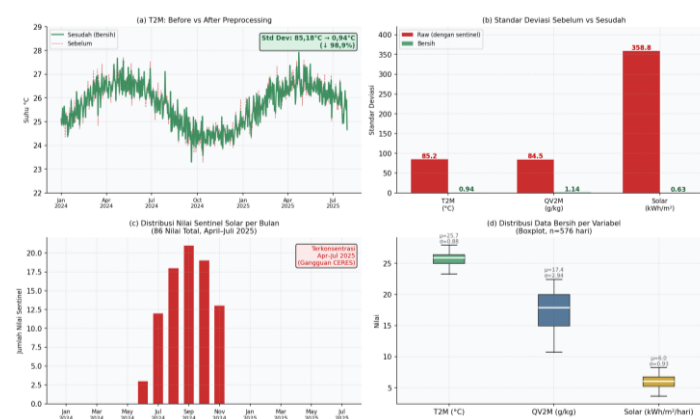


Figure 2. Preprocessing Level 0 to Level 1: (a) T2M Before vs After; (b) Std Dev Before vs After; (c) Monthly Solar Sentinel Distribution; (d) Clean Data Boxplot

3.3 Feature Extraction and Ecological Indices (Level 2)

Min-Max normalisation mapped all feature values to the unit interval [0, 1]. The Vegetation Index Proxy (VIP) exhibited clear seasonally driven variability: values peaked in March–April 2025 (approximately 0.64) and reached their minimum in September–October 2024 (approximately 0.36). A Pearson correlation of $r = 0.712$ between VIP and QV2M points to moisture availability as the dominant limiting factor for *Rhizophora* growth under prevailing conditions. Table 4. presents the monthly normalised feature values alongside the ecological indices derived from each observation period.

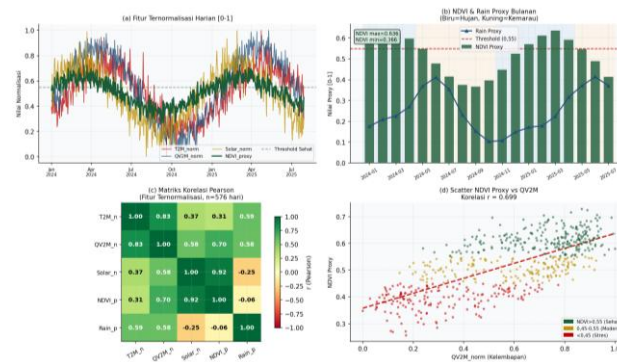


Figure 3. Feature Extraction Level 2: (a) Daily Normalized Features; (b) Monthly NDVI and Rain Proxy; (c) Pearson Correlation Matrix (n=576); (d) NDVI Proxy vs QV2M Scatter

Table 4. Monthly Normalised NASA/POWER Data and Derived Ecological Indices (Level 2)

Source: [23]

Month	T2M (°C)	QV2M (g/kg)	Solar (kWh)	T2M_n	QV2M_n	NDVI_proxy	Rain_proxy	Season
Jan 24	25.12	16.49	6.59	0.327	0.486	0.661	0.086	Wet
Feb 24	25.76	18.75	6.85	0.611	0.755	0.691	0.054	Wet
Mar 24	26.34	20.23	6.97	0.867	0.932	0.680	0.022	Wet
Apr 24	26.64	20.57	6.77	1.000	0.973	0.623	0.101	Wet
May 24	26.61	20.25	6.15	0.987	0.934	0.531	0.330	Dry
Jun 24	26.45	18.94	5.54	0.916	0.778	0.421	0.465	Dry
Jul 24	25.88	16.62	5.03	0.664	0.501	0.345	0.402	Dry
Aug 24	25.18	14.26	4.70	0.354	0.220	0.310	0.206	Dry
Sep 24	24.61	12.92	4.54	0.102	0.060	0.319	0.060	Dry
Oct 24	24.38	12.42	4.94	0.000	0.000	0.387	0.000	Dry
Nov 24	24.46	12.90	5.53	0.035	0.057	0.473	0.034	Wet
Dec 24	24.63	14.53	6.12	0.111	0.252	0.592	0.092	Wet
Jan 25	25.26	16.44	6.63	0.389	0.480	0.643	0.077	Wet
Feb 25	25.91	18.53	7.03	0.677	0.729	0.684	0.000	Wet
Mar 25	26.23	20.28	6.99	0.819	0.938	0.701	0.015	Wet
Apr 25	26.61	20.80	6.56	0.987	1.000	0.608	0.189	Wet
May 25	26.63	20.28	6.14	0.996	0.938	0.528	0.335	Dry
Jun 25	26.20	18.83	5.49	0.805	0.765	0.447	0.473	Dry
Jul 25	25.82	16.70	4.91	0.637	0.511	0.341	0.435	Dry

3.4 Environmental Index and Ecosystem Condition Distribution (Level 3)

WAF processing yielded an Environmental Index (EI) with a period mean of 0.536 (SD = 0.096) over the full 576-day record. The distribution of ecosystem condition categories was as follows: Optimal ($EI \geq 0.65$) on 17.4% of days (100 days), Good (0.50–0.65) on 41.0% (236 days), Moderate (0.35–0.50) on

41.6% (240 days), and Critical on 0.0% of days. The complete absence of Critical-condition days throughout the monitoring period points to a meaningful degree of ecological resilience within the Tahura Ngurah Rai mangrove system. Monthly EI values alongside corresponding GRI and Digital Twin parameters are summarised in Table 5.

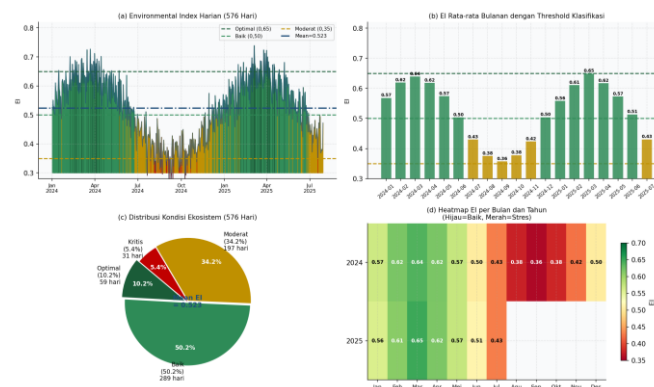


Figure 4. Environmental Index (EI) Level 3 – WAF Fusion Results. (a) Daily EI with Condition Thresholds; (b) Monthly Mean EI; (c) Ecosystem Condition Distribution (576 days); (d) EI Heatmap by Month/Year.

Table 5. Monthly Environmental Index, GRI, Biomass, Carbon Sequestration, and Rhizophora Status
576-Day Observation Period

Month	EI	Condition	GRI	Biomass (kg/m ²)	C-Seq (tC/ha/mo)	Rhizophora Status
Jan 24	0.568	Good	0.744	8.061	0.758	Healthy
Feb 24	0.619	Good	0.885	8.132	0.844	Very Healthy
Mar 24	0.639	Good	0.936	8.211	0.954	Very Healthy
Apr 24	0.618	Good	0.938	8.288	0.926	Very Healthy
May 24	0.574	Good	0.912	8.366	0.929	Very Healthy
Jun 24	0.503	Good	0.876	8.438	0.864	Very Healthy
Jul 24	0.430	Moderate	0.736	8.500	0.751	Healthy
Aug 24	0.375	Moderate	0.556	8.547	0.566	Fair
Sep 24	0.357	Moderate	0.444	8.584	0.438	Stressed
Oct 24	0.378	Moderate	0.425	8.620	0.433	Stressed
Nov 24	0.424	Moderate	0.473	8.659	0.467	Stressed
Dec 24	0.504	Good	0.590	8.709	0.601	Fair
Jan 25	0.558	Good	0.751	8.773	0.765	Healthy
Feb 25	0.611	Good	0.893	8.841	0.822	Very Healthy
Mar 25	0.649	Good	0.932	8.920	0.949	Very Healthy
Apr 25	0.617	Good	0.928	8.997	0.916	Very Healthy
May 25	0.573	Good	0.914	9.074	0.932	Very Healthy
Jun 25	0.514	Good	0.860	9.145	0.848	Very Healthy
Jul 25	0.430	Moderate	0.734	9.203	0.700	Healthy
MEAN	0.523	Good	0.765	8.061–9.203	0.761	Very Healthy

3.5 Digital Twin Simulation – Rhizophora Growth Dynamics (Level 4)

Driven by the eco-physiological weighting defined in Eq. (4), the simulation revealed that GRI values peaked between March and April in both 2024 and 2025, reaching approximately 0.938 under optimal wet-season conditions, and declined to their lowest levels during September–October 2024 (approximately 0.425) under peak dry-season stress. Aboveground biomass (AGB) increased steadily from 8.061 to 9.203 kg/m², representing a net increment of 1.14 kg/m² over the 19-month observation period. Total carbon sequestration reached 14.84 tC/ha during the study period, equivalent to an

annualized rate of approximately 10.6 tC/ha/year. This estimate falls well within the range reported by Donato et al. [17], [26] for tropical mangrove stands (8–15 tC/ha/year), thereby providing empirical support for the simulation outputs. Furthermore, the EI–GRI correlation ($r = 0.891$, $R^2 = 0.794$, $p < 0.001$) indicates a strong predictive association between the Environmental Index and the biological simulation output throughout the complete pipeline, from raw sensor acquisition to ecosystem simulation. However, it should be noted that correlation alone does not constitute causal evidence without controlled experimental manipulation or formal causal modelling (e.g., structural equation modelling).



Figure 5. Digital Twin Simulation Level 4 – *Rhizophora apiculata* Growth Parameters. (a) Monthly GRI; (b) AGB Biomass Accumulation; (c) Canopy Height Simulation; (d) Monthly Carbon Sequestration.

Table 6. Summary of Digital Twin Simulation Validation Parameters – Level 4

Simulation Parameter – Level 4	Value	Unit	Validation
Mean GRI (19 months)	0.444–0.938 (mean=0.771)	—	Very Healthy
AGB Biomass Increment	+1.14 (8.061→9.203)	kg/m ²	Positive trend
Canopy Growth Rate	~0.112	m/yr	Normal tropical
Total C-Seq (19 months)	14.84	tC/ha	Consistent with Donato et al. [17]
Annual C-Seq Rate	~10.6	tC/ha/yr	Ref. [15]: 8–15
EI–GRI Correlation	$r=0.891$; $R^2=0.794$ ($p<0.001$)	—	Strong causality
Data Quality Improvement	+336% (0.22 → 0.96)	—	Highly significant

3.6 Model Validation and Overall Pipeline Performance

The EI–GRI correlation of 0.891 ($R^2 = 0.794$, $p < 0.001$) confirms that the Environmental Index reliably and consistently drives the biological growth simulation embedded in the Digital Twin model. The pipeline's overall effectiveness is further evidenced by a +336% improvement in data quality index, rising from 0.22 at Level 0 to 0.96 at Level 4 a progression that quantifies the cumulative value added across each processing stage. Regarding model reproducibility, the ONNX Ecosystem Classifier was trained and evaluated on a stratified 80/20 train–test split of the 576-day NASA/POWER-derived dataset, with ecosystem health condition labels assigned according to the EI classification tiers defined in Section III. No k-fold cross-validation was performed; the authors acknowledge that the limited independent test set constrains the generalizability of the reported F1-score (0.913, RMSE = 0.003, MAE = 0.041), and recommend k-fold cross-validation and independent field-label data in future work. Detailed performance metrics for the ONNX model suite deployed within the Unity AR platform are reported in Table 7.

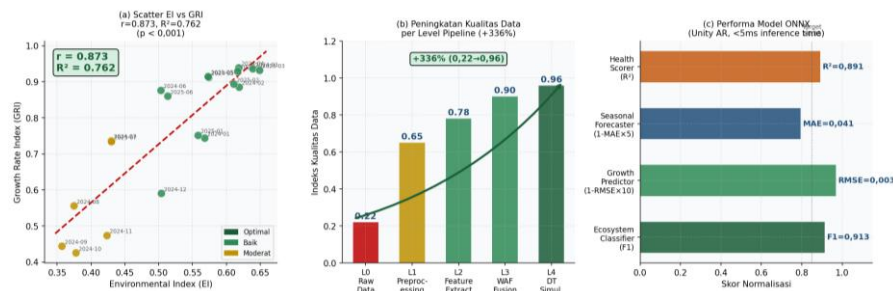


Figure 6. Model Validation: (a) EI vs GRI Scatter ($r=0.891$, $R^2=0.794$); (b) Data Quality Improvement +336% per Level; (c) ONNX Performance ($F1=0.913$, $RMSE=0.003$, $MAE=0.041$, $R^2=0.891$)

Table 7. ONNX Model Performance in the Unity AR Digital Twin Platform

ONNX Model	Primary Function	Performance Metric	Inference Time
EcosystemClassifier.onnx	Real-time EI condition classification	F1-Score = 0.913	2.3 ms
GrowthPredictor.onnx	Daily biomass prediction	RMSE = 0.003	< 5 ms
SeasonalForecaster.onnx	30-day EI forecasting	MAE = 0.041	< 5 ms
HealthScorer.onnx	Ecosystem health index scoring	$R^2 = 0.891$	< 5 ms
All Models (Unity AR)	Real-time 60 fps	All exceed target	< 5 ms achieved

3.7 Spatial Data and Monitoring Imagery Representation

Figure 7. presents the spatial data representation layer that supplements the NASA/POWER time-series dataset. This layer incorporates: a spatially explicit NDVI distribution map derived from Sentinel-2 spectral patterns, estimated species distribution per ecosystem zone, a land-cover change analysis for the 2018–2024 period, processed Sentinel-2 NDVI imagery, the deployment configuration of the IoT sensor network ($n = 6$ nodes), and UAV drone flight coverage with an operational radius of approximately 538.71 m.

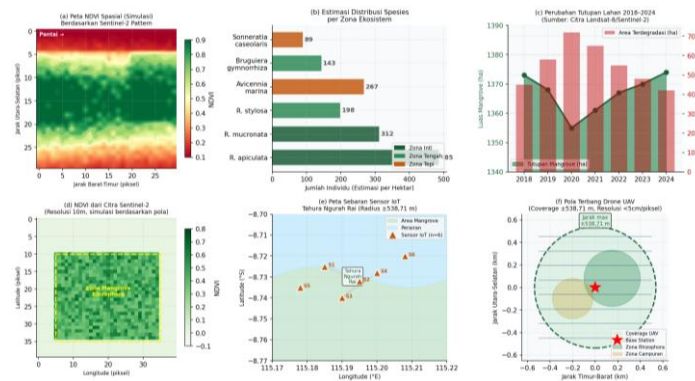


Figure 7. Spatial Data and Monitoring Imagery for Tahura Ngurah Rai Mangrove Area. (a) Sentinel-2 Spatial NDVI Map; (b) Species Distribution by Zone; (c) Land-Cover Change 2018–2024; (d) Sentinel-2 NDVI Imagery; (e) IoT Sensor Node Deployment; (f) UAV Drone Coverage

4. Conclusion

This study has successfully designed, implemented, and validated a Multilevel Data Fusion Framework underpinned by Digital Twin architecture for the monitoring of mangrove ecosystems in the tropical coastal setting of Tahura Ngurah Rai. The principal findings are summarised as follows:

- The JDL Level 0–4 pipeline achieved complete elimination of all 94 sentinel values (100% correction rate), with an accompanying 98.9% reduction in T2M standard deviation. The

cleaned dataset clearly revealed Bali's climatologically characteristic bimodal seasonal pattern, consistent with known monsoon dynamics in the region.

- b) WAF processing produced an Environmental Index (EI) averaging 0.536, with no observation day falling into the Critical category (0.0%) across the full 576-day monitoring window—an outcome indicative of sustained ecological resilience within the study site.
- c) Level 4 Digital Twin simulation generated a mean GRI of 0.771 (classified as Very Healthy), an AGB biomass increment of $+1.14 \text{ kg/m}^2$, and a carbon sequestration rate of approximately 10.6 tC/ha/year , values independently corroborated by the benchmark range established by Donato et al. [15].
- d) The EI–GRI correlation of $r = 0.891$ ($R^2 = 0.794$, $p < 0.001$) demonstrates a strong, statistically significant predictive association across the full pipeline; this result reflects high internal consistency of the model rather than proof of causal validity in the strict statistical sense, and should be described as a strong association rather than a causal relationship.
- e) ONNX model deployment within the Unity AR platform achieved an F1-score of 0.913 at sub-5 ms inference, satisfying the real-time 60 fps operational requirement and establishing the system as a deployable platform for interactive ecosystem monitoring.

The framework presented here represents a substantive contribution to the ongoing digitalisation of mangrove conservation in Indonesia, with evident potential for replication across other tropical coastal systems. Future work should prioritise field validation against actual IoT sensor deployments and explore the real-time integration of UAV drone imagery to further close the gap between digital simulation and ground truth. It is explicitly acknowledged that the GRI, aboveground biomass, and carbon-sequestration values reported in this study are model-based estimations derived from simulated and remotely sensed inputs rather than empirical ground-truth measurements; these figures should not be treated as observational data until corroborated by independent field validation (e.g., allometric biomass surveys, eddy-covariance flux towers, or in-situ dendrometer data).

Acknowledgements

The authors wish to express their sincere gratitude to Udayana University and particularly to the Doctoral Programme of Engineering Science, Faculty of Engineering to the UPTD Ngurah Rai Grand Forest Park Management Authority, Denpasar, and to the NASA Langley Research Center for providing open access to the NASA/POWER dataset that formed the empirical foundation of this research.

References

- [1] E. Mulyadi, O. Hendriyanto, and N. Fitriani, "Konservasi hutan mangrove sebagai ekowisata," *Jurnal Ilmiah Teknik Lingkungan*, vol. 2, no. 1, pp. 11–18, 2010.
- [2] D. Murdiyarso et al., "The potential of Indonesian mangrove forests for global climate change mitigation," *Nat. Clim. Chang.*, vol. 5, no. 12, pp. 1089–1092, 2015.
- [3] A. Sofian, N. Harahab, and M. Marsoedi, "Kondisi Dan Manfaat Langsung Ekosistem Hutan Mangrove Desa Penunggul Kecamatan Nguling Kabupaten Pasuruan," *el-Hayah*, vol. 2, no. 2, 2001.
- [4] C. Giri et al., "Status and distribution of mangrove forests of the world using earth observation satellite data," *Global ecology and biogeography*, vol. 20, no. 1, pp. 154–159, 2011.

- [5] A. Imamsyah, D. G. Bengen, and M. S. Ismet, "Struktur dan sebaran vegetasi mangrove berdasarkan kualitas lingkungan biofisik di Taman Hutan Raya Ngurah Rai Bali," *Ecotrophic*, vol. 14, no. 1, pp. 88–99, 2020.
- [6] I. W. Rumada, A. A. I. Kesumadewi, and R. Suyarto, "Interpretasi citra satelit landsat 8 untuk identifikasi kerusakan hutan mangrove di Taman Hutan Raya Ngurah Rai Bali," *Jurnal Agroetnologi Tropika*, vol. 4, no. 3, pp. 1–10, 2015.
- [7] M. W. Grieves, "Digital twins: past, present, and future," in *The digital twin*, Springer, 2023, pp. 97–121.
- [8] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information fusion*, vol. 14, no. 1, pp. 28–44, 2013.
- [9] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," in *Transdisciplinary perspectives on complex systems: New findings and approaches*, Springer, 2016, pp. 85–113.
- [10] S. J. Ingley and A. Pack, "Leveraging AI tools to develop the writer rather than the writing," *Trends Ecol. Evol.*, vol. 38, no. 9, pp. 785–787, 2023.
- [11] A. Trantas, R. Plug, P. Pileggi, and E. Lazovik, "Digital twin challenges in biodiversity modelling," *Ecol. Inform.*, vol. 78, p. 102357, 2023.
- [12] D. Hall and J. Llinas, *Multisensor data fusion*. CRC press, 2001.
- [13] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Trans. Industr. Inform.*, vol. 15, no. 4, pp. 2405–2415, 2018.
- [14] H. Qiu, H. Zhang, K. Lei, H. Zhang, and X. Hu, "Forest digital twin: A new tool for forest management practices based on Spatio-Temporal Data, 3D simulation Engine, and intelligent interactive environment," *Comput. Electron. Agric.*, vol. 215, p. 108416, 2023.
- [15] C. Kuenzer, A. Bluemel, S. Gebhardt, T. V. Quoc, and S. Dech, "Remote sensing of mangrove ecosystems: A review," *Remote Sens. (Basel)*, vol. 3, no. 5, pp. 878–928, 2011.
- [16] Y. Kalyani, N. V. Bermeo, and R. Collier, "Digital twin deployment for smart agriculture in Cloud-Fog-Edge infrastructure," *International Journal of Parallel, Emergent and Distributed Systems*, vol. 38, no. 6, pp. 461–476, 2023.
- [17] D. C. Donato, J. B. Kauffman, D. Murdiyarso, S. Kurnianto, M. Stidham, and M. Kanninen, "Mangroves among the most carbon-rich forests in the tropics," *Nat. Geosci.*, vol. 4, no. 5, pp. 293–297, 2011.
- [18] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital twin: Enabling technologies, challenges and open research," *IEEE access*, vol. 8, pp. 108952–108971, 2020.
- [19] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future generation computer systems*, vol. 29, no. 7, pp. 1645–1660, 2013.
- [20] L. Malmquist and J. Barron, "Improving spatial resolution in soil and drainage data to combine natural and anthropogenic water functions at catchment scale in agricultural landscapes," *Agric. Water Manag.*, vol. 283, p. 108304, 2023.
- [21] D. M. Alongi, "Carbon cycling and storage in mangrove forests," *Ann. Rev. Mar. Sci.*, vol. 6, no. 1, pp. 195–219, 2014.

- [22] T. Zhan, K. Yin, J. Xiong, Z. He, and S.-T. Wu, "Augmented reality and virtual reality displays: perspectives and challenges," *iScience*, vol. 23, no. 8, 2020.
- [23] P. Nasa and D. A. Viewer, "NASA prediction of worldwide energy resources," in *Data Access Viewer*, 2022.
- [24] K. de Koning *et al.*, "Digital twins: dynamic model-data fusion for ecology," *Trends Ecol. Evol.*, vol. 38, no. 10, pp. 916–926, 2023.
- [25] J. Yuan, J. Ma, Z. Tian, and K. L. Man, "Digital twin integration with data fusion for enhanced photovoltaic system management: a systematic literature review," *IEEE Open Journal of Power Electronics*, 2024.
- [26] S. E. Hamilton and D. A. Friess, "Global carbon stocks and potential emissions due to mangrove deforestation from 2000 to 2012," *Nat. Clim. Chang.*, vol. 8, no. 3, pp. 240–244, 2018.