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Soil carbon and wood decay models in Nigeria's Niger Delta environment

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Abstract

Decaying of wood is a major factor in modelling global carbon emissions and their effect on climate change. When not properly considered, trees used in urban greening have been observed to cause hazards and do a disservice in terms of carbon storage due to their degradation. This degradation process is aided by species properties and climatic and biological factors, but the quantitative characteristics of this process on commonly used avenue trees in Nigeria are scarce. The decay rate of wood-block samples of six commonly used avenue trees (*Azadirachta indica, Gmelina arborea, Delonix regia, Casuarina equisetifolia, Musanga cecropiodes,* and *Ficus elastica*), as well as soil carbon changes beneath the wood blocks, were monitored under natural varying climatic conditions (Soil temperature, air temperature, relative humidity) and incidence of termite attack over a period of 16 weeks. Soil and air temperature showed a quadratic trend with decay rate, with p-values less than 0.05 and 0.10, respectively, while density and incidence of termite attack were negatively linear ($p<0.05$) and positively linear ($p<0.01$), respectively. Among the species, D. regia had the highest coefficient for predicting decay rate. Soil depth and wood density were significant predictors of soil carbon accumulation from decaying wood samples. Soil temperature and other climatic variables of a region should be considered for various tree planting and management projects to discourage the selection of trees with a high decay rate and carbon loss in the area, such as *D. regia*.

Keywords: Decay modelling; Urban trees; Decay rates; Soil carbon accumulation

1. Introduction

The earth is a carbon-driven world, as carbon plays an important role in organic and inorganic processes, forming diverse compounds with other elements. Global warming, which is the heating up of the globe or rise in the earth's average temperature, has been linked with an increase in carbon dioxide (CO_2) in the atmosphere, which has drawn attention to the carbon cycle [1]. Trees are an important part of this cycle, as they utilise CO_2 and water in the presence of sunlight to manufacture their food in a process known as photosynthesis. Thus, they accumulate and store carbon in their biomass. Urban greening is an important agenda for incorporating built-up areas as part of the green cover of the earth, which helps balance the loss of trees, which act as carbon sinks, because of urbanisation [2]. This purpose can be defeated if trees are instituted in unmatched ecological zones, which expose them to stress conditions and deterioration by wood-feeding fungi that release carbon dioxide into the soil and atmosphere [3].

Wood decay is the breakdown of woody materials through the enzymatic activity of fungi [4]. Wood is also susceptible to deterioration by other organisms, such as insects, worms, etc. When trees are introduced in unsuitable ecological conditions, it can predispose the trees to degradation, which causes carbon release into the soil and environment. Predicting decay rates is a crucial aspect of understanding ecosystem processes, nutrient cycling, and carbon dynamics. Several approaches and models have been developed to estimate decay rates based on various factors such as temperature, moisture, substrate quality, microbial activity, and density [5, 6, 7, 8, 9, 10, 11]. These predictions help in assessing the impacts of climate change, land management practices, and environmental disturbances on

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decomposition processes and can also inform species selection for efficient carbon storage. According to Singh *et al.* [12], the rate and trend of carbon sequestration are influenced by the species of trees that are chosen and should be selected based on suitability [13].

Empirical models that link decay rates to environmental factors are a popular strategy, such as the Q10 models [14]. These models are frequently based on field or lab data, where decay rates are assessed in carefully controlled environments. Researchers gather information on decay rates and environmental variables like temperature and moisture before creating statistical correlations to forecast decay rates in various scenarios. The Q10 model predicts that decay rates double for every 10-degree Celsius increase in temperature [15]. In addition to empirical models, process-based models are also employed to predict decay rates [16, 17]. These models simulate decomposition processes by integrating biological, chemical, and physical factors. They often consider microbial activity, substrate quality, soil moisture, and temperature as key drivers of decay. By considering factors such as temperature, moisture, substrate quality, and microbial activity, these models contribute to our ability to assess the consequences of environmental changes on ecosystem functioning and carbon cycling.

The Niger Delta region of Nigeria is characterised by high temperatures and soils saturated with moisture [18], and the introduction of unmatched species has been observed with evidence of degradation and consequent carbon loss. A previous study by Egubogo et al. [18] describes the effect of various climatic and biotic factors on wood decay and carbon flux into the soil; however there, no predictive approach was employed to account for changes in climatic and biotic elements. Thus, this study goes further from the previous study to model the decay rate of introduced species (*Azadirachta indica, Gmelina arborea, Casuarina equisentifolia,* and *Delonix regia*) and indigenous species (*Musanga cecropioides* and *Ficus elastica*), the effects of soil temperature, air temperature, relative humidity, termite infestation, and density on the decay process, and the subsequent effect on soil carbon accumulation.

2. Material and methods

2.1. Field experiment

Wood blocks of 2cm by 5cm by 5cm were processed from the selected tree species and placed below ground at the University of Port Harcourt, Delta Campus, for a period of 16 weeks. The block samples of each species were replicated three (3) times for each time frame of 4, 8, 12, and 16 weeks of assessment, and the entire set-up was done at 0–15 cm and 15–30 cm depths. This totals 144 wood blocks for the experiment, with an additional 18 blocks comprising 3 replicates of each species used in estimating wood density. Before experimentation, soil samples were randomly collected on the site to obtain a baseline of its soil carbon content. This was followed up with soil sample collection at the point of soil contact with the base of wood blocks at the various time frames of the experiment's termination.

2.2. Climate and soil characteristics

A digital hygrometer (DC-103) was used to measure the air temperature in degrees Celsius and the relative humidity of the environment in percentages. Using a probe extension of the device, soil temperature was also measured in degrees Celsius. Soil organic carbon content was measured using the wet oxidation method [19] and calculated with the equation (Eq.1):

$$\text{Organic carbon (\%)} = \frac{0.003\text{g x N x 10ml x}\left(1-\frac{T}{S}\right)\text{ x }100}{\text{ODW}} = \frac{3\left(1-\frac{T}{S}\right)}{W} \qquad \text{……………. Eq. 1}$$

Where:

- N =Normality of $K_2Cr_2O_7$
- T =Volume of $FeSO_4$ used in the sample titration (ml)
- S =Volume of $FeSO_4$ used in blank titration (ml)
- ODW =Oven-dry sample weight (g)

2.3. Wood density and decay rate

Wood samples were oven-dried at a temperature of 1000 °C until a constant weight was achieved [20]. The volume of wood blocks with dimensions of 2cm by 5cm by 5cm was calculated using the formula (Eq.2):

$$\text{WD} = \frac{M}{V} \quad \text{………..Eq. 2}$$

The decay rate of each species was calculated using the decay rate *k* model as used by Fravolini et al. [21]:

$$x_t = x_0 e^{-kt} \qquad \text{……………} \qquad \text{Eq. 3}$$

Where:

- x_t=Mass of deadwood at a given time (t),
- x_0 =Initial mass

2.4. Model description

Simple linear models (LM), multiple linear models (MLM), quadratic models (QD), and an exponential model (EM) were used to fit the wood decay rate based on the observed exploratory analysis trend with the independent variables. Soil carbon changes were categorised either as influx (1) or efflux (0) depending on the net gain or loss from the initial soil carbon baseline, and a binary logistic regression model was employed in predicting soil carbon flux from the examined independent variables. Model equations are:

$$\text{Simple Linear model, } k = b_0 + b_1X_1 \qquad \text{………….. Eq. 4}$$

$$\text{Multiple Linear model, } k = b_0 + b_1X_1 \ldots + b_nX_n \qquad \text{……………. Eq. 5}$$

$$\text{Quadratic model, } k = b_0 + b_1X_1 + b_2X_1^2 \qquad \text{………… Eq. 6}$$

$$\text{Exponential model, } k = b_0 * \exp[b_1 * X] \qquad \text{…………….. Eq. 7}$$

Where;

- k= Wood decay rate
- X= Soil temperature, air temperature, humidity, weight loss, species, presence of termite infestation and density
- $b_0 \ldots b_n$ =Regression parameters

$$\text{logit}\{Y=1|X\} = b_0 + b_1X_1 \ldots + b_nX_n \qquad \text{……………} \qquad \text{Eq. 8}$$

Where;

- Y = Binary outcome (1 = influx, 0 = efflux)
- X = Soil temperature, air temperature, relative humidity, decay rate, depth, wood density and presence of termite infestation

2.5. Model evaluation

Models were evaluated using probability values, with significance at values lower than 0.05 and R-squared values

$$\text{Coefficient of determination } (R^2) = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \qquad \text{………… Eq. 9}$$

$$\text{Sum of squares total (SST)} = \sum(y - \bar{y})^2 \qquad \text{………..Eq. 10}$$

$$\text{Sum of squares regression (SSR)} = \sum\left(y' - \overline{y'}\right)^2 \text{…………Eq. 11}$$

$$\text{Sum of squares error (SSE)} = \sum(y - y')^2 \qquad \text{……………..Eq. 12}$$

R^2 describes the proportion of variance explained by the regression model for the dependent variable. If the regression model is perfect, SSE is equal to zero, and R^2 is equal to one (1). The model fails when R^2 equals zero.

2.6. Statistical analysis

Statistical analysis was done using R version 4.1.2. The regression models were fitted using the lm and glm functions in R, while the ggplot2 package version 3.3.5 was used for data and model visualisation.

3. Result

Simple models predicting decay rates from various independent variables are presented in Figure 1. Fitting an exponential curve and linear line over the decay rate and weight loss plot produced a significant model equation ($p < 0.000$). The exponential curve was a better fit as it explained 77.7% ($R^2 = 0.777$) of the variance in decay rate caused by weight loss, while the linear fit accounted for 56.9% ($R^2 = 0.569$) of the variance. Soil temperature was a significant predictor of decay rate using a quadratic fit ($p = 0.031$) but was not significant with a linear fit ($p = 0.784$) (Fig. 1). Only 4.5% ($R^2 = 0.045$) of the variation in decay rate is explained by changes in soil temperature using the quadratic fit. From Figure 1, both quadratic ($p = 0.075$) and linear ($p = 0.616$) models yielded a non-significant equation in predicting the decay rate from air temperature. Both quadratic ($p = 0.318$) and linear ($p = 0.598$) models yielded a non-significant equation in modelling decay rate using relative humidity. The slope of the linear fit is observed to have a negative value with low magnitude (-0.002), which means it projects a slight decrease in decay rate with an increase in relative humidity.

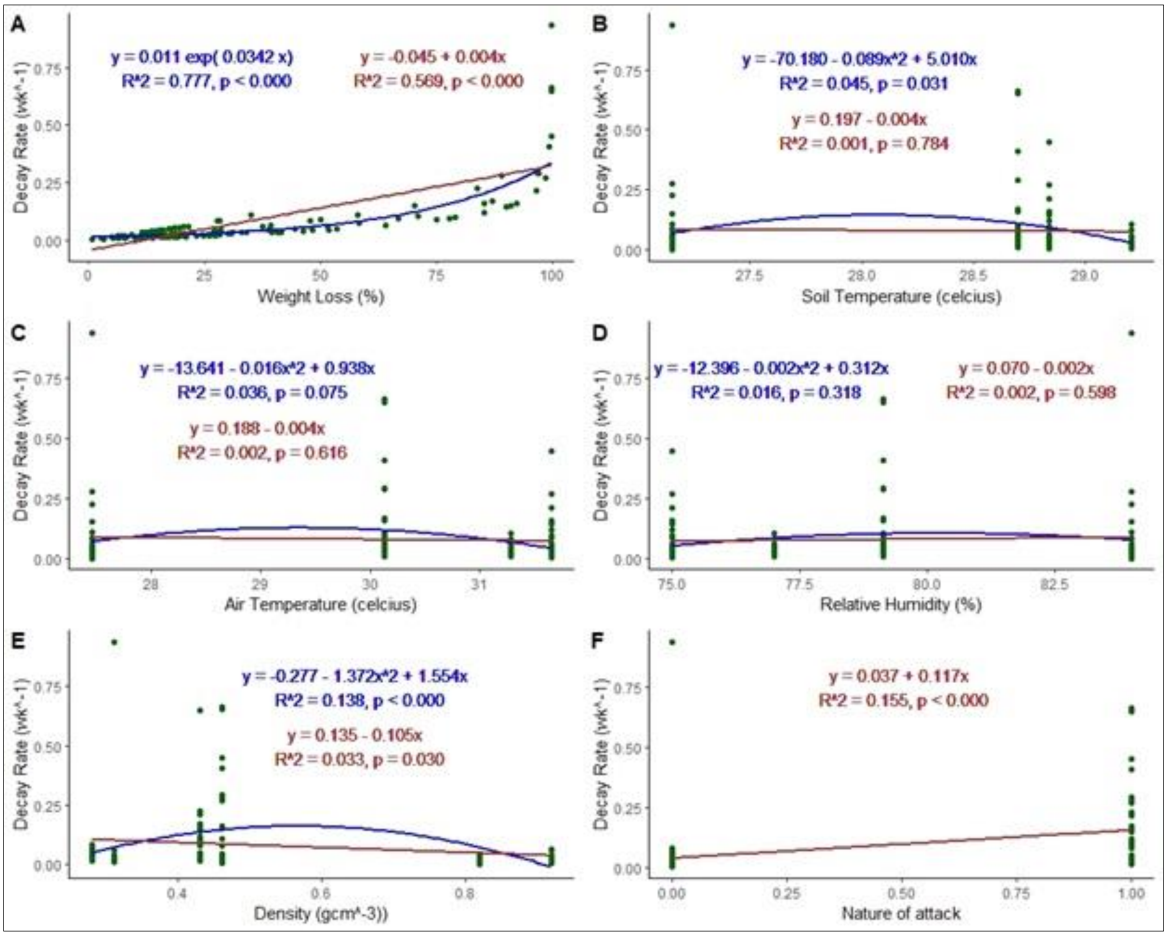

Figure 1 Plot grid of the modelled curve in predicting decay rate from weight loss (A), soil temperature (B), air temperature (C), relative humidity (D), density (E), and nature of the attack (F)

Density was a significant predictor of decay rate using quadratic ($p < 0.000$) and linear ($p = 0.030$) models. The linear trend line shows that the decay rate significantly decreased with increase in density with an R squared value of 0.033 while the quadratic curve yielded an R^2 of 0.138 (Fig. 1). Figure 1 also showed that decay rate significantly ($p<0.000$) increases with increase in the activity of termite on test block samples (slope = 0.117) using a simple linear model and this produced an R square value of 0.155.

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The combined effect of independent variables on the decay rate was mostly explained by species, soil and air temperature, humidity, and attack (R^2 = 0.285), followed by species and climatic effects (R^2 = 0.273), species and attack (R^2 = 0.225), climatic effects and attack (R^2 = 0.217), and species (R^2 = 0.214) only. The least-fitting models were climatic data (R^2 = 0.059) and climatic data and wood density (R^2 = 0.091). All multiple models yielded a probability value of less than 0.05 (Table 1). Among the species, *D. regia* contributes more to the decay rate (Coeff = 0.18), while *A. indica* contributes less (Coeff = -0.01). The climatic data model also shows that soil temperature (Coeff = 0.85) had a positive effect on the decay rate, while air temperature and relative humidity were negative (Table 1).

Table 1 Multiple Regression Coefficient for Predicting Wood Decay

S/N	Model	R	R^2	p-value	Equation
1	Y ~ Species	0.463	0.214	$2.84e^{-6}$	$Y = 0.03 - 0.01X_1 + 0.02X_2 + 0.03X_3 + 0.18X_4 + 0.08X_5$
2	Y ~ Climatic data	0.243	0.059	0.037	$Y = 43.88 + 0.85X_7 - 1.21X_8 - 0.40X_9$
3	Y ~ Climatic data + density	0.302	0.091	0.009	$Y = 43.94 + 0.85X_7 - 1.21X_8 - 0.40X_9 - 0.10X_{10}$
4	Y ~ Climatic data + attack	0.466	0.217	$6.72e^{-7}$	$Y = 42.74 + 0.85X_7 - 1.19X_8 - 0.39X_9 + 0.11X_{11}$
5	Y ~ Species + Climatic data	0.522	0.273	$5.90e^{-7}$	$Y = 43.83 - 0.01X_1 + 0.02X_2 + 0.03X_3 + 0.18X_4 + 0.08X_5 + 0.85X_7 - 1.21X_8 - 0.40X_9$
6	Y ~ Species + attack	0.474	0.225	$3.58e^{-6}$	$Y = 0.02 - 0.01X_1 + 0.02X_2 + 0.03X_3 + 0.14X_4 + 0.04X_5 + 0.06X_{11}$
7	Y ~ Species + Climatic data + attack	0.534	0.285	$5.91e^{-7}$	$Y = 43.27 - 0.01X_1 + 0.02X_2 + 0.03X_3 + 0.13X_4 + 0.03X_5 + 0.85X_7 - 1.20X_8 - 0.40X_9 + 0.06X_{11}$

Y = decay rate; x1 = *A. indica*; x2 = *M. cecropiodes*; x3 = *G. arborea*; x4 = *D. regia*; x5 = *F. elastica*; *x6 = C. equisentifolia*; x7 = soil temperature; x8 = air temperature; x9 = relative humidity; x10 = density; x11 = presence of termite

Depth and wood density were the only significant predictors of soil carbon flux (Table 2). The odds ratio of having carbon influx is 2.59×10^{-3} times higher at a soil depth of 30cm compared to 15 cm ($p = 4.5 \times 10^{-5}$, CI = 6.32×10^{-5}, 2.56x10-2), while the odds ratio increased by a factor of 2.89×10^{-2} with a unit increase in density (P = 0.04, CI = 5.72×10^{-4}, 6.72×10^{-1}). That is, there is likely to be more carbon influx into the soil at 15cm depth and with wood of lower density.

Table 2 Binary Logistic Estimates and Odds Ratio of Soil Carbon Influx

Variables	Estimate (β)	Std. Err	P	Exp(β)	Confidence Interval (CI)	
					2.5%	97.5%
Intercept	-1107.86	566.02	0.05	0.00	0.00	$7.77e^{-30}$
Soil temperature	-16.19	10.40	0.12	$9.34e^{-8}$	$2.59e^{-17}$	$3.21e^{1}$
Air temperature	27.42	15.10	0.07	$8.11e^{11}$	$5.40e^{-1}$	$1.06e^{26}$
Relative humidity	9.52	5.13	0.06	$1.36e^{4}$	1.01	$8.84e^{8}$
Decay rate	-0.42	3.92	0.91	$6.60e^{-1}$	$8.11e^{-5}$	$9.47e^{2}$
Depth (30cm)	-5.96	1.46	4.5^{e-5}*	$2.59e^{-3}$	$6.32e^{-5}$	$2.56e^{-2}$
Density	-3.54	1.74	0.04*	$2.89e^{-2}$	$5.72e^{-4}$	$6.72e^{-1}$
Termite (Yes)	-0.16	1.03	0.87	$8.49e^{-1}$	$1.14e^{-1}$	7.34

Significant at p<0.05

4. Discussion

The relationship between decay rate and weight loss showed a significant exponential and linear increase, with the highest R^2 attributed to the exponential model. This high percentage of explained variability of decay rate by weight loss could be attributed to the derivability of decay rate from weight loss. Air and relative humidity were not significant predictors of wood decay rates. While air temperature and humidity can influence soil temperature and moisture, they have less direct effect on microbial activity which in turn affects decomposition rates compared with soil temperature [22]. Air temperature affects soil temperature, but it may not always accurately reflect the actual temperature conditions within the soil, which can be more variable. On the other hand, soil temperatures and soil moisture conditions are especially taken into consideration [23], which could be due to their direct contact with decomposition materials. Soil type, vegetation, and land use can affect soil temperature and water content [24, 25].

The quadratic model of decay rate and soil temperature was significant but only explained 4.5% of the decay rate. Cortez [6] showed a significant relationship in decomposition using a quadratic model with soil temperature and humidity ratio as predictors, with R^2 values over 0.9. Xiao *et al.* [11] also reported the same trend with peak litter decomposition at the mid-soil temperature and fitted a quadratic model that explained 58% of the variations and was significant. They also presented a positive linear increase in decomposition with an increase in soil water content, but this was not a significant fit ($R^2 = 0.04$). Temperature and moisture combined effects on litter decomposition are correlated with litter decomposition with high decomposition at high temperature and moisture [5]. A linear fit using density to predict the decay rate showed a significant negative slope, which is in corroboration with the negative relationship observed between wood decay rate and density by Owoyemi et al. [10] but with a larger R^2 value of 0.70. Hérault et al. [8] reported higher-density trees having a greater half-life, indicating a longer period of decomposition, as seen in higher-density species in this study.

The impact of termite infestation on wood also significantly affected weight loss and, as such, decay rate. It has been acknowledged that level decompositions in neotropical forests are strongly affected by termite activity [8]. Multiple linear regression gave a significant improvement over the simple linear models of the climatic data. Only *A. indica* had a negative coefficient with decay rate, while *D. regia* and *F. elastica* had higher positive magnitudes of 0.18 and 0.08, respectively, in reference to the intercept (*C. equisetifolia*). Species, climatic data, and attacks jointly accounted for 28.5% of the variation in decay rate, which is also an improvement from the simple quadratic and linear models. The prediction of the decay rate of *D. regia* is higher, which could lead to carbon inflow to the soil, as reported by Egubogo *et al*. [18]. The study showed that density had a negative relationship with decay rate and could be attributed to the resulting prediction of reduced soil carbon content in soils where higher-density wood blocks had soil contact. Decomposition rates are usually higher in the topsoil as they contain a higher microbial load, which could explain the positive turnover of soil carbon at lower depths as the model predicts an influx with a decrease in depth.

5. Conclusion

Soil properties such as soil temperature, wood properties such as density and species, and the activities of termites were significant predictors of wood decomposition rate. While air temperature and relative humidity did not produce significant models, their effects could be indirect. Among the species, *D. regia* had the highest coefficient in predicting decay rate and can contribute more carbon to the study area. Soil depth and wood density also play important roles in soil carbon accumulation from wood decay, with a higher probability of inflow at lower depths and low-density wood. Thus, Soil temperature and other climatic variables of a region should be considered for various tree planting projects and management to discourage the selection of trees with a high decay rate and carbon loss, such as *D. regia.*

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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