

## Article

# Sea-Level Fall over Rainfall: Mask-Applied Satellite Reassessment of Gulf of Carpentaria Mangrove Dieback

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## Abstract

Mangrove forests deliver globally significant climate-mitigation and coastal-protection benefits, yet their resilience to climate extremes remains poorly quantified—a key uncertainty for sustainable coastal management. We reassess the unprecedented 2015–2016 mangrove dieback along ~1000 km of the Gulf of Carpentaria, northern Australia, to determine its driver and whether the collapse was structurally abrupt. Combining a mangrove-extent mask, an 11-year radar backscatter series, satellite precipitation, the modeled sea level, the reanalysis temperature and atmospheric dryness, and an El Niño index, we show that an apparent abrupt radar decline during the event was an artifact of non-vegetated tidal-flat and open-water pixels: once analysis was restricted to mangrove pixels, the signal remained stable throughout. Independent spaceborne lidar confirmed that canopy structure concentrates within the mapped mangrove zones, validating the mask. The dieback coincided with a strong sea-level fall, with anomalies reaching about −15 cm, under near-to-average rainfall and low atmospheric dryness, indicating that sea-level fall, not rainfall deficit, was the proximate stressor. These findings advance sustainable, mask-applied satellite monitoring of blue-carbon ecosystems and provide an evidence base for climate-adaptive coastal-resilience planning under intensifying climate variability.

**Keywords:** mangrove dieback; sea-level anomaly; vapor pressure deficit; spaceborne lidar validation; blue-carbon sustainability; climate-adaptive coastal management



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## 1. Introduction

Mangrove forests rank among the most carbon-dense ecosystems on Earth, storing large stocks in biomass and especially in waterlogged soils, and underpin coastal protection, fisheries, and biodiversity that sustain millions of people [1,2]. The Indo-Pacific holds the world's highest mangrove diversity and the largest share of global mangrove area, making its forests disproportionately important for blue-carbon storage and ecosystem-service provision and a global priority for conservation [3,4]. Conserving and restoring mangroves is therefore a cornerstone natural climate solution and a Sustainable Development Goal-relevant strategy for resilient coasts [2,5].

Although global mangrove loss rates have slowed over the past decade, the remaining forests are still highly vulnerable to interacting climatic and human pressures, and recent syntheses continue to identify hydrologic variability, including sea-level fluctuation, as a

major driver of instability, canopy decline, and dieback [6,7]. Dense satellite time-series analyses show that repeated severe disturbances are eroding mangrove resilience and the capacity to sustain ecosystem functions, with recovery trajectories persisting for years [7,8].

The El Niño–Southern Oscillation (ENSO) is the dominant mode of interannual tropical climate variability, reorganizing convection and the Walker circulation to produce large precipitation and sea-level anomalies across the Indo-Pacific [9,10]. In northern Australia, strong El Niño events drive short-term sea-level drops, reduced rainfall, and higher temperatures that increase water stress in intertidal mangroves [11].

Mangroves occupy the dynamic intertidal zone and extract water against a steep osmotic gradient, so saline soils place them under chronic physiological drought [12,13]. Large-scale mortality is increasingly understood as the convergence of multiple stressors—salinity, altered inundation, hypoxia, heat, and atmospheric dryness—on hydraulic dysfunction, rather than any single climatic variable acting alone [12,14]. Reduced tidal inundation or sea-level fall elevates soil salinity and pore-water deficit, driving xylem cavitation, canopy loss, and whole-tree death, whereas persistent waterlogging in low, poorly drained sites kills mangroves through root-zone anoxia [15–17]. Elevated temperature and vapor pressure deficit (VPD) further raise evaporative demand, amplifying water stress in already salt-stressed trees and shifting hydraulic regulation from roots toward leaves [18,19]. The strongest current evidence thus supports a multi-stressor threshold model of crown dieback [13,14].

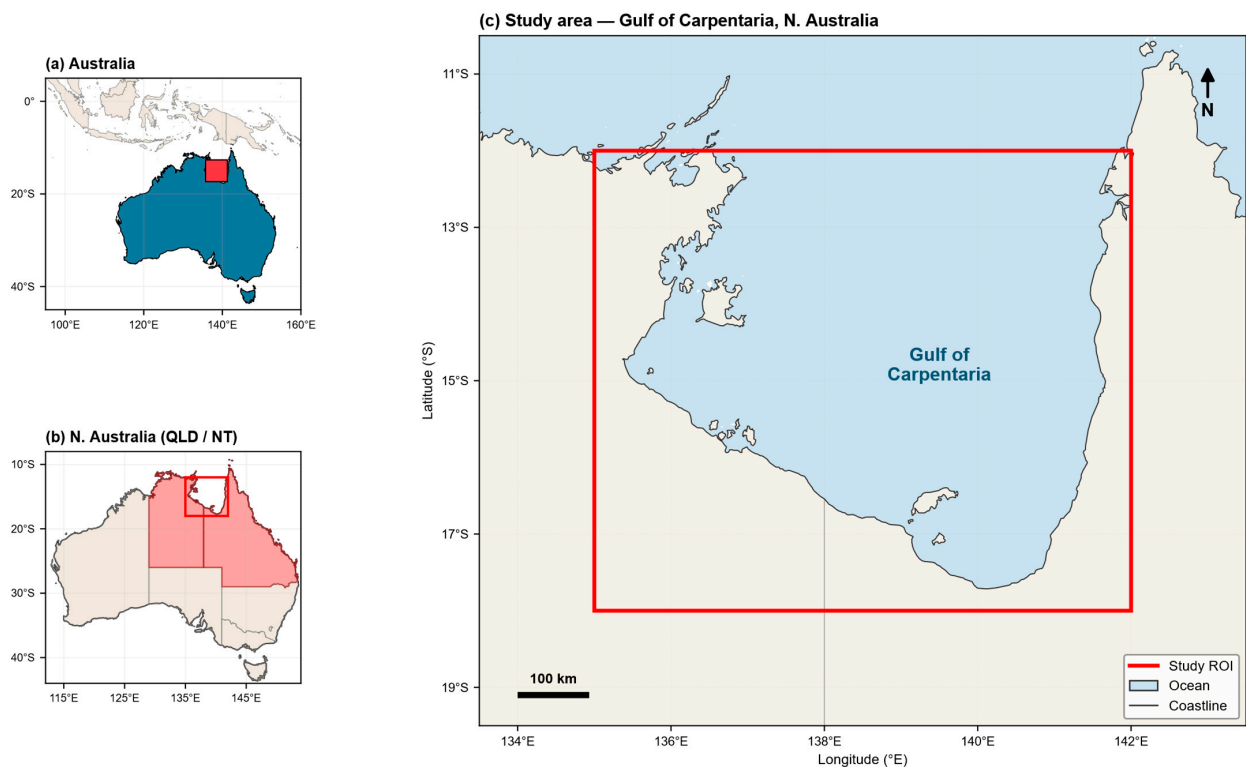
These coupled stressors culminated in the 2015–2016 Gulf of Carpentaria dieback, in which more than 7000 ha, approximately 6% of regional mangroves, died along ~1000 km of coastline during the strong 2015–2016 El Niño [11,20]. The most strongly supported mechanism attributes the event to an exceptional ENSO-linked sea-level fall, a temporary drop of about 0.4 m for up to six months, that exposed root zones and elevated soil salinity in upper-zone mangroves [11,21]. Concurrent drought, record-high temperatures, and reduced rainfall acted jointly with low sea level, a combination apparently unprecedented in recent decades [22,23]. Hydraulic failure provides the unifying physiological endpoint: in severely affected *Avicennia marina*, native loss of conductivity reached about 39% versus about 6% in minimally impacted zones, consistent with lingering embolism damage [12]. Most prior assessments, however, relied on field surveys, aerial mapping, optical canopy cover, or geochemical proxies, not satellite radar structural metrics [21,23].

Two questions remain unresolved: whether the dieback was an abrupt structural collapse detectable by satellite radar, and whether precipitation deficit or sea-level fall was the proximate driver—two effects difficult to separate because El Niño depresses both simultaneously [24]. Synthetic Aperture Radar (SAR) is well suited to address structure because backscatter responds to canopy architecture and water content, with cross-polarized signals especially sensitive to vegetation structure [25,26]. Yet regional-mean SAR can be confounded by non-vegetated surfaces such as tidal flats and open water. We test the hypothesis that restricting SAR to mangrove pixels, using an authoritative extent mask validated independently by spaceborne lidar, fundamentally changes the interpretation of the dieback signal. Specifically, we (i) partition the mangrove extent into persistent and variable zones; (ii) compare whole-region and mangrove-masked backscatter across the event; (iii) co-analyze precipitation, sea level, temperature, and VPD as candidate drivers; and (iv) validate the mask against canopy structure. We frame results around mangrove resilience and sustainable, climate-adaptive coastal monitoring.

## 2. Materials and Methods

### 2.1. Study Area

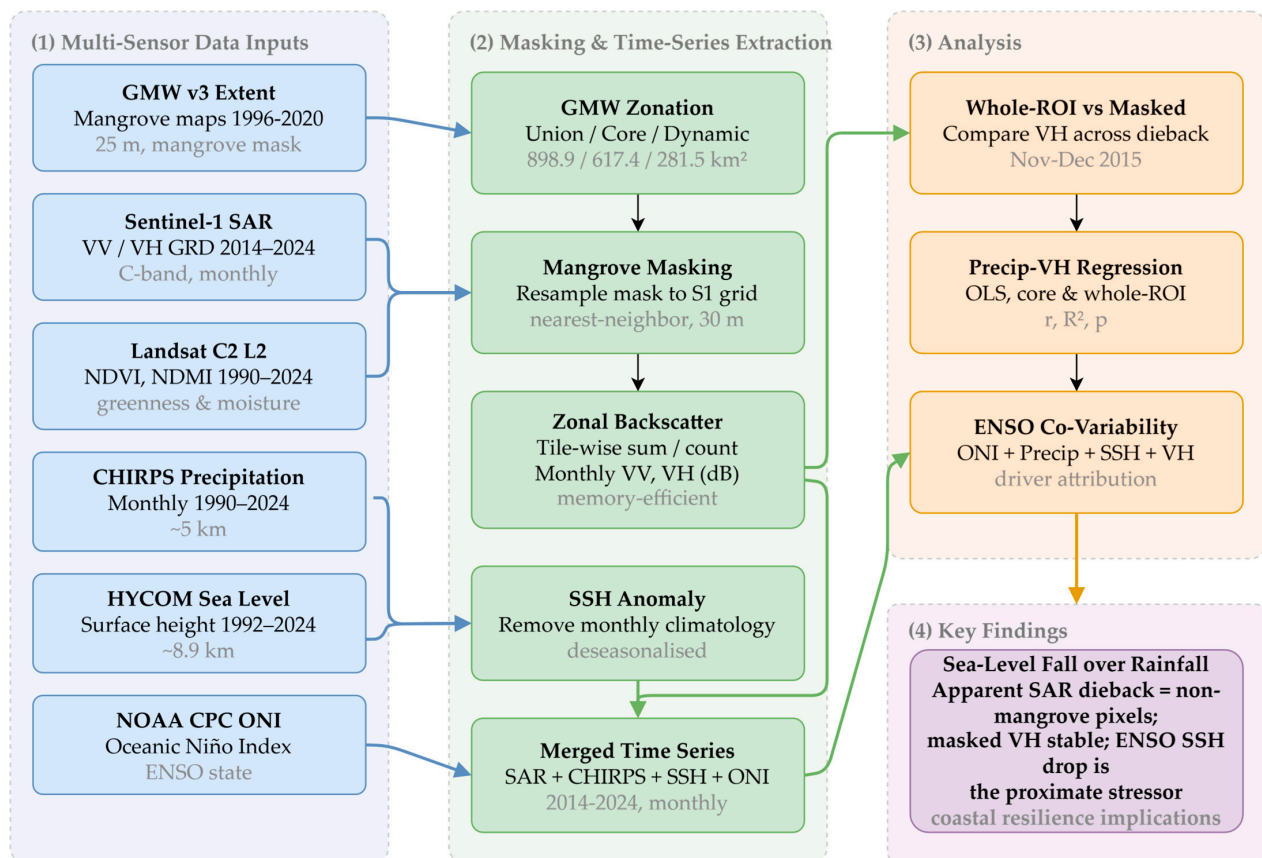
The Gulf of Carpentaria is a large, shallow embayment of northern Australia spanning Queensland and the Northern Territory (approximately 135–142° E, 14–18° S; Figure 1). Within the Indo-Pacific, the world's most mangrove-rich and biodiverse region, its extensive low-lying intertidal mudflats and narrow fringing mangroves represent a regionally important but climatically marginal blue-carbon system, making it a sentinel site for ENSO-driven coastal change [4,21]. The region has a monsoonal climate with a wet season from December to March and a dry season from June to September.



**Figure 1.** Study area. (a) Location of Australia within the Indo-Pacific region; (b) northern Australia showing Queensland and the Northern Territory with the study region of interest (ROI); (c) detailed map of the Gulf of Carpentaria coastline with the analysis ROI, coastline, and bathymetric/terrestrial context. North arrow and scale bar included.

### 2.2. Data and Analytical Workflow

The workflow, from multi-sensor inputs through mangrove masking, time-series extraction, and climate co-variability analysis to attribution, is summarized in Figure 2; datasets are listed in Table 1. We used the Global Mangrove Watch (GMW) v3 mangrove-extent mask [27,28]; Landsat Collection 2 Level-2 surface reflectance (1990–2024) [29]; Sentinel-1 GRD dual-polarization backscatter (2014–2024); CHIRPS precipitation (1990–2024); HYCOM sea-surface height (1992–2024); ERA5-Land 2 m air temperature and dewpoint (1990–2024); the Oceanic Niño Index (ONI, 1950–present); and GEDI canopy-structure metrics (2019–2023) for independent mask validation. All raster processing was performed using Google Earth Engine (Python API v1.7.26) and local Python (v3.12.9) with rasterio (v1.5.0), GeoPandas (v1.1.3), and NumPy (v2.4.4).



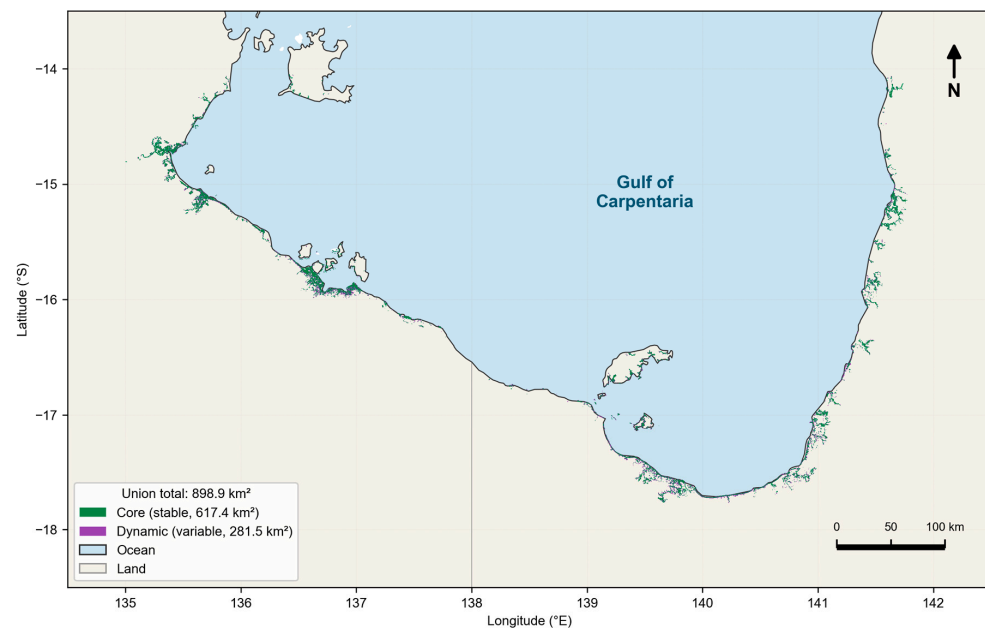
**Figure 2.** Analytical workflow of this study. Multi-sensor data inputs are processed through GMW zonation and mangrove masking, monthly zonal backscatter and sea-surface-height anomaly extraction, and a merged time series, followed by whole-ROI versus masked comparison, climate-backscatter regression, and ENSO co-variability analysis, leading to the attribution of the dieback to ENSO-driven sea-level fall.

**Table 1.** Summary of datasets used in this study, including variable, product, spatial resolution, temporal coverage, and processing note.

| Variable           | Dataset/Product          | Spatial Resolution | Period       | Processing Note           |
|--------------------|--------------------------|--------------------|--------------|---------------------------|
| Mangrove extent    | Global Mangrove Watch v3 | 25 m               | 1996–2020    | Union/core/dynamic mask   |
| Vegetation indices | Landsat C2 L2 (L5/7/8/9) | 30 m               | 1990–2024    | NDVI, NDMI; monthly       |
| SAR backscatter    | Sentinel-1 GRD (VV, VH)  | 30 m               | 2014–2024    | Monthly mean (dB)         |
| Precipitation      | UCSB-CHG CHIRPS          | ~5 km              | 1990–2024    | Monthly total (mm)        |
| Air temp. and VPD  | ECMWF ERA5-Land          | ~9 km              | 1990–2024    | 2 m temp., dewpoint → VPD |
| Sea surface height | HYCOM surface elevation  | ~8.9 km            | 1992–2024    | Monthly anomaly (cm)      |
| ENSO index         | NOAA CPC ONI/Niño3.4     | —                  | 1950–present | Monthly                   |

### 2.3. Mangrove Masking and Zonation

To restrict analysis to mangrove pixels, we used the GMW v3 dataset, which provides globally consistent maps of mangrove extent and change from 1996 to 2020 [27,28]. From the annual extent layers, we derived three zones—the union (any pixel mapped as mangrove in at least one year), the core (mangrove in all available years), and the dynamic zone (union minus core)—representing the temporally variable, ENSO-sensitive fringe. Latitude-corrected pixel areas yielded a union extent of 898.9 km<sup>2</sup>, a core of 617.4 km<sup>2</sup>, and a dynamic zone of 281.5 km<sup>2</sup> (Figure 3), in close agreement with prior regional estimates [30].



**Figure 3.** GMW v3 mangrove zones in the Gulf of Carpentaria. Core (stable) and dynamic (variable) zones are shown over a Natural Earth basemap, with ocean and land context, scale bar, and north arrow. Mangrove pixels enlarged for visualization.

#### 2.4. Vegetation Indices

The vegetation condition was characterized using the NDVI and NDMI computed from Landsat surface reflectance, widely used proxies for canopy greenness and vegetation water content, respectively [31,32], which have been applied to detect mangrove disturbance and recovery in recent multi-temporal analyses [7]. Monthly composites were generated across the full 1990–2024 record.

#### 2.5. SAR Processing and Time-Series Extraction

Landsat scenes were quality-screened using the QA\_PIXEL band to mask clouds and cloud shadows before index computation, and monthly median composites were generated to suppress residual atmospheric contamination [29,33]. Sentinel-1 GRD imagery (interferometric wide-swath mode, VV and VH polarizations) was aggregated to monthly mean backscatter in decibels over the ROI for 2014–2024; only valid, finite, and non-zero, pixels were retained in zonal averaging. Cross-polarized VH is generally more sensitive to vegetation structure than co-polarized VV, and backscatter responds to canopy structure and water content [25,26]. To handle the large raster volume, per-tile sums and pixel counts were accumulated band-by-band into zonal means. No additional speckle filtering or radiometric terrain correction was applied beyond the GRD product's standard processing; we treat this explicitly as a limitation, since analysis-ready frameworks often add these steps [34,35].

The GMW mask (25 m, EPSG:4326) was reprojected to the Sentinel-1 grid (30 m) using nearest-neighbor resampling to preserve the binary mangrove and non-mangrove class values; bilinear interpolation was avoided because it generates non-integer values at class boundaries that would degrade the mask [34]. Of the 132 expected months, 26, predominantly in 2014 and parts of 2015–2016, lacked Sentinel-1 acquisitions and were treated as data gaps. These gaps were excluded from all statistical analyses; no interpolation was applied to gap months, and the regression used observed values only. In the time-series figures, only observed months are connected, and gap months are omitted without interpolation.

## 2.6. Climate Co-Variability and Recovery Definition

We examined the co-variation in the ONI, CHIRPS precipitation, HYCOM sea level, ERA5-Land temperature, and VPD, and mangrove-masked backscatter over 2014–2024. VPD was computed as the difference between the saturation vapor pressure at air temperature and at dewpoint temperature, each estimated with the Tetens formulation [36], and was analyzed because atmospheric dryness is a recognized driver of mangrove water stress [18,37]. HYCOM surface elevation (native scale 0.001, meters) was converted to monthly sea-surface-height anomalies by subtracting the month-of-year climatology computed over the full 1992–2024 record, isolating ENSO-related variability from the seasonal cycle; anomalies are reported in centimeters. Relationships between backscatter and precipitation, temperature, and VPD were quantified by ordinary least-squares regression for the core mangrove zone and the whole ROI.

Because mangrove-masked C-band backscatter remained within its pre-event baseline ( $\text{mean} \pm 1\sigma$ ) throughout the record, no single SAR-based recovery date could be objectively defined; we therefore report representative post-event time points rather than a discrete recovery threshold (Appendix A, Figure A1).

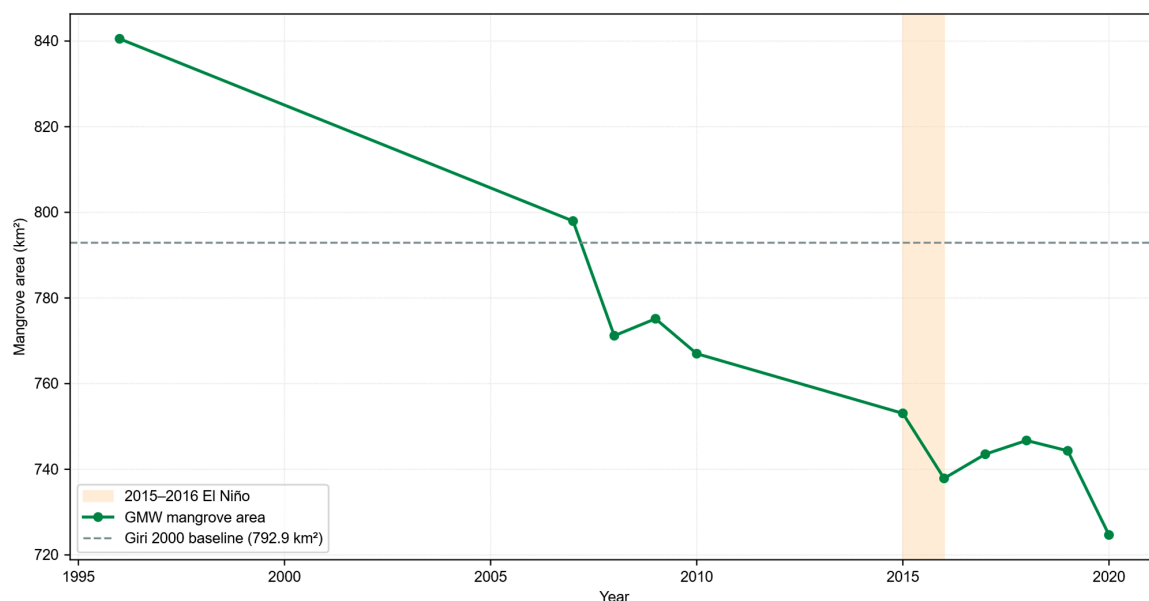
## 2.7. Independent Mask Validation with GEDI

To validate the mangrove mask independently of the extent product, we intersected GEDI canopy-height shots with the GMW zones and computed the proportion of valid canopy shots per zone, providing a structural cross-check from an independent spaceborne lidar sensor [38].

# 3. Results

## 3.1. Mangrove Extent and Long-Term Change

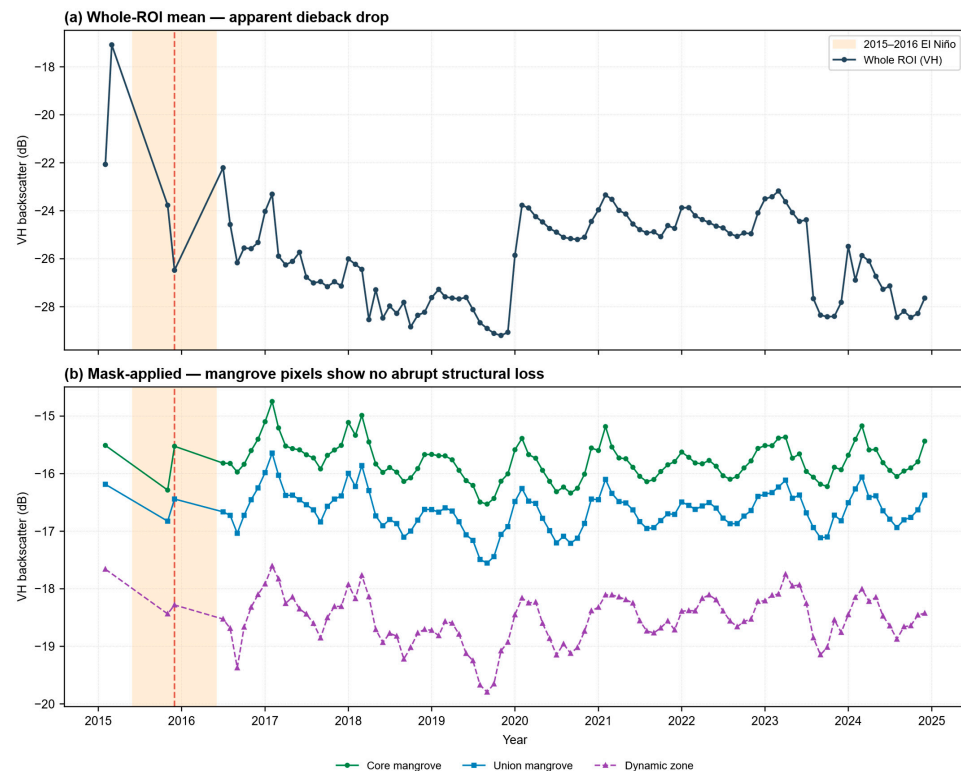
The GMW v3 mangrove extent declined from approximately 840 km<sup>2</sup> in 1996 to 738 km<sup>2</sup> in 2016, falling below the 792.9 km<sup>2</sup> 2000 baseline [30] and continuing to about 725 km<sup>2</sup> by 2020 (Figure 4). The decline was broadly progressive rather than a single abrupt step, with a local minimum coinciding with the 2015–2016 El Niño embedded within a longer-term downward trend.



**Figure 4.** Annual mangrove extent (GMW v3), 1996–2020, with the 2015–2016 El Niño period shaded and the 2000 baseline (792.9 km<sup>2</sup>) indicated.

### 3.2. Apparent Versus Masked SAR Signal

The whole-ROI mean VH backscatter declined sharply from approximately  $-23.8$  dB in November 2015 to  $-26.5$  dB in December 2015, apparently consistent with abrupt dieback (Figure 5a). Restricting the analysis to mangrove pixels removed this drop (Figure 5b): the core-zone VH was stable across the transition, from  $-16.29$  to  $-15.52$  dB, and the union-zone VH likewise rose from  $-16.83$  to  $-16.44$  dB (Table 2). Backscatter followed a consistent zonal ordering, with 2014–2024 mean VHs of  $-15.78$ ,  $-16.64$ , and  $-18.52$  dB for the core, union, and dynamic zones, respectively (Table 2), and even the dynamic fringe showed no abrupt decline, from  $-18.44$  to  $-18.28$  dB.



**Figure 5.** Monthly VH backscatter time series (2014–2024). (a) Whole-ROI mean, showing an apparent abrupt decline during the 2015–2016 El Niño; (b) mask-applied core, union, and dynamic-zone series, showing stable seasonal cycles without abrupt structural loss. Shading marks the El Niño period; the dashed line marks December 2015. Connected points represent observed months only; gap months are omitted without interpolation.

**Table 2.** Mangrove zone areas and VV/VH backscatter (dB) at key time points (baseline, pre-dieback, post-dieback, post-event) and 2014–2024 means for the union, core, and dynamic zones.

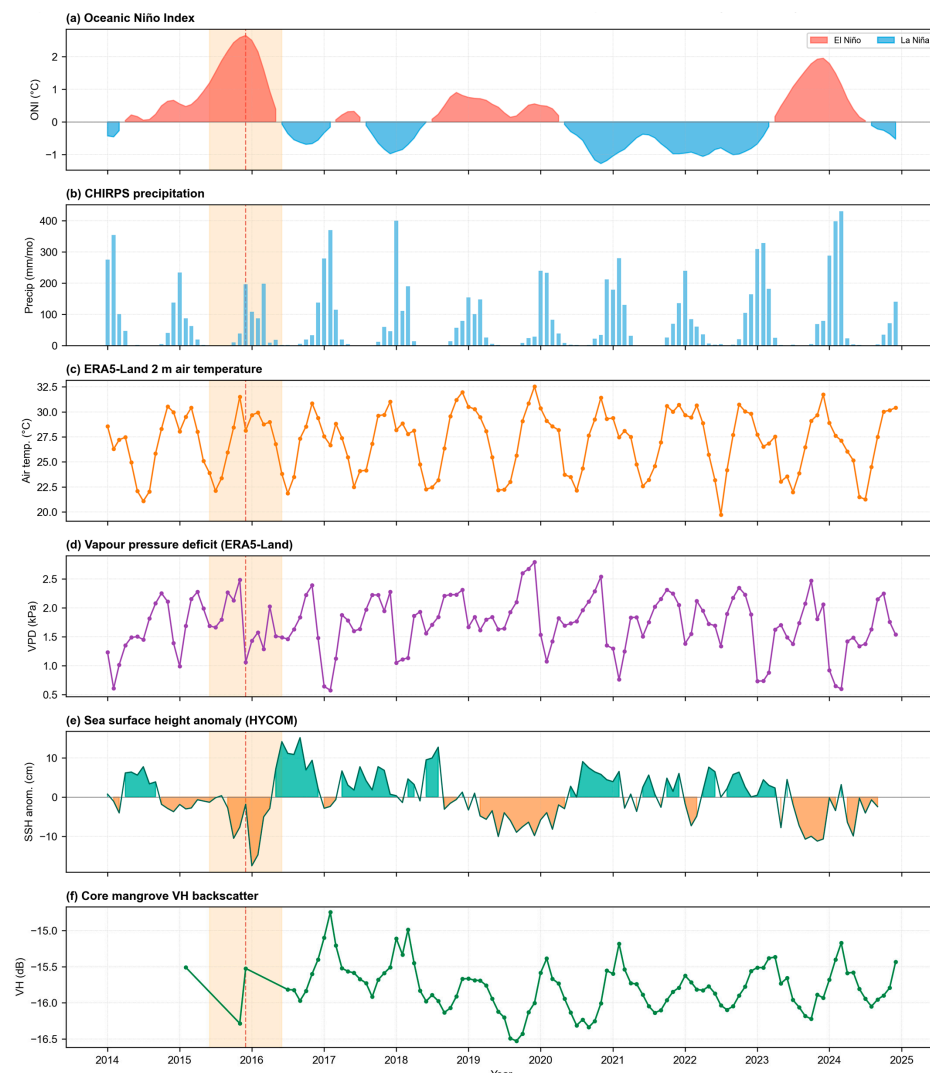
| Variable                | Union  | Core   | Dynamic |
|-------------------------|--------|--------|---------|
| Area (km <sup>2</sup> ) | 898.9  | 617.4  | 281.5   |
| VV baseline (dB)        | −10.25 | −9.82  | −11.20  |
| VH baseline (dB)        | −16.19 | −15.51 | −17.66  |
| VV pre-dieback (dB)     | −11.59 | −11.28 | −12.49  |
| VH pre-dieback (dB)     | −16.83 | −16.29 | −18.44  |
| VV post-dieback (dB)    | −10.69 | −10.26 | −11.57  |
| VH post-dieback (dB)    | −16.44 | −15.52 | −18.28  |
| VV post-event (dB)      | −11.17 | −10.44 | −12.79  |
| VH post-event (dB)      | −17.04 | −15.97 | −19.37  |
| VV mean 2014–2024 (dB)  | −10.65 | −10.16 | −11.73  |
| VH mean 2014–2024 (dB)  | −16.64 | −15.78 | −18.52  |

### 3.3. Independent Validation of the Mangrove Mask

The GEDI canopy coverage decreased monotonically across zones, with valid canopy shots covering 3.2% of core, 1.2% of dynamic, and 0.1% of non-mangrove pixels; approximately 80% of valid canopy shots fell inside the mapped mangrove zones, with negligible coverage over tidal-flat and open-water areas (Figure A3). This confirms that the GMW mask reliably separates structured mangrove canopy from non-vegetated surfaces.

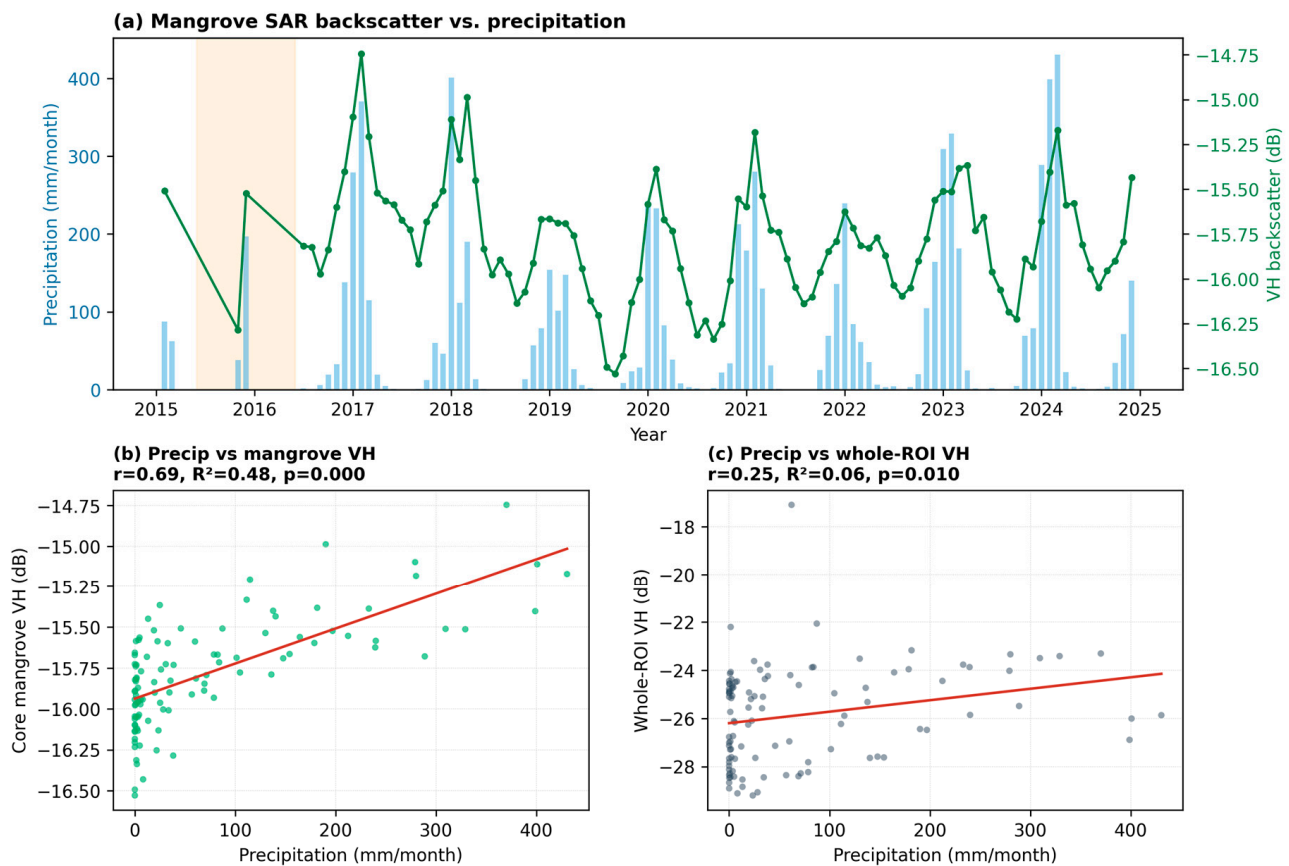
### 3.4. ENSO, Sea Level, Precipitation, and Atmospheric Dryness

The dieback coincided with a strong positive ONI and a pronounced negative sea-level anomaly reaching about  $-15$  cm, with a minimum of  $-17.5$  cm in January 2016, during late 2015 and early 2016 (Figure 6). Regional precipitation was near-to-above average at dieback onset, with December 2015 recording approximately 197 mm, and atmospheric dryness was low, with VPD of approximately 1.06 kPa, among the lowest of the record, while air temperature was unremarkable at approximately  $28^{\circ}\text{C}$ . Core-zone VH showed no corresponding collapse (Figure 6).



**Figure 6.** Co-variation of (a) the Oceanic Niño Index (ONI), (b) CHIRPS precipitation, (c) ERA5-Land 2 m air temperature, (d) vapour pressure deficit, (e) HYCOM sea-surface-height anomaly, and (f) core mangrove VH backscatter over 2014–2024. In (a), red and blue shading indicate positive (El Niño) and negative (La Niña) ONI values, respectively. In (e), teal and orange shading indicate positive and negative sea-surface-height anomalies, respectively. The light-orange vertical band marks the 2015–2016 El Niño period across all panels, and the dashed line indicates December 2015.

Regression confirmed a strong seasonal coupling of core-zone VH with precipitation ( $r = 0.69$ ,  $R^2 = 0.48$ ,  $p < 0.001$ ) and an inverse coupling with VPD ( $r = -0.67$ ,  $R^2 = 0.45$ ,  $p < 0.001$ ), whereas the relationship with temperature was weak ( $r = 0.24$ ,  $R^2 = 0.06$ ; Table A1, Figures 7 and A2). Whole-ROI VH was related only weakly to precipitation ( $r = 0.25$ ,  $R^2 = 0.06$ ). At dieback onset, December 2015 showed high precipitation and low VPD relative to the regression lines (Figure A2), confirming that the event coincided with conditions of low water-deficit stress.



**Figure 7.** Mangrove SAR backscatter versus precipitation. (a) Monthly core mangrove VH backscatter (green line with circles, right axis) and CHIRPS precipitation (blue bars, left axis) over 2014–2024; (b) scatter plot and regression of core-zone VH versus precipitation; (c) scatter plot and regression of whole-ROI VH versus precipitation. In (a), each circle is a monthly VH value and the connecting line is shown for visualization only. In (b,c), each circle represents one monthly observation and the red line is the ordinary least-squares (OLS) regression fit; the corresponding  $r$ ,  $R^2$ , and  $p$  values are given above each panel. The light-orange band in (a) marks the 2015–2016 El Niño period.

## 4. Discussion

### 4.1. Reinterpreting the SAR Dieback Signal

The apparent abrupt SAR decline during the 2015–2016 dieback was an artifact of mixing mangrove and non-mangrove pixels. Once the analysis was restricted to GMW-defined mangrove pixels, independently validated here by the GEDI canopy structure (Figure A3), the abrupt VH drop vanished, leaving a stable, seasonally modulated signal. The whole-ROI series instead reflects bare intertidal surfaces and shallow water responding to inundation and acquisition geometry, including the onset of the wet season in December 2015 [25,26]. Methodologically, this cautions that unmasked, regional-mean radar can substantially overstate apparent structural change in fringing coastal ecosystems. For the blue-carbon community, where satellite indicators increasingly underpin carbon accounting

and ecosystem-condition reporting, this distinction is consequential: a spurious collapse signal could misdirect conservation resources or distort the evidence base for climate-adaptive coastal management, making mask-applied analysis a prerequisite for credible, sustainable monitoring.

#### 4.2. Sea-Level Fall as the Proximate Stressor

The co-variability analysis points to ENSO-driven sea-level fall, rather than precipitation deficit, as the most likely proximate stressor during the dieback onset. The pronounced negative sea-level anomaly is consistent with attributions of the event to a persistent sea-level drop that exposed mangrove root zones and elevated soil salinity, ultimately driving hydraulic failure [11,12,21]. Our atmospheric analysis sharpens this interpretation: at dieback onset, rainfall was near-to-above average and VPD was at a seasonal minimum (Figures 6 and A2; Table A1), so neither rainfall deficit nor atmospheric dryness offers a straightforward explanation for the event.

We nonetheless emphasize that fully isolating the sea-level signal from concurrent climatic variability is not trivial. The regression analysis shows that core-zone VH is strongly coupled to both precipitation ( $R^2 = 0.48$ ) and VPD ( $R^2 = 0.45$ ), confirming that these climatic variables exert a substantial influence on the observed backscatter. Because El Niño simultaneously depresses sea level and modulates rainfall and atmospheric demand, the effects of these drivers are partially collinear and cannot be statistically disentangled from a single radar time series. Two considerations, however, mitigate this confounding aspect but do not resolve it. First, the direction of the climatic anomalies is inconsistent with a water-deficit mechanism: precipitation was high and VPD low at dieback onset, the opposite of what drought-driven stress would require, so the residual unexplained stress is most plausibly attributed to the sea-level fall. Second, the strong seasonal couplings of VH with precipitation and VPD indicate that short-term backscatter variability is dominated by canopy moisture dynamics rather than by structural change; this moisture-driven component must be accounted for before any structural or sea-level signal can be inferred from C-band SAR. We therefore frame sea-level fall as the most strongly supported proximate stressor consistent with the combined evidence, while acknowledging that the overlapping influence of precipitation and VPD on the radar signal precludes a fully independent attribution from the present data. Correctly identifying the dominant stressor is more than an academic exercise: management interventions for salinity- and inundation-driven stress differ fundamentally from those for rainfall deficit, so robust driver attribution is central to designing effective, sustainable adaptation responses for ENSO-exposed coasts.

#### 4.3. C-Band Limitations and Mask Dependence

C-band backscatter saturates at high biomass and is strongly modulated by canopy moisture, which limits its sensitivity to subtle structural change. As a consequence, gradual canopy thinning, partial defoliation, or slow biomass loss may produce backscatter changes that fall within the seasonal moisture envelope and are therefore difficult to detect; the absence of a masked-SAR decline does not by itself prove the absence of structural change. The result is thus best interpreted conservatively, as showing no abrupt, radar-detectable structural collapse rather than no structural change of any kind [26]. Similarly, the masked-baseline stability (Figure A1) constrains the rate of detectable structural change but does not directly resolve the temporal pattern of area loss, so signal stability should not be equated with the rate of mangrove area reduction. Integrating L-band SAR, which penetrates the canopy more deeply and saturates at higher biomass, together with GEDI canopy-structure metrics would substantially improve sensitivity to the gradual and subtle structural changes that C-band cannot reliably capture [39].

Our conclusions also depend on the accuracy of the mangrove–non-mangrove separation. The GEDI cross-check supports the mask at the zone level, but it is not a substitute for high-resolution imagery or field-based validation, and classification uncertainty is expected to be greatest along the narrow land–water transition that defines the fringing mangrove boundary. Such boundary misclassification has a direct and asymmetric effect on the interpretation: erroneously including non-vegetated tidal-flat or open-water pixels would import the very inundation- and geometry-driven variability that produces the spurious whole-ROI decline (Section 4.1), biasing masked backscatter downward and potentially mimicking structural loss, whereas erroneously excluding true mangrove pixels would narrow the sampled population and could mask localized change. The core zone, defined as pixels mapped as mangrove in every available year, is the most robust to this effect because it is least exposed to boundary ambiguity, and the consistent zonal ordering of backscatter (core > union > dynamic; Table 2) is the pattern expected if the mask is correctly stratifying canopy density rather than introducing artifacts. We therefore regard the stability of the core-zone signal as comparatively robust to plausible classification error, while recognizing that conclusions resting on the mangrove–non-mangrove distinction remain conditional on the accuracy of the GMW product and would benefit from independent field or high-resolution validation in the boundary regions. For operational blue-carbon monitoring, this implies that mask quality—particularly along the dynamic fringe where most change occurs—is not a peripheral technical detail but a prerequisite for credible, decision-relevant assessments of ecosystem condition, reinforcing the case for validated, multi-sensor products in sustainable coastal-management workflows.

#### *4.4. Implications for Sustainable Coastal Resilience*

Beyond their carbon-storage function, mangroves act as nature-based coastal infrastructure that attenuates waves and reduces flood damage, often more cost-effectively than engineered defenses, supporting sustainable coastal development [40–42]. Our findings indicate that this protective capacity is climate-sensitive: ENSO-driven sea-level fall can push mangroves across physiological failure thresholds, temporarily eroding the services they provide [21,43]. The marginal, climatically exposed setting of the Gulf of Carpentaria makes it a sentinel for the kind of episodic, ENSO-amplified stress that other low-lying blue-carbon coasts are likely to face more frequently under intensifying climate variability, so the monitoring approach demonstrated here has transferable value for sustainable management elsewhere in the Indo-Pacific. Because such impacts and recoveries unfold over multi-year timescales, sustained, mask-applied, multi-sensor satellite monitoring is essential for tracking the blue-carbon ecosystem condition and for informing climate-adaptive management, hybrid coastal defenses, and disaster-risk reduction [44]. Embedding validated, mask-applied radar indicators within these monitoring systems would help ensure that adaptation decisions rest on the actual condition of mangrove canopy rather than on signals contaminated by surrounding non-vegetated surfaces.

#### *4.5. Limitations*

Several limitations should be noted. Most importantly, although Sentinel-1 observations begin in 2014, 26 months lack acquisitions over the ROI, and these gaps include the January–June 2016 interval (Table A2), which coincides with the most intense phase of the negative sea-level anomaly, reaching  $-17.5$  cm in January 2016 and  $-14.7$  cm in February 2016. The absence of radar observations during precisely this critical window means that any rapid structural change occurring at the depth of the sea-level minimum would not have been captured. Our conclusion that no abrupt, radar-detectable structural collapse occurred must therefore be interpreted with corresponding caution: it is well supported

for the observed months bracketing the event but cannot exclude an unobserved abrupt change during the data gap itself. This limitation reinforces the value of the longer optical record (Figure 4), which shows a progressive rather than single-step decline, but it cannot be fully resolved with the present SAR series and should be borne in mind when weighing the structural conclusions.

Additionally, HYCOM anomalies rather than absolute heights are reported, because the absolute calibration is uncertain in this implementation, although the relative ENSO-related variability is robust. The collinearity of sea level with precipitation and VPD limits formal driver partitioning, as discussed in Section 4.2, and C-band saturation, reduced sensitivity to gradual change, and mask dependence are discussed in Section 4.3. No speckle filtering or terrain normalization was applied to the SAR series beyond the standard GRD processing. Taken together, these constraints define a concrete agenda for building monitoring systems robust enough to support the long-term, sustainable stewardship of blue-carbon ecosystems: denser multi-sensor coverage, validated fringe-aware masks, and complementary structural sensors are needed if satellite records are to reliably inform adaptive management before, during, and after extreme climatic events.

## 5. Conclusions

Combining a validated GMW v3 mangrove mask, Sentinel-1 SAR, CHIRPS precipitation, HYCOM sea level, ERA5-Land temperature and VPD, and the ONI, we reassessed the 2015–2016 Gulf of Carpentaria mangrove dieback. The apparent abrupt SAR decline during the event originated from non-mangrove pixels; mangrove-masked backscatter remained stable across the observed months of the dieback, indicating no abrupt, radar-detectable structural collapse rather than a precisely resolved rate of area loss, and GEDI independently confirmed the mask at the zone level. This structural conclusion should be read with appropriate caution because Sentinel-1 acquisitions are absent during January–June 2016, the period of deepest sea-level anomaly, so an unobserved rapid change within that window cannot be excluded. The event coincided with a strong ENSO-driven sea-level fall under near-to-above-average rainfall and low VPD, indicating that sea-level fall, rather than precipitation deficit, was the most strongly supported proximate stressor; we note, however, that the radar signal is itself substantially coupled to precipitation and VPD, so the overlapping influence of these climatic drivers precludes a fully independent statistical attribution. Within these constraints, our results demonstrate the value of mask-applied, multi-sensor satellite monitoring for the sustainable management of blue-carbon ecosystems and for safeguarding mangrove-based coastal resilience under intensifying climate variability. Future work integrating L-band SAR, GEDI, and in situ or high-resolution validation—particularly across the mangrove fringe and during the early-2016 observational gap—would further constrain structural change and driver partitioning and strengthen the evidence base for climate-adaptive coastal stewardship.

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**Data Availability Statement:** All primary datasets used in this study are publicly available. Global Mangrove Watch (GMW) v3 mangrove extent data are available from the GMW data portal (<https://www.globalmangrovetwatch.org>, accessed on 1 June 2026) and via Bunting et al. (2022) [27]. Copernicus Sentinel-1 GRD imagery and Landsat Collection 2 Level-2 surface reflectance were accessed through Google Earth Engine (<https://earthengine.google.com>, accessed on 1 June 2026). CHIRPS precipitation data are provided by the University of California, Santa Barbara Climate Hazards Group (<https://www.chc.ucsb.edu/data/chirps>, accessed on 1 June 2026). HYCOM sea surface height fields are available from the HYCOM consortium (<https://www.hycom.org>, accessed on 1 June 2026). The Oceanic Niño Index (ONI) and Niño3.4 data are distributed by the NOAA Climate Prediction Center (<https://www.cpc.ncep.noaa.gov>, accessed on 1 June 2026). The derived time-series datasets (monthly zonal SAR backscatter, CHIRPS precipitation, HYCOM SSH anomalies, and mangrove area by year) and the analysis code generated in this study are available from the corresponding author upon reasonable request.

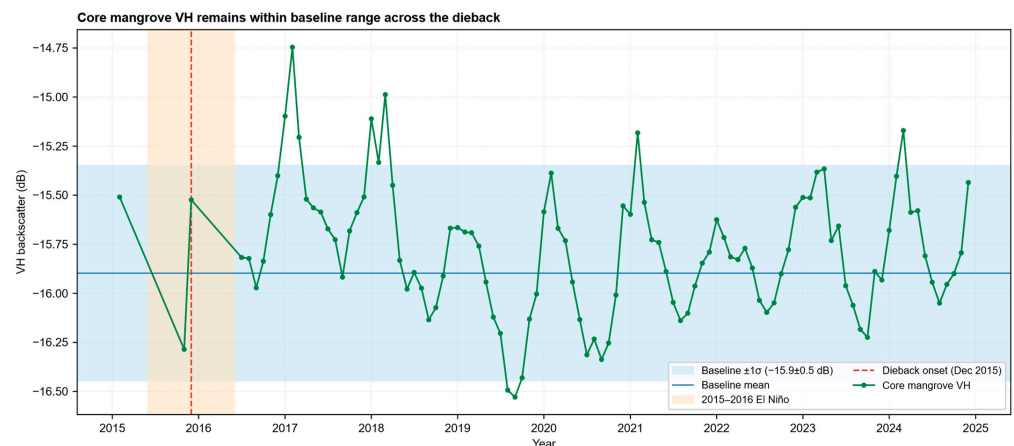
**Conflicts of Interest:** The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

## Abbreviations

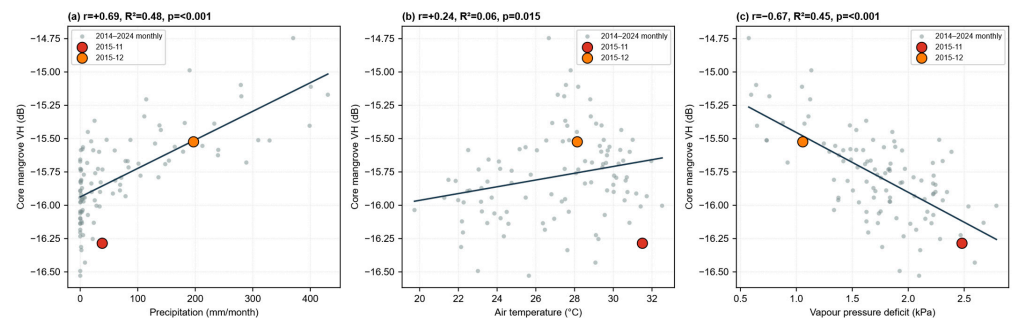
The following abbreviations are used in this manuscript:

|          |                                                                           |
|----------|---------------------------------------------------------------------------|
| AGB      | Above-Ground Biomass                                                      |
| CHIRPS   | Climate Hazards Group InfraRed Precipitation with Station data            |
| C-band   | SAR microwave band at ~5.4 GHz (~5.6 cm wavelength)                       |
| dB       | Decibel                                                                   |
| ENSO     | El Niño–Southern Oscillation                                              |
| EPSG     | European Petroleum Survey Group (coordinate reference code)               |
| GEDI     | Global Ecosystem Dynamics Investigation                                   |
| GEE      | Google Earth Engine                                                       |
| GMW      | Global Mangrove Watch                                                     |
| GRD      | Ground Range Detected                                                     |
| HYCOM    | HYbrid Coordinate Ocean Model                                             |
| L-band   | SAR microwave band at ~1.3 GHz (~23 cm wavelength)                        |
| MODIS    | Moderate-Resolution Imaging Spectroradiometer                             |
| NDMI     | Normalized Difference Moisture Index                                      |
| NDVI     | Normalized Difference Vegetation Index                                    |
| NOAA CPC | National Oceanic and Atmospheric Administration Climate Prediction Center |
| ONI      | Oceanic Niño Index                                                        |
| ROI      | Region of Interest                                                        |
| SAR      | Synthetic Aperture Radar                                                  |
| SSH      | Sea Surface Height                                                        |
| SWIR     | Short-Wave Infrared                                                       |
| UCSB-CHG | University of California, Santa Barbara—Climate Hazards Group             |
| VH       | Vertical transmit, Horizontal receive (cross-polarization)                |
| VV       | Vertical transmit, Vertical receive (co-polarization)                     |

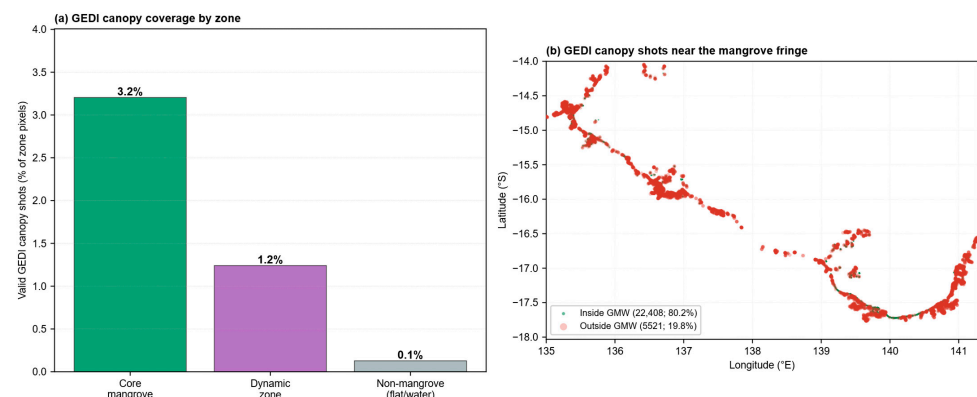
## Appendix A



**Figure A1.** Core mangrove VH backscatter relative to the pre-event baseline (mean  $\pm 1\sigma$ ) across 2015–2024. The series remains within the baseline range throughout the dieback and post-event period, indicating no abrupt, radar-detectable structural transition. Shading marks the 2015–2016 El Niño; the dashed line marks the December 2015 dieback onset.



**Figure A2.** Core mangrove VH backscatter versus (a) precipitation, (b) air temperature, and (c) vapour pressure deficit over 2014–2024. In each panel, gray circles are individual monthly observations and the solid dark-blue line is the ordinary least-squares (OLS) regression fit; the corresponding  $r$ ,  $R^2$ , and  $p$  values are given in each panel title. The pre-dieback (November 2015, red) and post-dieback (December 2015, orange) months are highlighted, showing that the dieback onset coincided with high precipitation and low VPD.



**Figure A3.** Independent validation of the GMW mask using GEDI canopy shots. (a) Proportion of valid GEDI canopy shots per GMW zone; (b) spatial distribution of GEDI canopy shots near the mangrove fringe, classified by whether they fall inside or outside the GMW mask.

**Table A1.** Ordinary least-squares regression of mangrove-masked and whole-ROI VH backscatter against precipitation, air temperature, and vapor pressure deficit (2014–2024).

| Predictor                    | Response     | r      | R <sup>2</sup> | p      | Slope   | n   |
|------------------------------|--------------|--------|----------------|--------|---------|-----|
| Precipitation (mm/month)     | Core VH      | 0.693  | 0.48           | <0.001 | 0.0021  | 105 |
| Precipitation (mm/month)     | Whole ROI VH | 0.25   | 0.063          | 0.01   | 0.0048  | 106 |
| Air temperature (°C)         | Core VH      | 0.237  | 0.056          | 0.015  | 0.0254  | 105 |
| Air temperature (°C)         | Whole ROI VH | −0.008 | 0              | 0.933  | −0.0054 | 106 |
| Vapor pressure deficit (kPa) | Core VH      | −0.668 | 0.446          | <0.001 | −0.4488 | 105 |
| Vapor pressure deficit (kPa) | Whole ROI VH | −0.313 | 0.098          | 0.001  | −1.2881 | 106 |

**Table A2.** Sentinel-1 acquisition-gap periods (2014–2024) and their temporal relationship with the dieback window and the period of deepest sea-level anomaly.

| Gap Period                   | Months | Note                                                                         |
|------------------------------|--------|------------------------------------------------------------------------------|
| January 2014 to January 2015 | 13     | Pre-mission (before Sentinel-1 operational start)                            |
| April 2015 to October 2015   | 7      | Includes SSH minimum of −10.5 cm (October 2015)                              |
| January 2016 to June 2016    | 6      | Includes deepest SSH anomaly (−17.5 cm January 2016; −14.7 cm February 2016) |

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