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Determining Early Warning Thresholds to Detect Tree Mortality Risk in a Southeastern U.S. Bottomland Hardwood Wetland

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Abstract

Prolonged inundations are altering coastal forest ecosystems of the southeastern US, causing extensive tree die-offs and the development of ghost forests. This hydrological stressor also alters carbon fluxes, threatening the stability of coastal carbon sinks. This study was conducted to investigate the interactions between hydrological drivers and ecosystem responses by analyzing daily eddy covariance flux data from a wetland forest in North Carolina, USA, spanning 2009–2019. We analyzed temporal patterns of net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE) under both flooded and non-flooded conditions and evaluated their relationships with observed tree mortality. Generalized Additive Modeling (GAM) revealed that groundwater table depth (GWT), leaf area index (LAI), NEE, and net radiation (Rn) were key predictors of mortality transitions ($R^2 = 0.98$). Elevated GWT induces root anoxia; declining LAI reduces productivity; elevated NEE signals physiological breakdown; and higher Rn may amplify evapotranspiration stress. Receiver Operating Characteristic (ROC) analysis revealed critical early warning thresholds for tree mortality: GWT = 2.23 cm, LAI = 2.99, NEE = 1.27 g C m⁻² d⁻¹, and Rn = 167.54 W m⁻². These values offer a basis for forecasting forest mortality risk and guiding early warning systems. Our findings highlight the dominant role of hydrological variability in ecosystem degradation and offer a threshold-based framework for early detection of mortality risks. This approach provides insights into managing coastal forest resilience amid accelerating sea level rise.

Keywords: coastal forest decline; carbon fluxes; groundwater table depth; ghost forests; early warning thresholds; Generalized Additive Models (GAM)



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1. Introduction

Global climate change is accelerating sea level rise (SLR), posing a significant and growing threat to coastal ecosystems worldwide. Projections from the Intergovernmental Panel on Climate Change [1] estimate that global mean sea levels could increase by 0.29 to 1.1 m by the year 2100, depending on the trajectory of greenhouse gas emissions. Coastal forests, located at the boundary between terrestrial and marine environments, are especially susceptible to the impacts of SLR and related hydrological shifts, such as saltwater intrusion, rising groundwater tables (GWTs), and extended periods of flooding [2].

These hydrological stressors impose multiple physiological challenges on trees. Prolonged inundation leads to hypoxic or anoxic soil conditions, impairing root respiration and nutrient uptake, while elevated salinity disrupts osmotic balance and damages cellular membranes [3,4]. These stressors collectively contribute to the formation of “ghost forests”—landscapes characterized by widespread tree mortality—and replacement of once-forested areas with salt-tolerant marsh vegetation [5]. Ghost forest formation reflects not only a loss of biodiversity and forest function but also a shift in the carbon balance of coastal ecosystems. As trees die and vegetation cover diminishes, formerly productive carbon sinks can become net sources of carbon dioxide to the atmosphere [6–8]. This shift raises particular concern amid ongoing climate change, given that coastal forests serve as critical reservoirs for long-term carbon sequestration [9,10].

Despite increased recognition of ghost forest dynamics, major knowledge gaps remain. Most existing studies have focused on describing vegetation decline or estimating overall carbon losses, but few have quantitatively identified the key drivers and nonlinear thresholds that lead to ecosystem collapse. Understanding the conditions under which mortality occurs and predicting those conditions in advance requires integrated analysis of carbon fluxes, hydrological stressors, and vegetation responses. The emerging field of studying ecological tipping points emphasizes the importance of detecting early warning signals that precede rapid ecosystem transitions [11]. However, the application of such concepts to real-world forest mortality events remains limited.

To advance understanding of how hydrological variability influences coastal forest ecosystems, this study integrates 11 years of eddy covariance flux tower data with field-based observations of tree mortality. Our objectives are to (1) assess the effects of hydrological fluctuations on net ecosystem exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (RE); (2) determine the key drivers underlying shifts in tree mortality; and (3) develop a predictive framework for early warning by identifying critical thresholds in relevant variables through statistical modeling and Receiver Operating Characteristic (ROC) analysis. Our work offers an analysis of the interactions between groundwater table (GWT), carbon balance metrics (NEE, GPP, RE), and vegetation stress indicator (LAI). The use of Generalized Additive Modeling (GAM) and ROC analyses enable the identification of key predictors and empirically derived thresholds for mortality risk. While previous studies have examined individual drivers of ghost forest formation [5,12,13], our study provides an integrated framework that links hydrological processes with carbon dynamics and mortality outcomes at multiple temporal and spatial scales. By employing this integrative approach, we aim to enhance predictive capacity for anticipating and alleviating the effects of coastal ecosystem decline in the face of ongoing sea level rise.

2. Materials and Methods

2.1. The Study Site

The carbon flux monitoring tower for this study was situated within the Alligator River National Wildlife Refuge (ARNWR) in Dare County, North Carolina, USA (35°45′16.44″ N, 75°54′13.64″ W) (Figure 1). The site experiences persistent inundation resulting from impeded groundwater drainage into the adjacent ocean, a condition exacerbated by rising sea levels. Tree-rooted ‘hummocks’ generally remain above the water table, while the lower, unvegetated ‘hollows’ are inundated for approximately 70% of the year. Groundwater table (GWT) data from this study from 2009 to 2012 indicate episodic flooding; however, from 2013 to 2019, GWT levels were predominantly above the soil surface, indicating sustained inundation. Consistent with findings from previous studies [14–16], sea level rise (Figure 2b) has led to the retreat of the lower wetland boundary, increasing flooding

in coastal wetlands. This phenomenon has adversely impacted vegetation survival at our study location, similar to observations reported in other wetland ecosystems [2,3,17,18].

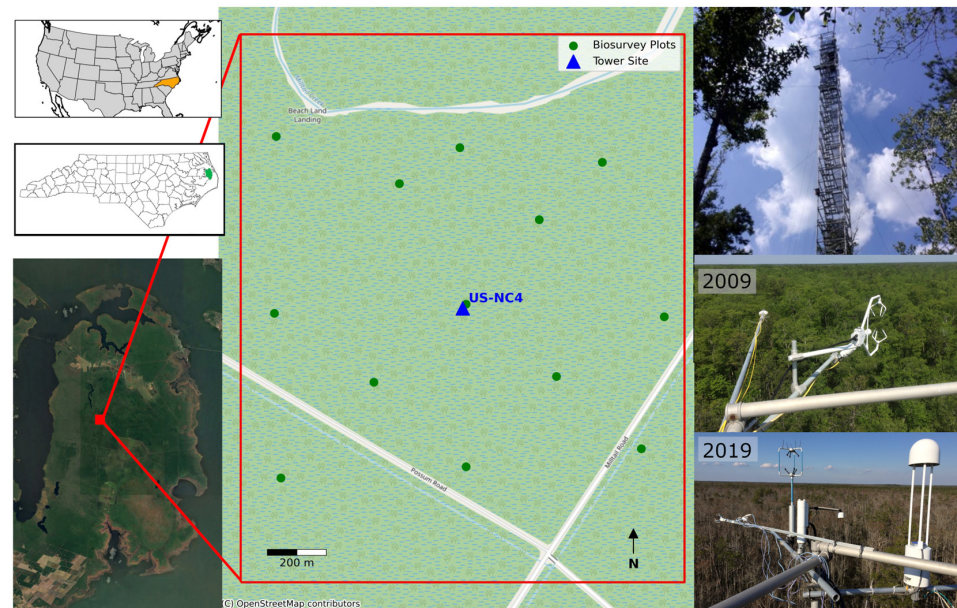


Figure 1. Study site at the Alligator River National Wildlife Refuge, Dare County, North Carolina, USA, showing the location of the flux tower and surrounding plots. Top photo: flux tower structure; middle: site conditions in 2009; bottom: canopy structure in 2019.

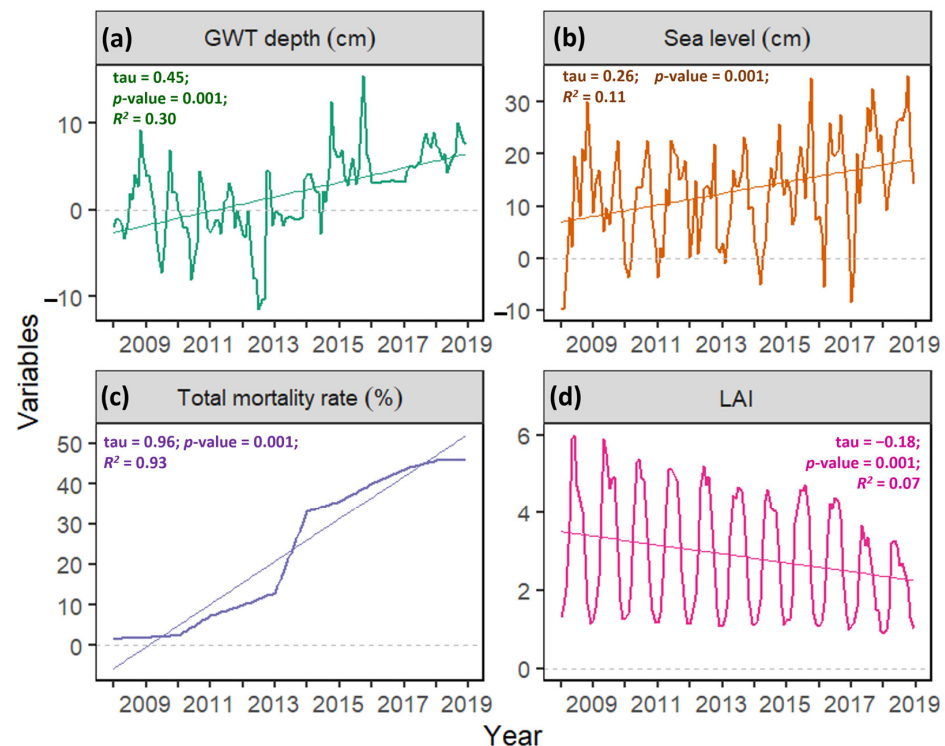


Figure 2. Temporal variation in (a) relative groundwater table (GWT) depth, (b) relative sea level, (c) cumulative tree mortality rates, and (d) leaf area index (LAI) from 2009 to 2019. The tau value for GWT, relative sea level, total mortality rates, and LAI were taken from Kendall trend analysis. All data were collected within the flux footprint of US-NC4 tower at Alligator River National Wildlife Refuge in North Carolina, USA.

As documented in previous studies [19–21], dominant tree species include American holly (*Ilex opaca* Aiton), tupelo (*Nyssa sylvatica* Marshall.), sweetgum (*Liquidambar styraciflua*

L.), loblolly pine (*Pinus taeda* L.), and red maple (*Acer rubrum* L.). The canopy averages approximately 23 m in height, with an estimated density of 2320 trees per hectare. Soils at the site are classified as Pungo series Haplosaprists, featuring an organic layer between 0.3 and 1.0 m thick. Elevation at the site is less than 1 m above sea level. The regional average annual precipitation over 1981–2019 was 1168 ± 204 mm, and the mean annual temperature from 2005–2019 was 15.8 ± 1.8 °C [19–21].

2.2. Flux Measurements

Turbulent fluxes of carbon dioxide (CO₂) were quantified using the eddy covariance (EC) method. The EC setup comprised an open-path infrared gas analyzer (LI-7500, LI-COR, Lincoln, NE, USA) to measure CO₂ exchange, paired with a Gill WindMaster 3D sonic anemometer (Gill Instruments, Lymington, UK) to capture three-dimensional wind velocity components. All sensors were installed at the top of a 32 m tall tower.

Additional environmental variables were monitored at the same height. Air temperature was monitored with an HMP45AC probe (Vaisala, Finland), while photosynthetically active radiation (PAR) was measured using a LI-190 quantum sensor (LI-COR, Lincoln, NE, USA). Net radiation was recorded by a CNR-1 radiometer (Kipp & Zonen, Delft, The Netherlands), and precipitation was captured using a TE-525 tipping-bucket rain gauge (Campbell Scientific Inc., Logan, UT, USA).

Half-hourly net ecosystem exchange (NEE) of CO₂ was computed using EddyPro software version 7.0.9, LI-COR (<https://www.licor.com/support/EddyPro/software.html>, accessed on 20 November 2024). A friction velocity (u^*) threshold of 0.3 m s^{-1} was applied for filtering nighttime fluxes. Standard corrections and quality control procedures were implemented, including spike detection [22], planar fit coordinate rotation [23], time lag compensation, air density corrections [24], and frequency response adjustments for both high- [25] and low- [26] pass filtering. Data quality was classified on a scale from 0 (high) to 2 (low) [27], with values labeled as 2 excluded from further analysis.

To fill data gaps and partition net ecosystem exchange (NEE) into gross primary production (GPP) and ecosystem respiration (RE), we utilized the REdyProc processing tool developed by the Max Planck Institute for Biogeochemistry (<https://www.bgc-jena.mpg.de/5622399/REdyProc>, accessed on 20 February 2025). Daily NEE was calculated by summing the 30 min values across each 24 h period. Annual totals for NEE, GPP, and RE were derived by aggregating the corresponding daily sums.

2.3. The Key Drivers of Tree Mortality

Groundwater table depth (GWT) was measured using an ultrasonic water level logger (Infinities, Port Orange, FL, USA) installed within a perforated PVC pipe positioned at the soil surface. The system operated continuously throughout the year, collecting data at 30 min intervals. Due to sensor malfunctions, data from 2017 were excluded from the analysis. Measurements were conducted from January 2009 through 2019.

Based on GWT readings, the site was categorized as either flooded ($\text{GWT} > 0$) or non-flooded ($\text{GWT} < 0$) (Figure 2a). To contextualize local hydrologic conditions, sea level trends were retrieved from NOAA tide gauge data at Oregon Inlet Marina, North Carolina (<https://tidesandcurrents.noaa.gov/sltrends/>, accessed on 20 August 2024).

Net radiation was measured using a CNR-1 radiometer (Kipp & Zonen, Delft, The Netherlands) mounted at the top of the flux tower to provide representative exposure to incoming and outgoing radiation.

LAI was estimated using monthly surface reflectance data at a $30 \text{ m} \times 30 \text{ m}$ spatial resolution, generated by integrating Landsat and MODIS observations through the Tempo-

ral Adaptive Reflectance Fusion Model (TARFM) algorithm [28]. The fused reflectance data were then used as input to a trained artificial neural network to calculate LAI values [29].

2.4. Tree Mortality Determination

In 2009, thirteen circular vegetation plots with a 7 m radius were established to monitor forest biomass and tree mortality. Within each plot, all tree species with a diameter at breast height (DBH; measured at 1.4 m above the ground) greater than 2.5 cm were identified, tagged, and measured. Surveys were conducted annually during the winter months (December to March) on the same tagged trees from 2009 through 2019. Tree mortality within plots was recorded by identifying and counting both downed individuals and standing dead trees. The degree of decomposition in both standing and fallen dead trees was assessed following the guidelines outlined in the Forest Inventory and Analysis (FIA) Field Guide by the USDA Forest Service [30]. Following the methods from previous studies [31,32], the tree mortality was expressed as

$$\lambda = \frac{\ln(n_0) - \ln(n_t)}{t} \quad (1)$$

where λ is the mortality rate, n is the total number of trees of all species, n_0 is the number of trees during the previous census date, and n_t is the number of surviving trees to time t (annually). The time between the two tree censuses is t .

2.5. Data Analysis

Temporal trends were assessed using the nonparametric Mann–Kendall (MK) test [33–35], a widely applied method for detecting monotonic trends in environmental time series. A positive standardized test statistic (Z) indicates an increasing trend, while a negative Z denotes a decreasing trend. Statistical significance is evaluated by comparing the absolute value of Z to a critical threshold; specifically, if $|Z| > 1.96$ (corresponding to a 0.05 significance level under the standard normal distribution), the null hypothesis (H_0) of no trend is rejected, indicating a statistically significant temporal change [33].

To identify key environmental predictors of mortality transitions, we employed Generalized Additive Models (GAMs) using the *gam* function from the *mgcv* and *MuMin* packages [36]. GAMs allow for flexible, nonlinear relationships between predictors and the response variable. Predictor variables considered include GWT, LAI, NEE, and R_n , based on prior ecological understanding and correlation analysis. Model performance was evaluated using the Adjusted R^2 for goodness-of-fit, Akaike Information Criterion (AIC) for model parsimony, and significance levels for each predictor variable [36].

Early warning thresholds for tree mortality risk were identified using Receiver Operating Characteristic (ROC) curve analysis [37]. For each continuous predictor variable, optimal thresholds were determined using Youden's Index, which maximizes the difference between the true positive rate (sensitivity) and the false positive rate (1–specificity) [37]. To assess the overall classification performance, the area under the ROC curve (AUC) was calculated and reported.

Linear regression and anomaly detection were applied to assess interannual and seasonal trends in NEE, GPP, and RE under both flooded and non-flooded conditions. Graphics are performed using *ggplot2* [38], *ggpubr*, *plotly* [39], *tidyverse* [40], and *reshape* [41]. All analyses were performed using R Statistical Language Tool [42].

3. Results

3.1. Hydrology and Tree Mortality Trends

Using a relative reference point [10], groundwater table depth (GWT) increased from -4.3 cm below the ground surface to 1.2 cm above ground between 2009 and 2014. From 2015 onward, GWT consistently ranged between 3.2 cm and 6.9 cm above the land surface, indicating a sustained rise over time ($R^2 = 0.30$; $p < 0.05$; Figure 2a). A weak but detectable relationship was observed between rising groundwater table depth (GWT) and increasing sea level rise (SLR) over the 2009–2019 period ($R^2 = 0.11$, $p < 0.01$), suggesting that even at a distance of approximately 20 km from the Croatan Sound and 40 km from the Atlantic Ocean, changes in sea level may influence local hydrology. During the same period, total tree mortality exhibited a pronounced and consistent upward trend (Figure 2c), increasing from nearly 0% at the beginning of the study to over 45% by 2019. The increase in mortality corresponds with a steady decline in leaf area index (LAI) observed throughout the study period (Figure 2d).

The linear regression also showed an excellent fit ($R^2 = 0.93$, Figure 2c), reflecting the accelerating rate of cumulative mortality in the study area. This rapid increase aligns temporally with both the rise in GWT and SLR, suggesting a potential linkage between prolonged hydrological stress and wetland forest decline.

3.2. Temporal Trends of Carbon Fluxes

Under flooded conditions, the wetland ecosystem frequently oscillated between acting as a net carbon sink and a net carbon source, with daily NEE values ranging from -7.57 to 22.49 $\text{g C m}^{-2} \text{d}^{-1}$ (mean = 0.40 $\text{g C m}^{-2} \text{d}^{-1}$) (Figure 3a). In contrast, gross primary production (GPP) exhibited a strong and recurring seasonal pattern (Figure 3b), with peak values typically observed during the warm growing months from May to August. The average daily GPP under flooded conditions was 4.06 $\text{g C m}^{-2} \text{d}^{-1}$, with observed values ranging from 0.01 to 27.45 $\text{g C m}^{-2} \text{d}^{-1}$. Ecosystem respiration (RE) followed a similarly pronounced seasonal cycle (Figure 3c), with higher rates during summer and early autumn. The average daily RE was 4.51 $\text{g C m}^{-2} \text{d}^{-1}$, ranging from 0.01 to 29.78 $\text{g C m}^{-2} \text{d}^{-1}$. Notably, flooded periods were associated with significantly lower RE.

During non-flooded conditions, the system also displayed substantial carbon flux dynamics. The daily average NEE was 0.44 $\text{g C m}^{-2} \text{d}^{-1}$, ranging from -9.19 to 21.31 $\text{g C m}^{-2} \text{d}^{-1}$. The GPP during non-flooded periods was higher, averaging 6.54 $\text{g C m}^{-2} \text{d}^{-1}$ and ranging from 0.01 to 31.44 $\text{g C m}^{-2} \text{d}^{-1}$. Similarly, RE also increased under drier conditions, with an average daily value of 6.95 $\text{g C m}^{-2} \text{d}^{-1}$ and a range of 0.32 to 32.03 $\text{g C m}^{-2} \text{d}^{-1}$.

Comparing flooded and non-flooded fluxes revealed that NEE values exhibited a higher variance during the flooded (-7.57 $\text{g C m}^{-2} \text{d}^{-1}$ to 22.49 $\text{g C m}^{-2} \text{d}^{-1}$) than in non-flooded (-9.19 $\text{g C m}^{-2} \text{d}^{-1}$ to 21.31 $\text{g C m}^{-2} \text{d}^{-1}$) periods ($p < 0.01$). GPP and RE both showed statistically significant increases under non-flooded conditions ($p < 0.01$). The daily average GPP (6.54 $\text{g C m}^{-2} \text{d}^{-1}$) during the non-flooded period was higher compared to the flooded period (4.06 $\text{g C m}^{-2} \text{d}^{-1}$). Similarly, a higher RE was observed during the flooded (6.95 $\text{g C m}^{-2} \text{d}^{-1}$) compared to the non-flooded period (4.51 $\text{g C m}^{-2} \text{d}^{-1}$).

Non-flooded periods became increasingly rare after 2016. Prior to this shift, GPP and RE under flooded and non-flooded conditions were largely comparable, showing overlapping seasonal peaks and similar magnitudes. However, from 2015 onward, a clear divergence emerged: both GPP and RE became consistently higher during non-flooded periods, with RE in particular showing pronounced increases in both peak intensity and duration. This pattern suggests a potential regime shift in the wetland's carbon dynamics, likely driven by prolonged inundation and altered ecosystem processes.

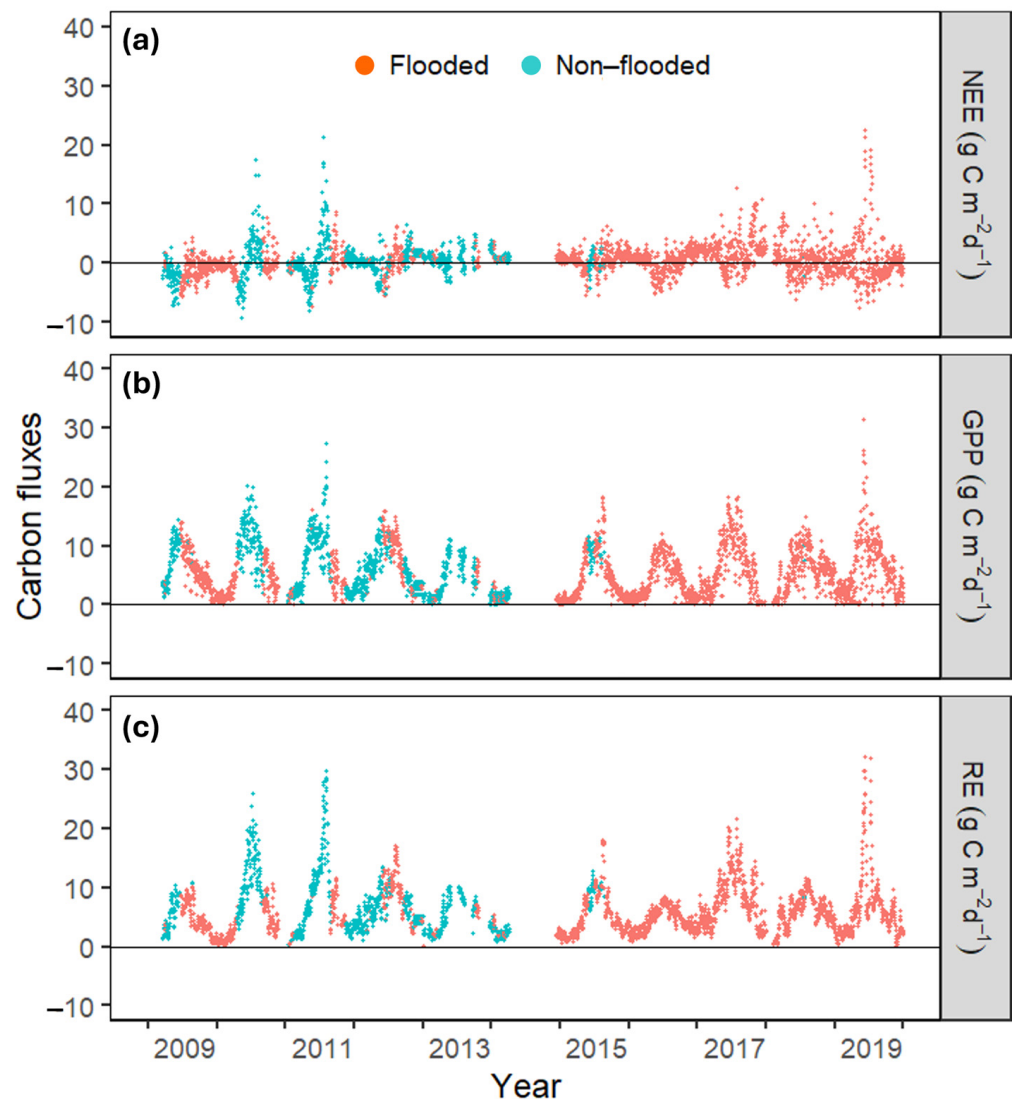


Figure 3. The temporal variation of (a) net ecosystem exchange (NEE), (b) gross primary productivity (GPP), and (c) ecosystem respiration (RE) under flooded and non-flooded conditions in the US-NC4 flux tower at Alligator River National Wildlife Refuge (ARNWR), Dare County, NC, USA. Daily flux data from 2009 to 2019 was used.

The sustained elevation of RE under non-flooded conditions—likely driven by enhanced microbial decomposition and root respiration due to increased oxygen availability—began to outpace GPP more frequently. As a result, NEE variability increased, and the wetland system increasingly functioned as a persistent net carbon source. This shift underscores the sensitivity of carbon cycling in wetland ecosystems to hydrological fluctuations and emphasizes the critical need for long-term monitoring of water regime dynamics, particularly in the face of climate variability and land-use changes.

3.3. Groundwater Table as a Dominant Driver of Carbon Fluxes

While SLR represents a long-term boundary condition affecting coastal ecosystems, it is the more immediate and variable changes in GWT that exert the strongest influence on ecosystem carbon dynamics. To evaluate the relative importance of these two hydrological drivers, we conducted linear regression analyses of daily and annual NEE, GPP, and RE against SLR and GWT across the 11-year dataset (Figure 4).

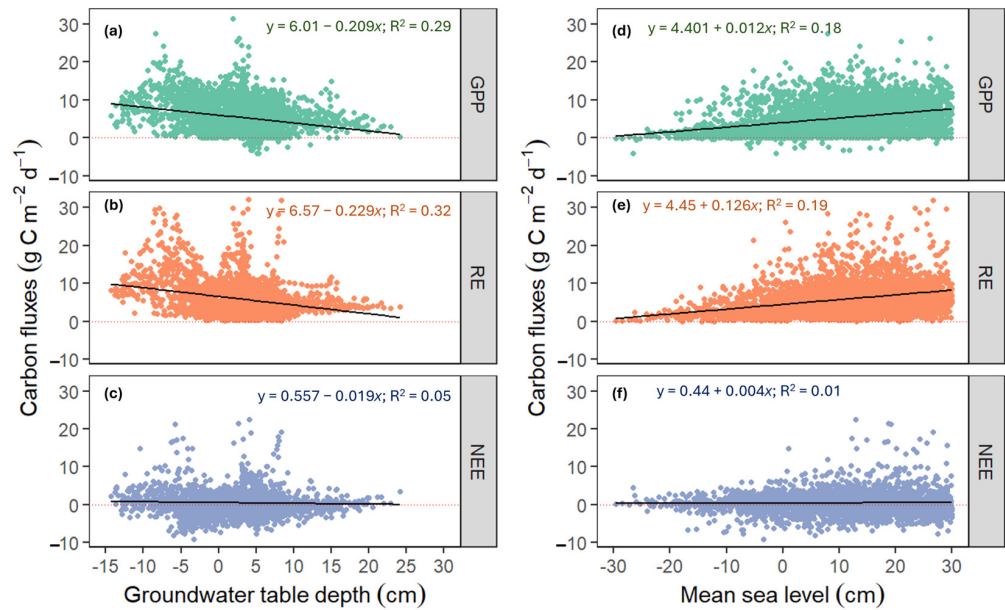


Figure 4. Linear regression analyses of the impacts of sea level rise (SLR) and groundwater table depth (GWT) on carbon fluxes: gross primary productivity (GPP, (a,d)), ecosystem respiration (RE, (b,e)), and net ecosystem exchange (NEE, (c,f)) at daily timescales from 2009 to 2019.

Our results reveal that GWT is a consistently stronger predictor of carbon fluxes than SLR. At the daily scale, groundwater table depth (GWT) demonstrated moderate to strong positive correlations with GPP and RE ($R^2 = 0.29$ and 0.32 , respectively), whereas its association with NEE was weaker and more variable ($R^2 = 0.01$).

SLR exerted a relatively weaker influence overall. Both GPP and RE increased modestly with rising sea level ($R^2 = 0.18$ and 0.19 , respectively), but with shallower slopes and greater scatter compared to the GWT regressions. Again, RE exhibited a stronger response than GPP, supporting the interpretation that elevated sea levels indirectly stimulate carbon loss through enhanced respiration. NEE showed no meaningful trend with sea level ($R^2 = 0.01$), underscoring the complexity of net carbon exchange dynamics in response to regional hydrological forcing.

3.4. Tree Mortality

Using field-observed mortality data from 13 permanent plots between 2009 and 2019, we found an increasing tree mortality from 5 trees ha^{−1} in 2010 to 74 trees ha^{−1} in 2019 (Table 1). The downed trees accounted for most of the cumulative tree mortality compared to the cumulative standing dead trees (Table 1).

Table 1. Cumulative percent tree mortality rates across 13 plots surrounding the flux tower at Alligator River National Wildlife Refuge in North Carolina, USA, from 2009 to 2019.

	Mortality Rate (%)										
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Standing dead	1.09	1.10	1.10	2.87	5.23	5.97	10.69	11.31	14.95	18.30	19.01
Downed dead	0.55	0.82	1.38	4.55	4.95	7.41	24.54	26.92	28.57	29.81	31.61
Total mortality	1.64	1.91	2.46	7.29	9.94	12.97	33.00	35.67	40.01	43.70	45.82

By the end of the monitoring period in 2019, *Persea palustris* exhibited the highest mortality rate among angiosperm species at 67.58%, while *Ilex opaca* recorded the lowest at 10.54%. *Nyssa* species, which had the greatest tree density at 140 trees per hectare,

experienced a mortality rate of 43.08% during the same period (Table 2). *Pinus taeda* had the highest overall mortality rate of any species, reaching 69% by the end of the study.

Table 2. Tree mortality by species across 13 plots surrounding the flux tower at Alligator River National Wildlife Refuge in North Carolina, USA, in 2019.

General Species Composition	Scientific Name	Total Tree Density (TPH)	Population Percentage (%)	Tree Mortality in 2019 (per Species in TPH)			Live Trees in 2019 (TPH)	Mortality Rate (%) in 2019
				Standing Dead	Downed Dead	Total Dead		
American holly	<i>Ilex opaca</i>	10	3	1	0	1	9	11
Bald cypress	<i>Taxodium distichum</i>	34	9	5	5	10	24	35
Black gum	<i>Nyssa sylvatica</i>	140	38	13	36	49	91	43
Loblolly pine	<i>Pinus taeda</i>	40	11	9	11	20	20	69
Red maple	<i>Acer rubrum</i>	50	14	8	8	16	34	39
Swamp bay	<i>Persea palustris</i>	57	15	8	20	28	29	68
Sweet gum	<i>Liquidambar styraciflua</i>	39	11	5	7	12	27	37

3.5. Predictive Modeling of Tree Mortality

Since using a univariate model using GWT alone explained 75.0% of the variance in mortality ($R^2 = 0.75$), we used this as the main key variable. Incorporating LAI increased the R^2 to 0.89, suggesting that productivity adds explanatory power beyond hydrology alone. When NEE was added, the model achieved an R^2 of 0.93, indicating that carbon imbalance—particularly net loss of carbon—is a strong indicator of impending mortality. The final model, which included Rn to account for energy input and evaporative demand, achieved a remarkably high R^2 of 0.98, with the lowest Akaike Information Criterion (AIC = 57.84), signifying a well-fitted and parsimonious model. Thus, the four key predictor variables GWT, LAI, NEE, and Rn were used in the GAM analysis due to their ability to explain the changes in mortality with high predictive power (Table 3).

Table 3. Results of the Generalized Additive Model (GAM) analysis ranking predictor variables: groundwater table depth (GWT), leaf area index (LAI), net ecosystem exchange (NEE), and net radiation (Rn) based on their explanatory power for variation in tree mortality.

Response Variable	Predictor Variables	Multiple R ²	p-Value	F-Value	AIC
Mortality ~	GWT	0.75	0.002	17.99	84.07
	GWT+LAI	0.89	0.002	20.52	75.33
	GWT+LAI+NEE	0.93	0.0006	35.55	71.48
	GWT+LAI+NEE+Rn	0.98	0.0001	124.01	57.84

3.6. Thresholds for Early Warning

Building on the high predictive performance of the GAM model, we applied ROC analysis to identify critical thresholds in key ecosystem variables—GWT, LAI, NEE, and Rn—that distinguish between high- and low-mortality transition states.

ROC analysis evaluates the diagnostic ability of each predictor by quantifying its sensitivity (true positive rate) and specificity (true negative rate) in classifying binary outcomes—in this case, whether a given plot-year experiences high (>25%) or low (≤25%) tree mortality. Using Youden’s Index, which identifies the threshold that maximizes the difference between sensitivity and 1–specificity, we derived optimal cutoff values for each variable (Table 4). For context, we first converted the continuous tree mortality rates into a binary classification variable, designating plot-years with mortality above the median as high-mortality cases and those below or equal to the median as low-mortality cases. Based on this classification, ROC curves were constructed for each key predictor to evaluate their ability to discriminate between high- and low-mortality states.

Table 4. Optimal thresholds for key variables identified through ROC analysis. Threshold values are calculated based on Youden’s Index to maximize the distinction between high- and low-mortality transition states.

Variable	Threshold Value	95% Confidence Interval	
		Lower Limits	Upper Limits
GWT	2.23	1.37	3.68
LAI	2.99	2.90	3.30
NEE	1.27	−1.11	5.64
Rn	167.54	163.23	213.92

For each variable, the optimal threshold was identified as the point on the ROC curve that maximizes Youden’s Index, calculated as sensitivity plus specificity minus one. This approach identifies the cutoff value at which the predictor achieves the best overall classification accuracy by balancing true positive and true negative rates. These threshold values reflect the critical boundaries beyond which the probability of high tree mortality increases significantly. The overall classification performance of each predictor was evaluated using the area under the curve (AUC), which reflects the model’s ability to discriminate across all possible thresholds (Figure 5). An AUC of 1.0 indicates perfect classification, while a value of 0.5 denotes no predictive ability. An AUC value of 1.0 represents perfect classification, whereas a value of 0.5 indicates no predictive power. In this study, GWT achieved an AUC of 1.0, indicating near-perfect separation between mortality states. LAI and Rn also exhibited strong classification performance with AUCs of 0.90 and 0.80, respectively, while NEE showed moderate discriminatory ability with an AUC of 0.67.

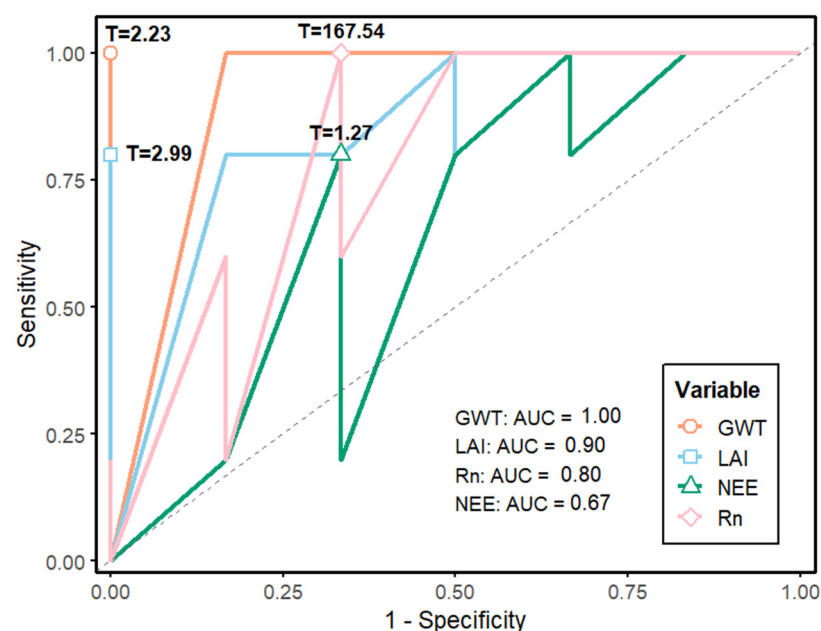


Figure 5. ROC curves with optimal thresholds for key ecosystem predictors distinguishing high-versus low-mortality states. Optimal thresholds (T) for GWT, LAI, NEE, and Rn were determined by maximizing Youden’s Index. AUC values indicate the classification performance of each variable. The dotted line indicates the line of no discrimination (i.e., a 1:1 line) between sensitivity and 1—specificity.

Using our ROC curve and Youden’s Index to quantify each variable’s ability to discriminate between high- and low-mortality states yielded threshold values of 2.23 cm (min. = 1.37, max. = 3.68) for GWT, 2.99 (min. = 2.90, max. = 3.30) for LAI, 1.27 g C m^{−2} d^{−1}

(min. = -1.11 , max. = 5.64) for NEE, and 167.54 W m^{-2} (min. = 163.23 , max. = 213.92) for R_n (Table 4, Figure 5).

4. Discussion

4.1. Temporal Trends in Carbon Fluxes

The fluctuations in daily net ecosystem exchange (NEE) underscore the highly dynamic behavior of carbon fluxes within wetland ecosystems. During periods of inundation, the wetland alternated between acting as a carbon sink and a carbon source, with daily NEE values ranging from -7.57 to $22.49 \text{ g C m}^{-2} \text{ d}^{-1}$. This high variability underscores the sensitivity of wetland carbon dynamics to hydrological conditions, particularly groundwater level fluctuations. An average NEE of $0.40 \text{ g C m}^{-2} \text{ d}^{-1}$ during flood conditions indicates that the system functioned as a modest carbon source overall, aligning with observations from other inundated ecosystems [43,44].

In contrast, gross primary production (GPP) exhibited a strong seasonal pattern, with peaks aligned with the warm growing season (May–August). This pattern reflects the temperature and light dependence of photosynthetic activity, commonly reported in temperate wetlands [45]. While GPP reached up to $27.45 \text{ g C m}^{-2} \text{ d}^{-1}$, ecosystem respiration (RE) frequently exceeded GPP, particularly during periods of prolonged flooding. The average daily RE during flooded conditions was $4.51 \text{ g C m}^{-2} \text{ d}^{-1}$, occasionally peaking at nearly $30 \text{ g C m}^{-2} \text{ d}^{-1}$. Increased RE during non-flooding may be attributed to enhanced root respiration and anaerobic microbial processes in waterlogged soils [46,47].

Non-flooded periods, which were rarely observed after 2016, were associated with higher average daily GPP ($6.54 \text{ g C m}^{-2} \text{ d}^{-1}$) and RE ($6.95 \text{ g C m}^{-2} \text{ d}^{-1}$) compared to flooded periods, with average daily GPP and RE of $4.06 \text{ g C m}^{-2} \text{ d}^{-1}$ and $4.51 \text{ g C m}^{-2} \text{ d}^{-1}$, respectively. This result indicates that drier conditions supported more active vegetation growth and microbial decomposition. The larger flux magnitudes during non-flooded periods suggest enhanced oxygen availability in the rhizosphere, which can stimulate both autotrophic and heterotrophic respiration [48]. This shift underscores the sensitivity of carbon cycling in wetland ecosystems to hydrological fluctuations and emphasizes the critical need for long-term monitoring of water regime dynamics, particularly in the face of climate variability and land-use changes.

Importantly, a notable shift in ecosystem function was observed post-2015: GPP and RE became markedly higher under non-flooded conditions, while flooded conditions increasingly suppressed GPP but maintained elevated RE. This divergence indicates a possible regime shift in the wetland's carbon cycling processes, potentially due to increased inundation frequency or altered plant community structure caused by increased tree mortality (Table 1). As RE began to consistently outpace GPP, the ecosystem transitioned toward a persistent net carbon source. This phenomenon aligns with previous research indicating that prolonged flooding can degrade ecosystem productivity and carbon sequestration capacity [44].

Our findings illustrate how hydrological conditions significantly influence the carbon dynamics of wetland ecosystems. A delicate balance exists. While periodic flooding can promote carbon storage through reduced decomposition and organic matter accumulation, chronic inundation may inhibit photosynthesis and enhance anaerobic respiration, leading to long-term carbon losses. Understanding this balance is critical in light of projected climate-driven changes in precipitation, sea level rise, and water table dynamics.

4.2. Hydrological Impacts on Carbon Fluxes

A higher variance in flooded conditions than in non-flooded conditions reflects the nonlinear and threshold-like responses of wetland ecosystems to saturation stress. In

particular, NEE during flooding often fluctuated between net carbon uptake and release, suggesting that minor hydrological changes near critical thresholds can trigger large shifts in net carbon balance. This phenomenon is consistent with the concept of hysteresis in wetland carbon responses—where the same water level may result in different carbon flux outcomes depending on antecedent conditions and ecosystem memory [49]. Furthermore, saturated soils often reduce oxygen levels, leading to changes in microbial communities and enzyme functions that affect both autotrophic and heterotrophic respiration [50].

Impeded drainage due to sea level rise may be contributing to higher groundwater tables along coastal areas. The relationship between increasing GWT (e.g., closer to the soil surface) and increasing SLR from 2009 to 2019 ($R^2 = 0.11$) suggests that, despite the ~20 km distance of the flux tower from Croatan Sound and ~40 km from the Atlantic Ocean, we could still detect a signal between rising sea levels and localized groundwater level changes. This rise in GWT likely exacerbates physiological stress in trees by creating hypoxic or anoxic soil conditions, which impair root respiration, reduce water and nutrient uptake, and ultimately lead to root death and crown dieback [3,4]. Although not observed in the current study, saltwater intrusion in some coastal locations also introduces osmotic stress and ion toxicity that further disrupt cellular function and exacerbate hydraulic failure, predisposing trees to mortality under prolonged inundation [51,52]. These combined stressors, hydrologic and salinity, contribute to the formation of ghost forests in many low-lying coastal ecosystems globally, and disentangling the importance of each is the subject of ongoing research.

Meanwhile, greater RE relative to GPP during inundation reflects the activation of anaerobic decomposition pathways in saturated soils. Waterlogging may reduce CO_2 diffusion barriers while simultaneously enhancing fermentation and methanogenic processes in organic-rich substrates [53]. Notably, our observations suggest that RE is more consistently slightly elevated than GPP under prolonged flooding, indicating a potential shift toward net carbon loss. These results highlight the asymmetrical effects of hydrological stress on carbon fluxes. While both GPP and RE may initially increase under non-flooding, the prolonged imbalance between the two may lead to ecosystem destabilization. This aligns with previous studies in tidal wetlands and peatlands, showing that respiration tends to dominate under sustained inundation [54].

Together, these findings support the conclusion that hydrological regimes are among the most important environmental drivers of carbon exchange in coastal wetlands. Importantly, they suggest that future increases in sea level and storm-driven flooding could intensify carbon loss through increased respiration, thereby weakening the long-term carbon sink function of these wetland ecosystems [54].

4.3. Groundwater Table as the Key Driver in Carbon Fluxes

Our results identified GWT as a consistently stronger predictor of carbon fluxes than SLR directly, in particular GPP ($R^2 = 0.29$) and RE ($R^2 = 0.32$), although the NEE-GWT relationship was weak ($R^2 = 0.05$), reflecting GWT's indirect ecological effects on NEE. These findings are consistent with the hypothesis that GPP and RE are highly sensitive to soil water content and oxygen availability, both of which are directly regulated by shallow groundwater dynamics [55] during non-flooded conditions.

The high predictive power of GWT for RE supports previous findings that prolonged high water tables promote anaerobic microbial respiration, which becomes the dominant pathway for carbon mineralization in waterlogged soils [53,56]. Moreover, as GWT rises, the zone of active root respiration shifts closer to the surface, consuming available oxygen and intensifying the redox sensitivity of the system [53,56]. These hydrological controls are especially critical in forested wetlands, where fluctuations in GWT can determine

vegetation composition, productivity, and long-term carbon storage capacity. The weaker relationship between GWT and NEE, compared to its effect on GPP and RE, likely stems from the composite nature of NEE, which integrates opposing trends of carbon uptake and release. While GPP may respond positively to short-term soil water increases, RE often exhibits slight increases under saturated conditions relative to GPP, ultimately diminishing or reversing the net carbon sink capacity [57,58]. This decoupling highlights the importance of analyzing GPP and RE separately, especially in systems experiencing hydrological extremes.

Importantly, our analysis suggests that GWT serves as a proximal ecological control, mediating both biological activity and physical transport processes in the soil–plant–atmosphere continuum [59]. These effects are further modulated by factors such as vegetation type, microtopography, and antecedent hydrological conditions [59]. In contrast, SLR primarily acts through long-term shifts in baseline water levels and saltwater intrusion, which may only translate into ecological changes after sustained exposure or in topographically low-lying zones in proximity to sources of salinity [2,4].

Further, GWT functions as a proximate driver, that is, immediately and directly influencing tree mortality at the stand level. GWT directly controls root-zone saturation and oxygen availability, which critically affect physiological processes such as gas exchange, root respiration, and water uptake in wetland trees [3,60]. However, GWT is modulated by broader-scale boundary drivers, particularly long-term environmental forces such as sea level rise (SLR) [13].

Rising sea level can gradually alter hydrological regimes by increasing baseline groundwater levels, impeding the drainage of inland freshwater systems, and leading to persistently elevated groundwater tables, and in certain landscape settings, saltwater intrusion [2,8]. These changes effectively shift the environmental baseline over which proximate stressors operate, thereby intensifying tree stress and mortality risk. As a result, future ecosystem transitions from forested wetlands to marshlands or the development of “ghost forests” are likely to arise from the cumulative effects of proximate stress acting under evolving boundary conditions [5,6].

Overall, these results establish GWT as the dominant hydrological driver of carbon fluxes at our study site. With climate change driving faster sea level rise and more frequent extreme rainfall events, tracking groundwater table (GWT) changes will be vital for forecasting ecosystem shifts and guiding adaptive management efforts.

4.4. Interannual Tree Mortality

The striking increase in tree mortality over a decade, rising from 1.91% in 2010 to 45.72% in 2019 (Table 1), aligns with the rising mortality trajectory trends observed in coastal wetland forests throughout the southeastern United States. This is caused by increasing exposure to chronic and acute stressors, which has led to the expansion of so-called ghost forest zones due to sea level rise, saltwater intrusion, and altered hydrology [7,8]. In low-lying areas like eastern North Carolina, prolonged inundation and even modest increases in sea level or storm surge frequency can exacerbate soil saturation and salinity, decreasing oxygen availability and causing physiological stress that predisposes trees to mortality [3,61].

The dominance of downed trees over standing dead in cumulative mortality counts may indicate that many individuals died suddenly or lost anchorage due to root damage in waterlogged or saline soils. This is consistent with observations from bottomland hardwood and swamp forests experiencing hydrologic shifts, where prolonged inundation reduces root cohesion and increases treefall rates [62,63]. Moreover, the increasing occurrence and strength of hurricanes and tropical storms in the area, combined with saturated soil

conditions, can hasten structural damage, particularly in trees that are already under stress. Hurricanes cause extensive damage to forested ecosystems, often resulting in widespread windthrow and canopy loss over large areas [64,65]. In addition to wind damage, hurricanes are frequently accompanied by storm surges that transport large volumes of saltwater inland, exposing freshwater wetlands to acute salinity stress, although we have no evidence that this was a driver of tree mortality at our site. For instance, in the Atlantic Coastal Plain of North Carolina, the onset of ghost forest formation was observed following Hurricane Irene in 2011 and 2012, highlighting the role of extreme weather events in initiating ecosystem transitions [65]. While surface floodwaters typically recede within hours to days, elevated salinity can persist in soils and groundwater for years or even decades [66,67], leading to long-term physiological stress and growth suppression in trees. Despite the clear ecological significance of such disturbances, the impact of hurricanes on freshwater coastal wetlands remains understudied and warrants further investigation.

The implications of increased tree mortality are profound. Tree death alters stand structure, reduces canopy cover, and influences carbon cycling by shifting the balance from net carbon sink to source [68]. However, this study did not examine the physiological, mechanical, or structural factors contributing to tree mortality, which limits our ability to fully identify the primary drivers of tree death. We recommend that future research includes thorough evaluations of tree health, physiological function, and structural integrity to better understand how physiological stress develops and contributes to mortality in shifting ghost forest ecosystems. Gaining such knowledge is essential for identifying early warning signs of ecosystem decline and guiding adaptive management in the face of accelerating climate change and sea level rise.

4.5. Tree Species Composition and Mortality

Our findings indicate that bald cypress (*Taxodium distichum*), sweetgum (*Liquidambar styraciflua*), and American holly (*Ilex opaca*) demonstrated relatively low mortality rates. Among these species, bald cypress is particularly well known for its resilience to flooding. As a native deciduous conifer of the southeastern United States, it often dominates coastal freshwater wetland ecosystems [54]. While this study did not directly investigate adaptive traits, previous research has shown that bald cypress seedlings can tolerate flood conditions for up to 45 days; however, prolonged submergence, especially of the canopy, significantly increases mortality risk [51]. Moreover, bald cypress has been observed to persist long after its habitat is altered by saltwater intrusion, suggesting a high tolerance for environmental stressors [3,69,70]. These traits may help explain the relatively low mortality of bald cypress in our study. Further investigation into the physiological basis of bald cypress's tolerance mechanisms is warranted.

In contrast, loblolly pine (*Pinus taeda*) exhibited the highest mortality of the species studied. We suggest that this elevated mortality was likely driven by prolonged hydrologic stress, compounded by infestations from wood-boring insects such as the southern pine beetle (*Dendroctonus frontalis*), black turpentine beetle (*Dendroctonus terebrans*), and Ips engraver beetles (*Ips calligraphus*, *Ips grandicollis*, and *Ips avulsus*). These beetles typically target older, weakened trees whose defenses have been compromised by stress [58]. Although loblolly pine is considered moderately flood-tolerant, its capacity to survive is generally limited to a single growing season under inundated conditions [54]. It is likely that the persistently rising groundwater table observed at our site (Figure 3) decreased tree vigor, predisposing the pines to beetle attack and increased mortality risk. Southern pine beetle is native to the southeastern U.S. [59,60] and is particularly problematic in waterlogged forests, where hydrologic stress undermines tree resistance [61]. Flooding is known to impose physiological stress by reducing oxygen availability [4] and impairing secondary

metabolic functions [63], thereby creating favorable conditions for beetle infestation and mortality events [61].

4.6. Key Predictors of Mortality

Our findings indicate that tree mortality in coastal forests results from a multifaceted interaction among hydrological conditions, physiological responses, and carbon balance dynamics. Elevated GWT likely induces root anoxia and reduces uptake capacity; declining LAI (Figure 2d) reflects declining productivity; elevated NEE (i.e., reduced carbon sink strength or net emissions) signals physiological breakdown; and higher Rn may amplify evapotranspiration stress (Table 3).

Importantly, the GAM also revealed nonlinear threshold responses, especially with respect to GWT and NEE, supporting the hypothesis that tree mortality in wetlands is not simply a linear function of stress but rather a tipping-point phenomenon. These dynamics are consistent with broader theories of ecological collapse under climate extremes, where systems exhibit resilience up to a point before undergoing rapid transitions [11,71].

The GAM modeling analysis used here shows that a small number of measurable variables can be used to predict tree mortality, and that these predictors exhibit clear, interpretable relationships with ecosystem function. This approach provides a quantitative basis for establishing actionable thresholds and can be applied more broadly to understand the drivers of ecosystem transition in coastal systems around the world.

While the GAMs produced high explanatory power in the current study, it is important to recognize that driving relationships may be site-specific and influenced by local biophysical and hydrological conditions. Thresholds identified for tree mortality drivers such as GWT, LAI, NEE, or Rn may not be directly transferable to other forested wetlands or ecological settings with different species composition, soil characteristics, or disturbance regimes. Furthermore, even though our analysis reveals strong correlations between environmental variables and mortality patterns, causal inference is constrained by the observational nature of the study and the absence of direct physiological measurements. Consequently, readers should interpret the identified thresholds and relationships within the specific context of our study site. Further investigation across diverse wetland ecosystems is necessary to evaluate the generalizability of these findings and identify the most important drivers in other settings.

In addition to the primary drivers identified, factors such as salinity, nutrient availability, and extreme events (e.g., hurricanes, storm surges) can significantly influence tree mortality in wetlands, particularly during non-flooded periods when GPP and RE are most active [2]. Salinity pulses impair photosynthesis and promote canopy dieback [3], while nutrient limitation can hinder recovery [72]. Storm events further exacerbate mortality through windthrow, saltwater intrusion, and hydrologic disruption [73–76]. While these variables were not included in the current study, they are worth considering in future research to more fully capture the complexity of wetland tree mortality.

4.7. Threshold-Based Early Warning System

Detecting thresholds for early warning bridges statistical modeling with practical application, enabling the development of threshold-based early warning systems for ghost forest formation. Collectively, these thresholds define an empirical “vulnerability envelope”, a zone within which the likelihood of rapid forest decline and ghost forest formation is significantly elevated.

Our threshold values of 2.23 cm for GWT, 3.07 for LAI, 1.27 g C m^{−2} d^{−1} for NEE, and 167.54 W m^{−2} for Rn correspond with earlier studies that highlight how increasing groundwater levels and declining canopy cover contribute to forest dieback, especially in

coastal and lowland regions experiencing sea level rise and saltwater intrusion [5,13]. For example, groundwater levels above 2 cm have been linked to tree stress and mortality in saturated environments, while LAI thresholds below 3 have been associated with reduced photosynthetic capacity and carbon assimilation [77]. Similarly, low NEE values reflect a decline in net carbon uptake, a known precursor to ecological tipping points [78]. R_n , as a proxy for available energy, plays a role in modulating evapotranspiration and plant stress responses [79,80]. However, we advise that these results be interpreted with appropriate caution, as they may not be universally applicable without careful site-specific verification and local validation.

Prolonged flooding elevates tree mortality in wetlands, especially during leaf-out and active growth when root oxygen demand is high. Elevated groundwater tables (GWTs) during these periods hinder root respiration and carbon allocation, increasing stress susceptibility [81,82]. Leaf area index (LAI) peaks in spring–summer, enhancing transpiration, but excessive GWT can suppress it due to root hypoxia, limiting stomatal conductance and exacerbating inundation stress [60,63]. Increasing solar radiation in spring–summer boosts evapotranspiration and photosynthetic demand, but in waterlogged soils, limited oxygen intensifies physiological strain and reduces carbon assimilation [83]. Seasonal NEE is driven by LAI, radiation, and hydrology, with high GWTs promoting anaerobic soils that reduce both decomposition and root activity [84,85]. Persistent inundation lowers ecosystem respiration but also limits carbon uptake, shifting NEE toward a net carbon source. Chronic waterlogging may lead to carbon starvation and long-term tree decline [46,86].

Importantly, these thresholds are not fixed. They may shift with ongoing climate change, vegetation succession, and land-use interventions. However, their identification provides a critical step toward building dynamic, data-driven early warning systems for forest vulnerability. Combined with field-based tools like groundwater monitoring wells, remote sensing technologies such as satellite-derived LAI, and eddy covariance towers measuring NEE, these threshold values can facilitate proactive landscape-scale management and focused targeted intervention strategies.

Such analytical approaches are increasingly necessary as ecosystems undergo critical transitions as a function of intensifying climate pressures. By combining mechanistic understanding with statistical rigor, threshold-based frameworks can serve as the backbone of adaptive monitoring strategies, helping land managers anticipate and respond to ecological tipping points before irreversible damage occurs [11,71,87].

By translating complex statistical relationships into simple, interpretable thresholds, this study has developed an approach that bridges the gap between scientific understanding and actionable decision-making. Monitoring when ecosystems cross these biophysical boundaries can support proactive adaptive management, such as hydrological buffering, assisted migration, or targeted conservation, ultimately helping to sustain carbon sinks and biodiversity in vulnerable coastal regions.

4.8. Implications for Ecosystem Management

Our results have important consequences for the conservation and adaptive management of coastal forested wetlands, particularly in the face of rapid sea level rise and increasing climate variability. First, the central role of GWT suggests that local hydrological management (e.g., culvert modification, drainage ditch blocking/opening, or groundwater buffering) may be more immediately effective than broader coastal defenses in sustaining forest resilience. Second, the identification of LAI and NEE as early indicators supports the integration of remote sensing and flux tower networks into early warning systems, allowing managers to identify at-risk areas before visible decline occurs. Finally, this study reinforces the concept that ecosystem collapse is not random but predictable when key

stressors and feedbacks are adequately monitored. Anticipating rather than reacting to ecological thresholds offers the best hope for sustaining biodiversity, carbon storage, and ecosystem services in vulnerable coastal landscapes.

By translating complex statistical relationships into simple, interpretable thresholds, this study bridges the gap between scientific understanding and actionable decision-making. Monitoring when ecosystems cross these biophysical boundaries can support proactive adaptation, such as hydrological buffering, assisted migration, or targeted conservation, ultimately helping to sustain carbon sinks and biodiversity in vulnerable coastal regions.

Recent studies underscore the presence of ecological tipping points in coastal and wetland forests, where chronic sea level rise, groundwater salinization, and increasing climatic extremes (e.g., drought, storm surges) trigger abrupt shifts from tree-dominated ecosystems to open marshes or ghost forests—landscapes dominated by standing dead trees and herbaceous vegetation [4,7]. These transitions are frequently abrupt and irreversible, marking critical thresholds beyond which forest productivity, structure, and biogeochemical functioning collapse [88].

Our findings align with this growing body of evidence, suggesting that wetland tree mortality may be an early indicator of broader ecosystem regime shifts under compound hydroclimatic stress. Such transitions are not isolated; similar thresholds have been observed in tropical, boreal, and temperate forests globally, highlighting the universal vulnerability of forest systems to climate-driven perturbations [89,90]. These insights reinforce the need to incorporate hydrological, salinity, and disturbance dynamics into predictive models of forest resilience to capture the full range of possible future ecological states.

5. Conclusions

This study integrates long-term carbon flux observations, hydrological data, and tree mortality records to identify the key drivers, predictive indicators, and actionable thresholds of coastal forest decline under rising sea levels. From 2009 to 2015, the wetland ecosystem alternated between flooded and non-flooded conditions, with daily NEE fluctuating between net carbon uptake and release. Non-flooded periods saw significant increases in both GPP and RE. After 2016, non-flooded conditions became infrequent, and elevated RE, likely driven by enhanced microbial decomposition and root respiration during these brief non-flooded periods, consistently exceeded GPP. As a result, NEE variability increased, and the wetland transitioned to a persistent net carbon source. Our results also demonstrate that GWT dynamics, rather than SLR directly, is the dominant hydrological control shaping tree mortality risk and land-atmosphere C exchange. Through GAM, we found that GWT, LAI, NEE, and Rn together explained nearly all observed variations in tree mortality, underscoring the multi-dimensional nature of ecosystem collapse in waterlogged environments. However, these findings should be interpreted with caution, as their applicability may vary without site-specific verification. Broader studies across diverse wetland ecosystems, including assessments of tree health, physiological function, and structural integrity, are needed to evaluate generalizability and identify key drivers across varying contexts.

By applying ROC analysis, we established empirically derived thresholds for each variable, enabling the development of early warning systems to anticipate mortality transitions. While these thresholds may shift with climate change, plant succession, and land-use changes, they offer a crucial foundation for developing dynamic, data-driven early warning systems for forest vulnerability. These findings not only advance our mechanistic understanding of ghost forest formation but also provide practical tools for adaptive ecosystem management, such as hydrological buffering and remote canopy monitoring. Importantly, the framework developed here bridges the gap between process-based modeling and

real-world application, offering a replicable approach for other vulnerable bottomland hardwood wetland forests.

As climate change drives faster sea level rise, more extreme rainfall events, and altered hydrological regimes, the ability to anticipate and respond to ecological tipping points is critical for maintaining the resilience of coastal carbon sinks. Future research should prioritize refining these thresholds and testing their applicability across different spatial scales and vegetation types to inform sustainable coastal land use, guide wetland restoration, and improve carbon accounting practices.

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