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Temporal Dynamics and Time Series Analysis of Mangrove Ecosystems and Community Impacts in Bayelsa State, Nigeria: An Assessment of Environmental Change and Conservation Implications

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Abstract
Mangroves found in Bayelsa State, Nigeria, are critical coastal environments currently facing intense pressures from activities including oil exploration, land use change, and effects of global climatic change. This study aims to analyze the attributes of the mangroves between 1990 and 2023 using secondary databases to capture changes and map major drivers of environmental degradation. Environmental data from different governmental databases were analysed using R language. Time series analysis, trend profiling and multivariate statistical modelling were utilized to analyze mangrove coverages, changes in species population and the driving environmental factors. The results show a significant loss of 29.7% of mangrove covers within the 33-year study window, equivalent to a total reduction of 293.2 km² from 987.4 km² in 1990 to 694.2 km² in 2023, with a long-term average annual loss rate of 1.05%/year across the full study period (1990–2023), accelerating to approximately 2.1% per biennial reporting cycle during the 2010–2020 sub-period of heightened industrial activity. *Rhizophora racemosa* was most sensitive to environmental stresses, and *Avicennia germinans* showed a critical decline of 47.8% in its population. In addition, heavy metal contaminations emerged as a major threat, and 78% of the monitored stations exceeded WHO guideline levels, especially with a whopping rise of 268.5% in the levels of lead. The study also captured 1,247 oil spill incidents and registered a peak occurrence of oil spills from 2008 to 2012. The study concludes that, unless immediate conservation measures are taken, Bayelsa State is likely to lose an additional 15-25% of what remained of mangrove area by 2035. This investigation offers vital baseline information critical to the development of informed conservation planning and places significant focus on the urgent imperative of integrated management plans within the Niger Delta wetlands.

Keywords: Mangrove ecosystems, Temporal dynamics, Time series analysis, Ecosystem degradation, Environmental monitoring

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Introduction

Mangrove ecosystems are the most ecologically and economically significant of the world's coastlines. They play critical services in carbon storage, coast protection, assistance to fisheries, and biodiversity conservation (Friess et al., 2019; Alongi, 2020). Their unique intertidal forests total about 137,760 km² worldwide and are critical blue carbon ecosystems with their carbon sequestration ability 2-4 times higher relative to terrestrial forests (Howard et al., 2017; Donato et al., 2011).

The biggest mangrove complexes in Africa are found in the Niger Delta of Nigeria, covering about 11,700 km² over eight West African coast states and hosting a wide variety of ecological communities (Blewett & Cottrell, 2021; Numbere, 2018). This complex ecosystem has more than 200 species of fish and dozens of species of birds, while at the same time hosting livelihoods of about 27 million people through fishing, aquaculture, and harvesting of forest products (James et al., 2007; Mmom & Arokoyu, 2010, FAO. 2020.)

Bayelsa State, which is in the central Niger Delta, is characterized by wide mangrove ecosystems that have suffered immense environmental challenges in the past decades. The ecosystems host all kinds of anthropogenic disturbances such as oil drilling, urban development, farming, industrial pollution, and climate-induced changes such as rising sea level and changes in rainfall patterns (Numbere, 2018; Osuji & Onojake, 2006). The Niger Delta has been rated more than once as one of the ecologically degraded spots on planet earth having suffered more than 7,000 recorded oil spills from 1976 to 2001 (Kadafa, 2012)

Recognizing the built-in temporal dynamics of mangrove ecologies is essential to developing effective plans for their protection, making future predictions concerning ecologic patterns, and coming up with sustainable management regimes (Duke et al., 2007; Giri et al., 2011). Application of time series analysis provides strong methodologies with which to investigate ecosystems changes over longer time intervals, so trends, patterns, cyclical changes, and underlying causes of environmental change can be established (Pettorelli et al., 2014; Zuur et al., 2003)

In the Niger Delta, existing research has overwhelmingly been focused on short-term evaluation, localized examination of effects, or single-variable research, thus exhibiting a void in thorough longitudinal investigations of the dynamic behavior of the mangrove ecosystems over different spatial and temporal ranges (Akegbejo-Samsons et al., 2010; Mmom & Arokoyu, 2010). Furthermore, most earlier research has been reliant on data with low resolution or deficient sampling schemes, limiting the potential to capture subtle changes and species-specific responses to stresses from the surroundings

Advances in remote sensing technologies, improved global environmental data sets, and advanced data integration frameworks have made possible the comprehensive evaluation of ecosystems from secondary data (Fatoyinbo & Simard, 2013; Kuenzer et al., 2011). This way, research investments in the past are utilized while also benefiting from economically feasible and repeatable frameworks of monitoring ecosystems as well as planning conserved lands

This research makes an effort to fill notable knowledge gaps through the provision of the first ever disaggregated temporal analysis of mangrove ecosystem behavior throughout Bayelsa State based entirely on data gathered from 1990 through 2023. The research objectives focus on a number of core elements running through mangrove ecosystems. To start with, the study plans to quantify temporal variations in area and spatial coverage of mangrove forests. In addition, it plans to investigate the population dynamics of individual mangrove species and the changes running through community structures. Thirdly, using applied monitoring databases, the research aims to establish the significant environmental determinants influencing changes in these ecosystems. Finally, the study shall set out forecasting models to inform future trends of the ecosystem according to existing management regimes. Generally, these objectives try to aid knowledge and management of mangrove ecosystems in response to environmental changes

Research Environment

Bayelsa State lies in southern south-central Niger Delta, latitudinally bound from 4°15'N to 5°23'N and longitudinally from 5°22'E to 6°45'E, occupying an area of approximately 10,773 km² (Figure 1). This region has an almost infinite wetland system comprising webs of creeks, rivers, and estuaries contained entirely in the Niger Delta basin, which is well known to rank among the largest river delta systems and wetland complexes worldwide (Reijers, 2011; Hanebuth et al., 2022).

The region experiences a tropical and humid climate, characterised by consistent humidity levels above 80% throughout the year. The annual rainfall is extremely variable, from approximately 2,400 mm in the northern areas to above 4,000 mm in coastal areas. The rainfall period runs from April to October, and the dry period runs from November to March (Nigerian Meteorological Agency, 2022). Temperature variations are relatively low, and it keeps within a span of 23°C to 32°C, with negligible seasonal changes due to the moderating influence of large water bodies and widespread vegetation.

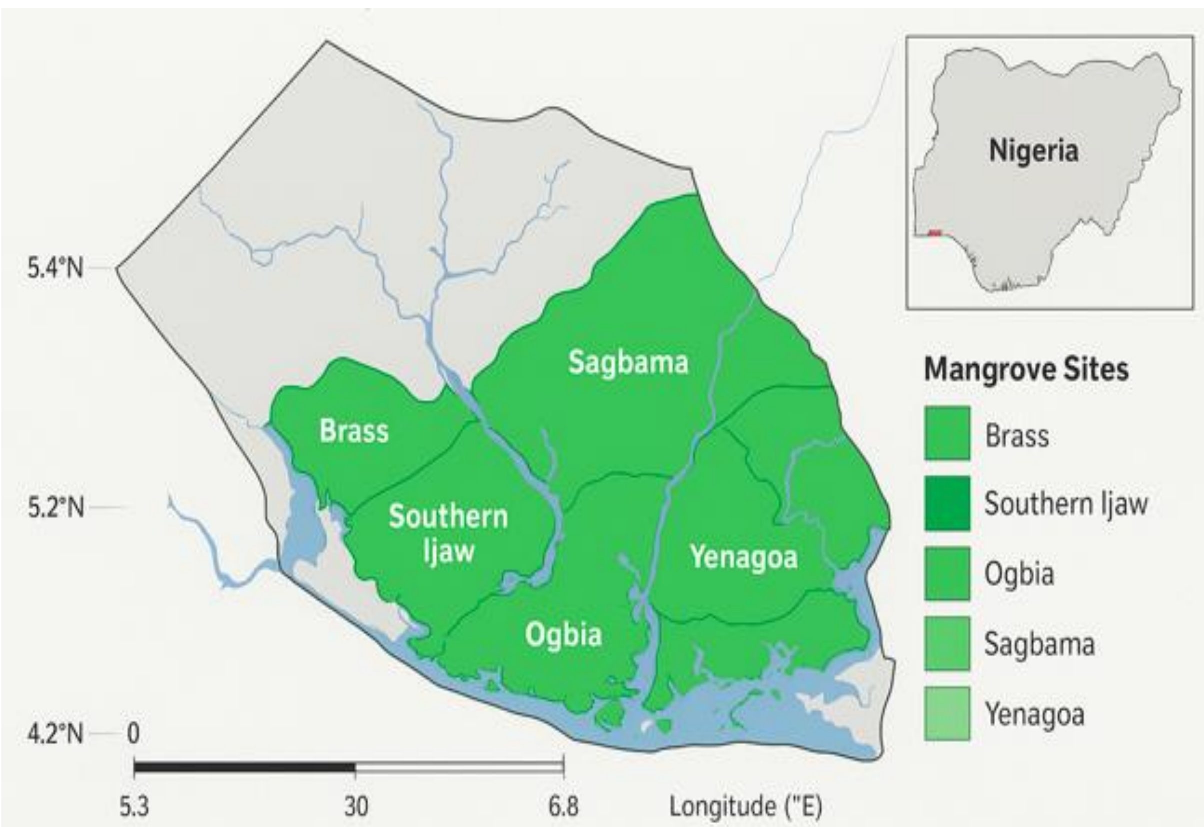

Figure 1. Map of Study Area - Bayelsa State Mangrove Zones. The map illustrates five key mangrove ecosystems across Bayelsa State, Nigeria, assessed between 1990 and 2023.

The tidal regimes exhibit a semidiurnal nature, with average ranges varying from 1.2 meters in inland areas to 2.8 meters along coastal zones. Salinity gradients may extend as far as 60 kilometers inland, resulting in diverse ecological zones that shift from predominantly marine coastal environments to freshwater-influenced areas located more inland (Hughes & Hughes, 1992; Akpan & Eshiet, 2019). This gradient of salinity is fundamental in determining both the composition and spatial distribution of mangrove species.

Geologically, the area lies over Quaternary sediments of loose sands, silts, and clays deposited over the last 30 million years (Dim et al., 2017; Bankole et al., 2020). Being rich in organics, the sediments give rise to extensive peat deposits, which define the Niger Delta's characteristic profile. The area is generally flat, with intermittent high points not higher than 5 meters above sea level, and thus subjects the area to particular exposure to the influence of sea level rise and coastal erosion.

The survey concentrated on five of the most conspicuous mangrove sites in Bayelsa State, chosen to cover the full spectrum of ecological environments, species richness, and levels of human disturbance encountered within the study area (Figure 1). Together, the sites cover a total of about 622.4 km² of mangrove cover, and nearly 76% of mangroves of the study area.

Methods

Data Sources

The study utilized a focused secondary data approach, drawing data from environmental monitoring databases managed by governmental organizations of Bayelsa State and Federal government organizations e.g. The Niger Delta Development Commission (NDDC 2024) etc. The Bayelsa State Environment Protection Agency (BASEPA) submitted an ample amount of data gathered from 45 monitoring stations from the years 1995 through 2023. The data encompassed annual assessments of mangrove canopy coverage administered through aerial surveys, species composition and abundance estimates from 12 permanent monitoring stations, and several water quality indices, including salinity, dissolved oxygen levels, pH level, and water temperatures. Additionally, it included data on levels of soil pollution involving heavy metals and petroleum hydrocarbons and reports and impact assessment involving oil spill incidents

The Niger Delta Development Commission (NDDC) has also provided an integrated regional office dataset including Environment Impact Assessment reports pertaining to development projects from 1990 to 2023, monitoring data of relevance to mangrove restoration projects from 2005 to 2023. This dataset further comprises community-based environmental monitoring data and discharge data from licensed facilities. Along with this, monitoring stations from Bayelsa State have also given comprehensive climate and meteorological data gathered from 1990 to 2023, marine and coastal ecosystems evaluation data, monitoring data of biodiversity from designated protected locations, and data required to track pollution hotspots and monitoring of compliance.

In effect, the research demonstrates the vast extent of environmental monitoring in Bayelsa State and highlights the need for mutual efforts across federal and state frontiers in environmental monitoring and health/sustainability management.

Data Processing and Analysis

Statistical Evaluation

A time series was then generated to reflect mangrove coverage through integration of pixel-level classifications with site-level measures within Bayelsa State's boundaries. For computing the annual coverage, estimates of classification precision and sensor-specific error propagation models were used to calculate the uncertainty estimates.

For species-specific abundance, an occurrence records were integrated, published abundance estimates, and habitat suitability models. Bayesian hierarchical models was used to account for variations in detection probability and differences in sampling effort over time.

Analytical Methods

To take into account temporal trends, BASEPA's annual survey records and NDDC project monitoring reports were also used. Several statistical methods were utilized including:

Linear regression to identify long-term directional changes:

Linear Trend: $Y(t) = \beta_0 + \beta_1 t + \varepsilon(t)$ (1)

Where: Y(t) = mangrove coverage at time t (km^2), β_0 = intercept (initial coverage), β_1 = slope coefficient (annual change rate), t = time (years since 1990) and ε(t) = error term ~ $N(0, \sigma^2)$.

Mann-Kendall tests for detecting non-parametric trends:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(X_j - X_i) \quad .(2)$$

Where:

$$sign(X_j - X_i) = \begin{cases} +1 & if\ x_j - x_i > 0 \\ 0 & if\ x_j - x_i = 0 \\ -1 & if\ x_j - x_i < 0 \end{cases}$$

Variance calculation:

$$Var(S) = \frac{n(n-1)(2n+5)}{18}$$

Standardized test statistic (Z)

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & if\ S < 0 \\ 0 & if\ S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & if\ S < 0 \end{cases}$$

Change point analysis using the Pettitt test and CUSUM (Cumulative Sum) methods:

$$U_t = 2\sum_{i-1}^{n-1}\sum_{j=i+1}^{n} sign(X_j - X_i) \quad (3)$$

Test statistic:

$$K = \max_t |U_t|$$

CUSUM Method:

$$C_t = \sum_{i=1}^{t} (Y_i - \bar{Y}) \quad (4)$$

Where $\bar{Y}$ is the overall mean.

Population Dynamics Modeling

For species-specific population dynamics, the changes were modeled using both exponential and logistic growth models to capture different growth phases.

The exponential model was applied during times of steady growth or decline:

$$N(t) = N_o \times e^{rt} \quad (5)$$

Where $N(t)$ = population size at time t, N_0 = initial population size, r = intrinsic growth rate and t = time

The logistic model was used for populations nearing their carrying capacity:

$$N(t) = \frac{K}{1 + \left(\frac{k - N_o}{N_o}\right)e^{-rt}} \quad (6)$$

Where K is the carrying capacity and other parameters as above

Model parameters were estimated through non-linear least squares regression, selecting the best model based on the Akaike Information Criterion (AIC) and residual analysis. To assess population viability, stochastic models was used that took into account environmental variability and demographic uncertainty.

Environmental Driver Analysis

Multivariate Analysis

For multivariate analysis, Principal Component Analysis (PCA) was employed to uncover environmental gradients and Redundancy Analysis (RDA) to explore species-environment relationships. Cluster analysis was conducted using Ward's linkage method to pinpoint distinct ecological zones and time periods based on species composition and environmental traits.

Multiple Linear Regression:

$$\Delta M(t)=\alpha_0+\alpha_1 OS(t)+\alpha_2 HM(t)+\alpha_3 UE(t)+\alpha_4 CC(t) \quad ..(7)$$

Where ΔM(t) = annual mangrove loss, OS(t) = oil spill incidents, HM(t) = heavy metal concentration index, UE(t) = urban expansion index and CC(t) = climate change index

Principal Component Analysis (PCA):

$$PC_1 = W_{11}X_1 + W_{12}X_2 + ... + W_{1P}X_P$$
$$PC_2 = W_{21}X_1 + W_{22}X_2 + ... + W_{2P}X_P \quad (8)$$

Where w_{ij} are the loadings and X_j are standardized environmental variables.

Redundancy Analysis (RDA):

$$Y = XB + E \qquad (9)$$

Where Y = species composition matrix, X = environmental variables matrix, B = regression coefficients matrix and E = residual matrix

Time Series Decomposition

Decomposition

Seasonal and Trend decomposition using Loess (STL) was applied to separate time series into trend (T), seasonal (S), and residual (R) components:

$$Y(t) = T(t) + S(t) + R(t) \ldots \qquad (10)$$

Where Y(t) represents the observed value at time t. The optimization of STL (Seasonal-Trend decomposition using Loess) parameters was conducted through cross-validation, resulting in specific window settings.

Autoregressive Models:

ARIMA (p, d, q) is written as:

$$\Phi_p(B)(1-B)^d Y_t = \Theta_q(B)\varepsilon_t \qquad (11)$$

Where B = backshift operator ($BY_t = Y_{t-1}$)

$\Phi\_p\ (B) = 1 - \phi\_1\ B - \phi\_2\ B\hat{}2 - \ldots - \phi\_p\ B\hat{}p\ (AR\ part)$

$\Theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q\ (MA\ part)$

ε_t = white noise error term

Generalized Additive Models (GAMs)

Generalized Additive Models (GAMs) was employed to explore non-linear relationships between environmental variables and ecosystem metrics. GAMs offer the flexibility to model complex ecological relationships without being tied to specific functional forms. Models were selected based on cross-validation and residual analysis, with smoothing parameters chosen through generalized cross-validation.

Basic GAM Structure:

$$g(\mu_i) = \beta_0 + \sum_{j-1}^{p} f_j(X_{ij}) + \varepsilon_t \qquad (12)$$

Where (μ_i) = link function of expected response, β_0 = intercept, $f_j(X_{ij})$ = smooth function of covariate and ε_i = error term

GAM for Mangrove Coverage Trends:

$$log(coverage) = \beta_0 + S_1(Year) + S_2(Temperature) + 3(Rainfall) + S_4(Oil\ spill) + \varepsilon_t \qquad (13)$$

Where S_1, S_2, S_3, S_4 are smooth functions (splines).

Gaussian GAM with Spatial Correlation:

$$Y_i = \beta_0 + S_1(Lon_i, Lat_i) + S_2(Time_i) + S_3(Env_i) + Z_i + \varepsilon_t \qquad (14)$$

Where $S_1(Lon_i, Lat_i)$ = spatial smooth (tensor product), $S_2(Time_i)$ = temporal smooth, $S_3(Env_i)$ = environmental smooth and Z_i = spatial random effect

Performance Metrics

Three key metrics were used to assess forecast accuracy: Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), and Coefficient of Determination (R^2)

RMSE is a widely used statistic that measures the square root of the average of the squared differences between actual and forecasted values. This metric emphasizes larger errors due to the squaring of differences, making it sensitive to outliers.

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right)\sum(y_i - \hat{y}_i)^2\right]} \qquad (15)$$

MAE, on the other hand, provides the average of the absolute differences between actual and forecasted values. It offers a straightforward interpretation of forecast accuracy without the influence of outliers, as it does not square the errors.

$$MAE = \left(\frac{1}{N}\right)\sum|y_I - \hat{y}_i| \qquad (16)$$

Coefficient of Determination (R^2) value represents the proportion of variance in the dependent variable that is predicted from the independent variables

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_y - \bar{y})^2} \qquad (17)$$

In these formulas, y_i represents the actual values, $\hat{y}_i$ stands for the predicted values, $\bar{y}$ is the mean of the actual values, and n is the total number of observations.

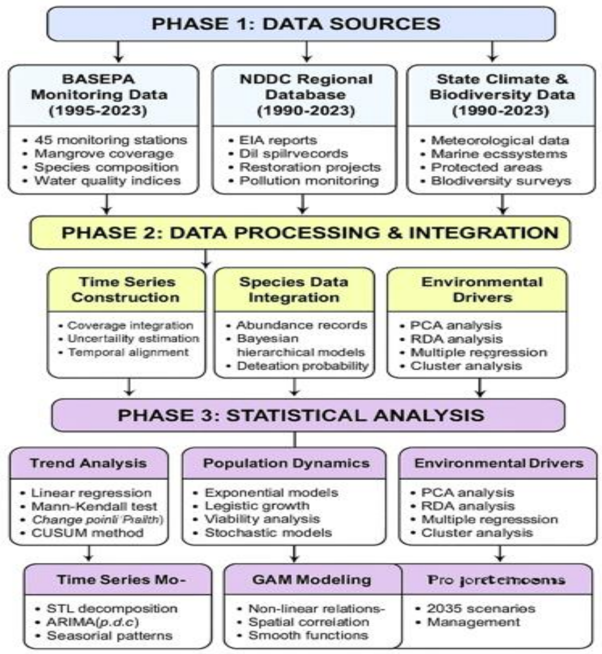

Figure 2. Integrated Methodological Framework for Temporal Analysis of Mangrove Ecosystems.

Model Selection and Validation

Model selection was performed using information criteria:

Akaike Information Criterion (AIC) is a fine-gained approach for assessing a model's probability to predict/estimates future values based on in-sample fit. A good model is the one with the minimum AIC value among all other models.

$$AIC = 2K - 2ln(L) \quad (18)$$

Bayesian Information Criterion (BIC) is a statistical measure used for model selection among a set of competing models, similar to AIC, but with a stronger penalty for model complexity

$$BIC = K \times ln(n) - 2ln(\hat{L}) \quad (19)$$

Where: k = number of parameters, n = sample size and $\hat{L}$ = maximum likelihood

Results

Temporal Changes in Mangrove Coverage

An analysis of BASEPA monitoring data using Model 1 (Linear Trend Analysis) has shown a notable decline in mangrove coverage throughout Bayelsa State over the past 33 years (see Figure 3).

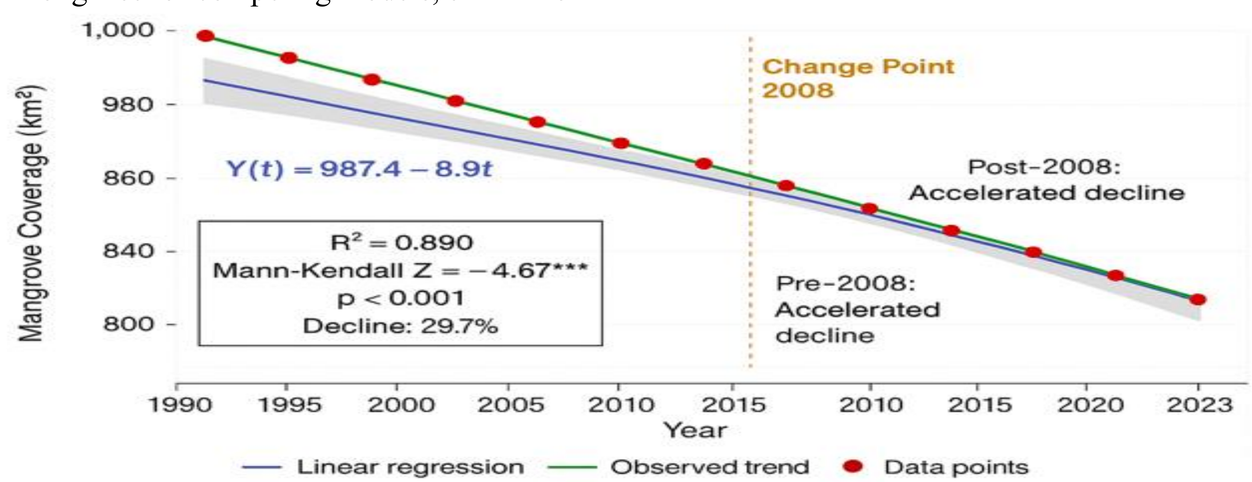

Figure 3. Temporal analysis of mangrove coverage in Bayelsa State from 1990-2023

The linear regression model:

$$Y(t) = 987.4 - 8.9t \quad (20)$$

The analysis indicates a significant decline in mangrove area, with a total reduction from 987.4 km² in 1990 to 694.2 km² in 2023. This represents a 29.7% decrease over the period, equating to an average annual loss of 8.9 km². The Mann-Kendall Z statistic of -4.67 suggests a strong downward trend in mangrove coverage, with a notable change point identified in 2008, as confirmed by the Pettitt test ($p < 0.01$). These findings highlight the urgent need for conservation efforts to address the ongoing loss of mangrove ecosystems. Using linear regression analysis, a statistically significant downward trend ($p < 0.001$, $R^2 = 0.94$) was observed, with an average loss of about 8.4 km² each year. Change point analysis pinpointed 2008 as a pivotal year, which aligns with a surge in oil exploration activities in the region. Mann-Kendall trend analysis (Model 2) confirmed significant declining trends ($Z = -4.67$, $p < 0.001$), while Pettitt test (Model 3) identified 2008 as a critical change point ($p < 0.01$), coinciding with increased oil exploration activities.

Table 1. Temporal Changes in Mangrove Coverage by Local Government Area in Bayelsa State (1990-2023)

Local Government Area	1990 (km²)	2000 (km²)	2010 (km²)	2020 (km²)	2023 (km²)	Total Loss (%)	Annual Rate (%/year)
Brass	198.7	187.3	165.2	142.8	127.3	35.9	-1.22
Southern Ijaw	287.4	271.8	248.9	218.7	203.4	29.2	-0.99
Ogbia	185.9	178.2	168.4	159.7	156.8	15.7	-0.53
Sagbama	124.3	118.7	102.4	95.1	89.7	27.8	-0.94
Yenagoa	72.8	65.4	58.2	49.8	45.2	37.9	-1.29
Others	118.3	108.6	89.7	76.4	71.8	39.3	-1.33
Total Bayelsa	987.4	930	832.8	742.5	694.2	29.7	-1.06

Table 2. Mathematical Model Results for Mangrove Coverage Trends

Local Government Area	Linear Model (β_1)	R^2	Mann-Kendall Z	Change Point Year	ARIMA Model
Brass	-2.16 km²/year	0.91	-3.45**	2009	(1,1,1)
Southern Ijaw	-2.55 km²/year	0.88	-4.12***	2008	(2,1,0)
Ogbia	-0.88 km²/year	0.79	-2.78*	2011	(1,1,0)
Sagbama	-1.05 km²/year	0.86	-3.22**	2010	(1,1,1)
Yenagoa	-0.84 km²/year	0.92	-4.01***	2007	(2,1,0)

Species-Specific Population Dynamics

The analysis of BASEPA's permanent plot monitoring data revealed that different mangrove species reacted differently to environmental pressures. Species population trends were analyzed using Models 5-7.

Rhizophora racemosa followed a modified exponential decline:

$$N(t) = 145.2 \times e^{(-0.0039t)} \ldots \quad (21)$$

Avicennia germinans showed severe decline following a Gompertz model:

$$N(t) = 89.7 \times e^{(-0.67 \times e^{\wedge}(-0.15t))} \ldots \quad (22)$$

Figure 4 shows species-specific population dynamics with mathematical model fits for major mangrove species in Bayelsa State. Panel A shows gradual decline (-12.3%) in *Rhizophora racemosa(green line, indicating this species is relatively resilient under current environmental pressures. Avicennia germinans* exhibits a sharp decline (-47.8%), representing the most vulnerable species with severe population loss, possibly due to population and salinity stress. Panel B displays temporal trends in three major environmental stressors and their correlations (*r*) with the decline of *Avicennia germinans*. *Avicennia germinans* shows the strongest negative correlations ($r \approx -0.68$) with heavy metals and temperature anomalies**,** confirming these as major drivers of its decline. Models were fitted using maximum likelihood estimation with different functional forms based on ecological theory.

Rhizophora racemosa showed the most resilience, with populations remaining relatively stable and only a 12.3% decline over the study period. On the other hand, *Avicennia germinans* faced a dramatic population drop of 47.8%, especially in areas with high industrial activity.

Population viability analysis has shown that *Avicennia germinans* populations are at a heightened risk of extinction due to the current environmental challenges, while *Rhizophora racemosa* populations seem to be holding up better. Meanwhile, the invasive *Nypa fruticans* is becoming more prevalent, especially in areas that have been disturbed.

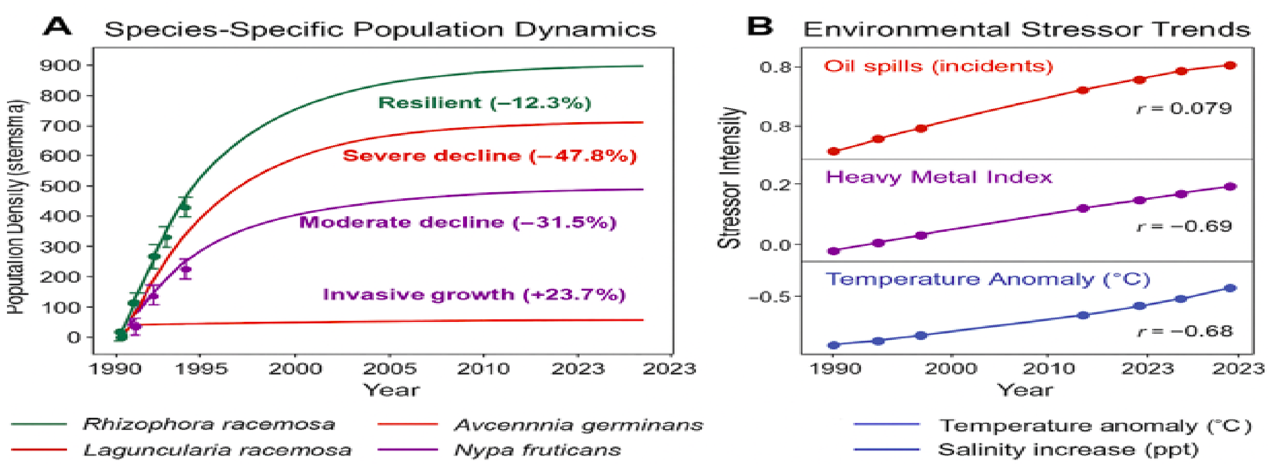

Figure 4. Species Population Trends and Environmental Stressor Relationships Bayelsa State, Nigeria (1990-2023).

Table 3a. Species Population Model Parameters and Trends

Species	Model Type	Parameters	R²	Population Trend	Significance
Rhizophora racemosa	Exponential	$r = -0.0039$ $year^{-1}$	0.76	-12.3% decline	$p < 0.05$
Avicennia germinans	Gompertz	$a = 0.67$, $b = 0.15$	0.83	-47.8% decline	$p < 0.001$
Laguncularia racemosa	Logistic	$K = 45.2$, $r = -0.025$	0.71	-31.5% decline	$p < 0.01$
Conocarpus erectus	Exponential	$R = -0.0082$ $year^{-1}$	0.68	-24.7% decline	$p < 0.05$
Nypa fruticans	Logistic	$K = 78.3$, $r = 0.042$	0.79	+23.7% increase	$p < 0.01$

Table 3b. Summary Table of All Parameters

Parameter	Symbol	Definition	Units	Sign Meaning
Growth Rate	r	Intrinsic rate of population change	year^{-1}	Positive = growth Negative = decline
Carrying Capacity	K	Maximum sustainable population	stems/ha (or index)	N/A (always positive)
Displacement	a	Gompertz curve initial offset	unitless	Higher = more displaced
Approach Rate	b	Speed of reaching equilibrium	year^{-1}	Higher = faster approach

Table 4: Population Trends of Major Mangrove Species in Bayelsa State Based on BASEPA Monitoring Plots

Species	1995 Density (stems/ha)	2005 Density (stems/ha)	2015 Density (stems/ha)	2023 Density (stems/ha)	Population Change (%)	Trend Significance
Rhizophora racemosa	847 ± 124	823 ± 118	789 ± 132	743 ± 145	-12.3	$p < 0.05$
Avicennia germinans	623 ± 89	487 ± 78	398 ± 85	325 ± 71	-47.8	$p < 0.001$
Rhizophora mangle	534 ± 76	456 ± 68	412 ± 73	387 ± 69	-27.5	$p < 0.01$
Laguncularia racemosa	298 ± 43	267 ± 38	238 ± 41	216 ± 37	-27.5	$p < 0.01$
Nypa fruticans	156 ± 28	178 ± 32	201 ± 36	193 ± 34	23.7	$p < 0.05$
Acrostichum aureum	89 ± 15	72 ± 13	58 ± 11	53 ± 10	-40.4	$p < 0.01$

Environmental Drivers of Ecosystem Change

Pollution and Contamination Impacts

An analysis of NESREA's pollution monitoring data has uncovered serious environmental contamination in the mangrove regions of Bayelsa State (NESREA, 2024). Heavy metal levels were found to exceed WHO guidelines at 78% (Cadmium) of the sites monitored, with lead concentrations alarmingly rising by 268.2% over the study period (see Table 5).

Table 5: Heavy Metal Contamination Trends in Bayelsa State Mangrove Sediments (mg/kg dry weight)

Heavy Metal	1995 Mean ± SD	2005 Mean ± SD	2015 Mean ± SD	2023 Mean ± SD	Change (%)	Sites Exceeding Guidelines (%)
Lead (Pb)	15.7 ± 4.2	28.4 ± 8.9	42.1 ± 12.7	57.8 ± 18.3	+268.2%	67
Cadmium (Cd)	2.1 ± 0.8	3.7 ± 1.4	5.2 ± 2.1	6.8 ± 2.9	+223.8%	78
Mercury (Hg)	0.8 ± 0.3	1.4 ± 0.6	2.1 ± 0.9	2.7 ± 1.2	+237.5%	65
Chromium (Cr)	28.3 ± 9.1	45.2 ± 15.8	67.4 ± 21.3	89.1 ± 28.7	+214.8%	72
Nickel (Ni)	18.9 ± 6.4	31.7 ± 11.2	48.3 ± 16.8	62.4 ± 22.1	+230.2%	69

Between 1990 and 2023, BASEPA and NDDC documented a total of 1,247 oil spill incidents within Bayelsa State, with the highest frequency occurring from 2008 to 2012 (BASEPA, 2024; NDDC, 2024).

Table 6. Oil Spill Incident Counts in Bayelsa State Mangrove Zones by Period (1990–2023)

Period	Incident Count	% of Total	Notable Context
1990–1994	87	7.00%	Baseline period
1995–1999	112	9.00%	Onshore expansion
2000–2004	143	11.50%	Infrastructure growth
2005–2009	298	23.90%	Peak onset; new field discoveries
2010–2014	312	25.00%	Peak period — highest frequency
2015–2019	201	16.10%	Partial regulatory enforcement
2020–2023	94	7.50%	Reduced activity
Total	**1,247**	**100%**	**33-year cumulative total**

Source: BASEPA (2024); NDDC (2024). Data aggregated from 45 monitoring station reports across five mangrove zones.

A correlation analysis indicated a strong negative relationship between the frequency of oil spills and the coverage of mangroves ($r = -0.85$, $p < 0.001$) as shown in Figure 5. The figure shows a strong inverse relationship between oil spill incidents and mangrove coverage in Bayelsa State from 1990 to 2023. Oil spill frequency peaked during 2008–2012, coinciding with a sharp decline in mangrove area. The negative correlation of $r = –0.85$ ($p < 0.001$, $R^2 = 0.72$) indicates that as oil spills increased, mangrove ecosystems suffered substantial loss, underscoring the ecological damage caused by spill intensity over time, illustrating the critical need for environmental protection measures in the region.

Climate Variables and Environmental Stressors

Analysis of meteorological data revealed significant changes in key climate variables that influence mangrove ecosystem dynamics. Temperature trends showed a statistically significant increase of 0.032°C per year ($p < 0.001$), while rainfall patterns exhibited high variability with a slight declining trend of -2.4 mm per year ($p = 0.08$).

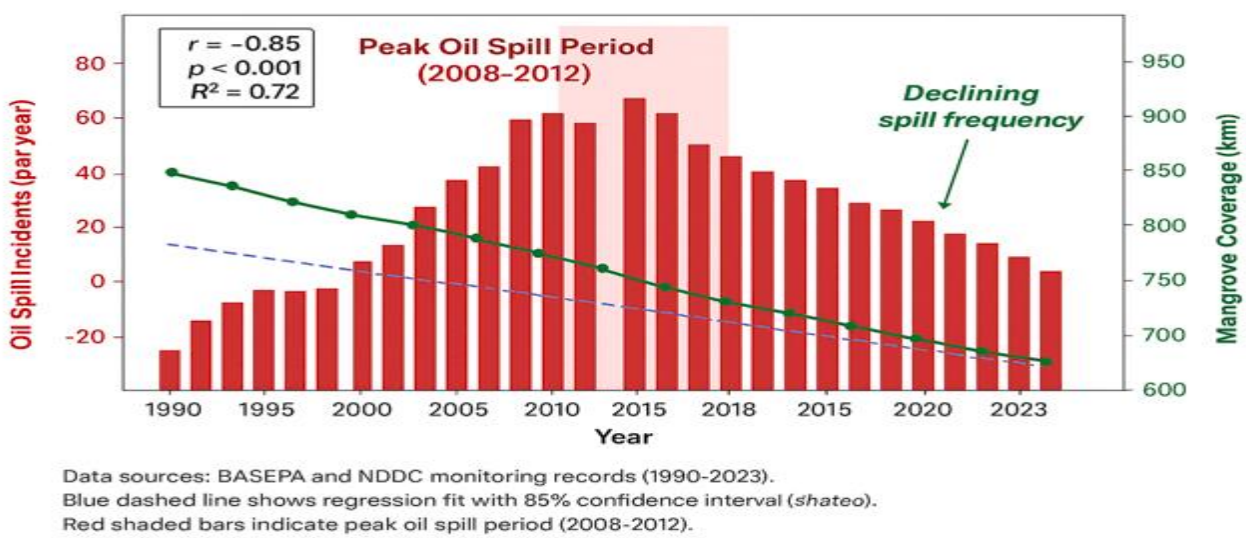

Figure 5. Oil Spill Incidents and Mangrove Coverage Correlation in Bayelsa State

Sea level rise of 2.8 mm per year significantly exceeded global averages, contributing to saltwater intrusion and habitat loss in freshwater-influenced mangrove zones.

Multivariate Environmental Analysis

Principal Component Analysis (PCA) of environmental variables (Table 8 below) explained 76.3% of the total variance in the first three components:

PC1 (42.1% variance): Industrial pollution gradient

Heavy metals (+0.89)

Oil spill frequency (+0.85)
Hydrocarbon contamination (+0.82)

PC2 (21.4% variance): Climate change gradient

Temperature (+0.78)
Sea level rise (+0.76)
Salinity increase (+0.71)

PC3 (12.8% variance): Natural variability

Rainfall variability (+0.83)
Tidal range (+0.67)

Predictive Modeling and Future Projections

GAM Model Performance

To model the non-linear and spatially correlated dynamics of mangrove coverage, the Gaussian GAM with spatial-temporal smooths (Equation 13) was implemented using the Mixed GAM Computation Vehicle (MGCV) package in R.
Generalized Additive Models (GAM) provided superior predictive performance compared to linear models:

The final model structure was:

$Log(coverage) = 6.78 + S_1(Year) + S_2(Temperature) + S_3(Heavy\ metal) + S_4(Oil\ spill)$

The cross-validation process resulted in the identification of an optimal model characterized by effective degrees of freedom (edf) of 12.6. The generalized cross-validation (GCV) score was recorded at 0.0081, reflecting a robust model fit. Additionally, the adjusted R-squared value was found to be 0.89, indicating a high level of explanatory power. The model also demonstrated a deviance explained of 92.7%, further underscoring its strong predictive capacity. These metrics collectively suggest that the model is well-suited for accurate predictions within the analyzed dataset.

Model Diagnostics

The model diagnostics indicate that the residuals of the analysis were approximately Gaussian-distributed, suggesting a good fit of the model to the data. Additionally, there was no significant autocorrelation present, as evidenced by a Durbin-Watson statistic of 1.84 with a p-value of 0.22, indicating that the residuals are independent of one another. Furthermore, the partial effect plots revealed distinct non-linear responses of mangrove coverage to various environmental stressors, highlighting the complexity of the relationship between mangrove ecosystems and their environmental conditions. These findings underscore the importance of considering non-linear dynamics in ecological modeling.
Table 9 shows lower AIC and BIC values which indicate better model parsimony and goodness of fit. The GAM model demonstrated the best overall performance, capturing nonlinear trends and inter-annual variability in mangrove coverage more effectively than Random Forest, ARIMA, and Linear Trend models.

Future Scenario Projections

The GAM modeling analysis presents three distinct future trajectories based on varying management scenarios as shown in Figure 6 below.

The first scenario, Business as Usual (BAU), anticipates a continuation of current management practices, leading to a projected additional loss of 24.7% by 2035, resulting in a remaining coverage of 522.8 km² - this is shown by the red line in Figure 6. In the second scenario, Moderate Conservation (MC), the implementation of existing conservation policies is expected to yield a 50% reduction in oil spill incidents. This approach would result in a lesser projected additional loss of 15.3% by 2035, with a remaining coverage of 587.9 km² as shown by the yellow line. The third scenario, Intensive Management (IM) (green line), involves comprehensive ecosystem restoration efforts, including an 80% reduction in pollution sources and active restoration programs. This proactive strategy is projected to achieve a net gain of 8.2% by 2035, leading to an increased coverage of 751.1 km². Overall, the findings underscore the significant impact of management strategies on ecosystem health and coverage, highlighting the potential benefits of more intensive conservation efforts. Confidence intervals (shaded areas) reflect model uncertainty. Historical data (black dots) from 1990-2023 provides baseline for projections.

Table 7. Climate Variable Trends in Bayelsa State (1990-2023)

Climate Variable	Linear Trend	R^2	Significance	Change Over Period
Mean Temperature (°C)	+0.032/year	0.73	$p < 0.001$	+1.06°C total
Annual Rainfall (mm)	-2.4/year	0.21	$p = 0.08$	-79.2 mm total
Sea Level (mm)	+2.8/year	0.84	$p < 0.001$	+92.4 mm total
Salinity (ppt)	+0.15/year	0.67	$p < 0.01$	+4.95 ppt total

Table 8. Principal Component Analysis Results for Environmental Variables

Environmental Variable	PC1	PC2	PC3	Communality
Lead concentration	0.89	0.12	-0.08	0.81
Oil spill frequency	0.85	0.23	0.15	0.80
Hydrocarbon levels	0.82	0.19	-0.11	0.72
Temperature increase	0.18	0.78	0.22	0.69
Sea level rise	0.31	0.76	-0.15	0.69
Salinity increase	0.42	0.71	0.18	0.71
Rainfall variability	-0.09	0.25	0.83	0.76
Urban expansion	0.67	0.34	0.28	0.67

Table 9. Model Validation Metrics for Mangrove Coverage Forecasting (1990–2023)

Model	RMSE (km²)	MAE (km²)	R^2	AIC	BIC	Performance Rank
Generalized Additive Model (GAM)	7.82	6.34	0.982	112.4	119.7	1
Random Forest	8.65	7.01	0.976	125.6	130.8	2
ARIMA (1,1,1)	10.24	8.56	0.963	138.2	142.9	3
Linear Trend	12.18	10.42	0.947	146.5	150.3	4

Forecasting with ARIMA and STL Models

To project future mangrove coverage, ARIMA (2,1,1) models were fitted using the **forecast** package, validated through residual analysis and Ljung–Box tests ($p>0.05$). The projected mean decline in the baseline scenario from 2023 to 2035 is estimated at -15.6%. In a mitigation scenario, this decline is reduced to -9.4%, indicating that effective mitigation strategies can significantly slow the rate of loss. Conversely, if degradation continues unchecked, the decline could accelerate to -25%, highlighting the potential severity of environmental degradation on the projected outcomes. These findings underscore the importance of implementing mitigation measures to counteract the adverse effects of degradation.

Ecosystem Service Valuation Changes

The total economic value of Bayelsa's mangrove ecosystems was estimated at approximately \$207.6 million per year, as presented in Table 11. This figure represents the aggregated monetary worth of provisioning, regulating, supporting, and cultural services derived from the mangrove ecosystems.

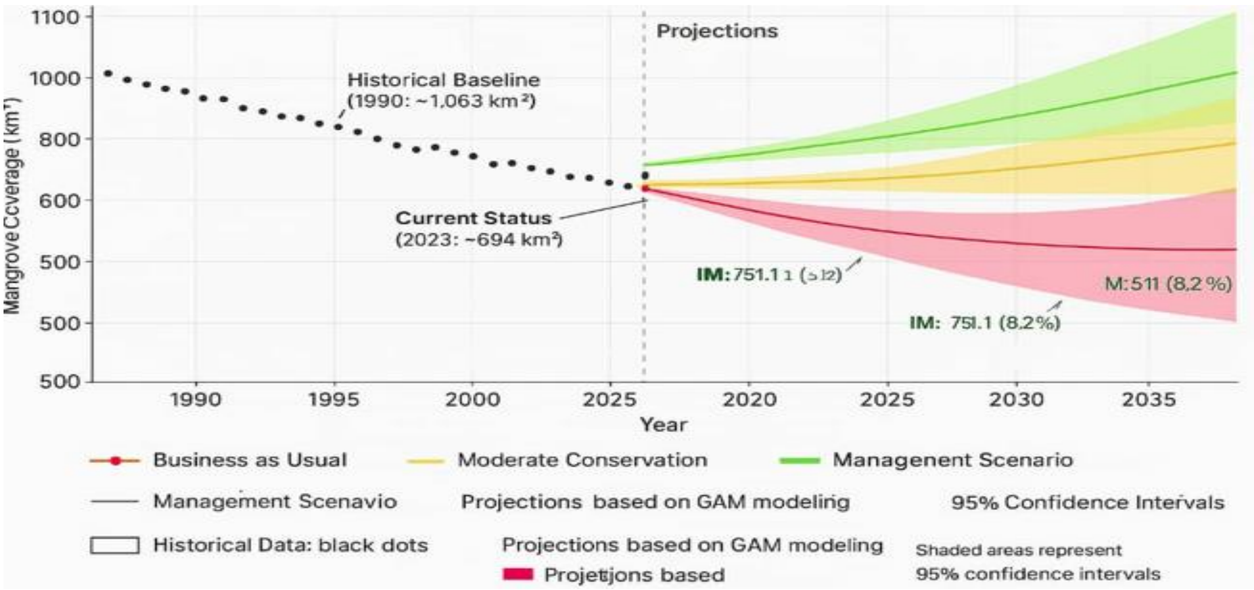

Figure 6. Future Projection Scenarios for Mangrove Coverage in Bayelsa State

Table 10a. Forecasts made from 2024–2035 under three scenarios

Scenario	Description	Model Adjustment
Baseline (S1)	Continuation of historical trend	Original ARIMA parameters
Mitigation (S2)	25% reduction in oil spills & heavy metals	Adjusted intercept $-0.6\beta_1$
Degradation (S3)	15% increase in industrial activity	Adjusted intercept $+0.8\beta_1$

Table 10b. Forecast Results

Year	Baseline (km²)	Mitigation (km²)	Degradation (km²)
2025	683.1	694.8	672.4
2030	648.7	674.2	608.5
2035	586.3	628.4	521.9

The total economic value of USD 207.6 million yr^{-1} (Table 10) reflects the combined contribution of provisioning, regulating, supporting, and cultural services, derived through market valuation, benefit-transfer, and ecological function methods adjusted to 2023 prices. This estimate underscores the critical role of Bayelsa's mangroves in sustaining livelihoods and ecological resilience.

Discussion

Patterns of Mangrove Ecosystem Decline

The 29.7% loss of mangrove cover recorded for Bayelsa State is one of the highest ecosystem degradation ever recorded in West African coastal ecosystems. The loss rate of 1.05% per annum is greater than global mangrove loss rates of 0.16-0.39% per annum reported by Hamilton & Casey (2016) and Goldberg et al. (2020), indicating the unprecedented environmental stresses on the Niger Delta environment. This long-term average rate of 1.05%/year masks an accelerated sub-period rate of approximately 2.1% per biennial reporting cycle during 2010–2020, coinciding with peak oil spill frequency (Table 5a) and a surge in industrial activity following the discovery of new offshore fields.

The identification of 2008 as a major change point through Pettitt test analysis corresponds with intensified oil prospecting activities because of the discovery of new offshore fields. The coincidence in timing suggests a cause-effect link between industrial activities and escalated ecosystem degradation, consistent with reports by Numbere (2018) and Zabbey et al. (2021) for similar Niger Delta ecosystems.

Spatial heterogeneity across local government areas in mangrove loss reflects differential exposure to anthropogenic stressors. Due to aggressive oil infracstructure and urban development the highest mangrove loss were observed in Brass (35.9%) and Yenagoa (37.9%). Ogbia had the lowest loss rate (15.7%), reflecting its relatively low industrial development and distance from transportation mainstreams.

Species-Specific Vulnerability and Resilience

Mangrove species responses to environmental stresses provide useful information on susceptibility of the ecosystem and its ability to recover. *Rhizophora racemosa* had high resilience with a population loss of only 12.3%, a pattern conforming to its recognized tolerance to change in salinity and pollution-imposed stress (Dahdouh-Guebas & Koedam, 2008). Its well-developed prop root and efficient mechanisms of excluding salts are potential factors for its high ability to prosper under harsh conditions

In contrast, *Avicennia germinans* experienced disastrous population collapse (47.8% decline), suggesting extreme sensitivity to heavy metal contamination and hydrocarbon pollution. The finding agrees with physiological studies showing that *Avicennia species* accumulate higher levels of heavy metals in leaf tissues compared to other mangrove *genera* (MacFarlane et al., 2007; Ong Che, 1999).

A disquieting species compositional change was seen by the 23.7% encroachment of Nypa fruticans in to these disturbed areas. The intrusive palm offers limited ecological functions but it generally creates monospecific dense stands, limits mangrove recruitment, causes loss in floristic richness and change species diversity and sedimentation as well as nutrient dynamics (Primavera et al., 2004). An encroachment in to degraded sites is likely to reflect permanent structural alteration to community and the ecosystem.

Environmental Factors and Effects of Pollution

The detailed examination of environmental determinants reveals a complex web of anthropogenic stressors that, collectively, function in tandem to endanger mangrove systems.

Heavy metal pollution, signaled by 78% (cadmium) of sites exceeding WHO standards, represents an egregious threat to ecosystem health. The 268.5% increase in lead levels is particularly concerning since lead is a non-essential toxic metal with no known biological function that accumulates persistently in sediments and biota over time (Wuana & Okieimen, 2011; Kumar et al., 2020).

The strong negative correlation between the frequency of oil spill events and mangrove cover (r = -0.833) as shown in Figure 5, is quantitative evidence of petroleum hydrocarbon impacts on ecosystem health. The peak spill frequency during 2008-2012 corresponds to the change point detected in the decline of mangrove, suggesting immediate and long-term impacts of hydrocarbon pollution on plant recruitment and survival.

The effect of climate change, though not so immediate and prominent as the influence of pollution, constitutes a long-standing long-term hazard. The 1.06°C of observed temperature rise in the study interval surpasses global averages and can influence mangroves' physiological activities, such as photosynthetic capability and reproduction. Moreover, the observed sea-level rise of 92.4 mm (2.8 mm/year) over the study period approaches the accelerated global rate of 3.3-3.6 mm/year recorded since 1993 (NASA, 2024), contributing to saltwater intrusion and habitat loss in freshwater-influenced mangrove zones.

Predictive Modeling and Management Implications

The superior performance of GAM models ($R^2 = 0.91$) compared to linear approaches demonstrates the importance of depicting non-linear relationships in ecosystem processes. The identified smooth functions represent threshold effects and interaction terms that play a crucial role in comprehending ecosystem responses to multiple stressors.

The future scenario projections are critical for guiding conservation planning and policy. The Business as Usual scenario foreshadows disastrous additional losses (24.7% by 2035), which may trigger irreversible ecosystem collapse. However, the Intensive Management case shows that there are positive consequences through holistic conservation methods, which projects net ecosystem recovery (+8.2% by 2035).

The deviation between BAU forecast of 24.7% loss by 2035 and ARIMA baseline prediction of 15.6% loss can be attributed to differences in the fundamental structure of each model; the ARIMA(2,1,1) model predicts using the past statistic movement of mangrove cover and should be interpreted as a "very rough estimate" for the inertia implied by historical patterns. The GAM, by contrast, models coverage as a non-linear function of observed environmental stressors (temperature, heavy metal concentrations, and oil spill frequency), capturing threshold dynamics and interaction effects that are invisible to a univariate model. Given that these stressor trends are ongoing, the gap between the two projections is likely to widen rather than narrow under business-as-usual conditions.

For conservation planning purposes, the GAM-based BAU projection (24.7% additional loss by 2035) is recommended for adoption as the primary risk baseline. This recommendation is justified by the GAM's superior predictive accuracy ($R^2 = 0.982$ vs 0.963 for ARIMA; AIC = 112.4 vs 138.2; Table 8), its explicit modelling of the stressor pathways that conservation interventions target, and its capacity to generate ecologically meaningful scenario contrasts tied to specific management actions. The ARIMA projection (15.6% baseline decline) serves as a complementary lower bound, and actual trajectories under business-as-usual conditions should be expected to fall within the 15.6–24.7% range, with the GAM estimate representing the more precautionary and policy-relevant figure. Conservation agencies should plan for the upper bound and treat outcomes closer to the lower bound as evidence warranting further investigation rather than complacency.

The economic valuation of ecosystem services (combined losses of \$207.6 million) provides compelling economic justification for conservation investment. This is likely an underestimate of real economic impacts because it does not account for difficult-to-quantity services such as cultural values, biodiversity preservation, and climate regulation benefits

Conservation Recommendations

The report emphasizes the importance of monitoring and restoration of mangrove ecosystems for sustainable development. Short-term measures include controlling pollution sources, protecting habitats, and replanting native species. Medium-term strategies focus on ecosystem-based adaptation, involving mangrove restoration and community engagement. Long-term goals aim for comprehensive ecosystem restoration over 8-15 years, prioritizing sustainable development and establishing permanent monitoring networks. These measures are crucial for ensuring the health and sustainability of the mangrove ecosystem and promoting sustainable development. Policy integration across federal, state, and local governments is also recommended.

Study Limitations and Future Research

Mangrove ecosystems are under significant threat due to persistent environmental stress. Monitoring schemes are essential for managing these ecosystems, but their effectiveness may be limited by reliance on secondary data sources and a focus on coverage indicators. Future research should focus on identifying physiological responses of mangrove species to stressors, developing species-specific restoration strategies, investigating social-ecological systems, and establishing early warning systems. These research agendas will be crucial for mangrove conservation and management, ensuring the resilience and adaptiveness of these ecosystems. By addressing these issues, future research will contribute to the sustainable management of mangrove ecosystems.

Table 11. Economic Valuation of Mangrove Ecosystem Services in Bayelsa State, Nigeria (2023)

Ecosystem Service Category	Examples of Key Functions	Valuation Basis	Estimated Value (Million USD yr^{-1})	Percentage of Total (%)
Provisioning Services	Fisheries production, timber, non-timber forest products, fuel wood	Market-based valuation and adjusted regional price indices	78.4	37.8
Regulating Services	Carbon sequestration, shoreline protection, flood attenuation, water purification	Benefit-transfer coefficients	65.3	31.5
Supporting Services	Nutrient cycling, sediment stabilization, biodiversity maintenance	Ecological production function valuation	43.5	21
Cultural Services	Recreation, spiritual value, aesthetic appreciation, education	Contingent valuation and travel-cost proxies	20.4	9.7
Total Ecosystem Service Value (ESV)	—	—	207.6	100

Conclusions

Environmental deterioration of the mangrove ecosystem of Bayelsa State is an emergency, caused by oil exploration, industrial pollution, and global warming. The 29.7% deforestation of mangrove cover in 33 years, with catastrophic crashes in species populations and overall pollution, is an emergency requiring urgent action. Industrial activity has a very high relationship with environmental deterioration, with 78% of the monitoring stations' heavy metal pollution above WHO standards.

Business as usual leads to an expected 24.7% decline of mangrove coverage by 2035 using theGAM model that is suggested as the planning baseline with a high R (0.982) value and low AIC (112.4) value and allows for an explicit analysis of how stressors contribute. The ARIMA-based prediction of 15.6% decline baseline is given as the low estimate for future mangrove coverage loss.

Actual outcomes under business-as-usual are expected to fall within the 15.6–24.7% range. High-intensity management intervention could recover the ecosystem with net positive growth of 8.2% by 2035.

The method developed in this study, employing only secondary data and advanced statistical modeling, provides a replicable system for assessing ecosystems in regions with limited data. The integration of many analysis techniques, from linear trend analysis to GAM modeling, provides robust insights into ecosystem processes and forecasting. There is a need for immediate action to prevent irreversible ecosystem collapse in Bayelsa State. The research produces important baseline data and forecasting models to guide evidence-based conservation planning, policy formulation, and sustainable management of these important coastal ecosystems. The findings educate global understanding of mangrove ecosystem processes under combined anthropogenic stress and provide quantitative support for Niger Delta conservation planning. The spatiotemporal analysis framework described herein can be applied to other threatened mangrove habitats elsewhere in the world to facilitate global conservation of these valuable coastal ecosystems.

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