Above-ground biomass and structure of 260 African tropical forests


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We report above-ground biomass (AGB), basal area, stem density and wood mass density estimates from 260 sample plots (mean size: 1.2 ha) in intact closed-canopy tropical forests across 12 African countries. Mean AGB is 395.7 Mg dry mass ha$^{-1}$ (95% CI: 143.3), substantially higher than Amazonian values, with the Congo Basin and contiguous forest region attaining AGB values (429 Mg ha$^{-1}$) similar to those of Bornean forests, and significantly greater than East or West African forests. AGB therefore appears generally higher in palaeo-compared with neotropical forests. However, mean stem density is low (426 ± 11 stems ha$^{-1}$ greater than or equal to 100 mm diameter) compared with both Amazonian and Bornean forests (cf. approx. 600) and is the structure- tural feature of African tropical forests. While spatial autocorrelation complicates analyses, AGB shows a positive relationship with rainfall in the driest nine months of the year, and an opposite association with the wettest three months of the year; a negative relationship with temperature; positive relationship with clay-rich soils; and negative relationships with C:N ratio (suggesting a positive soil phosphorus–AGB relationship), and soil fertility computed as the sum of base cations. The results indicate that AGB is mediated by both climate and soils, and suggest that the AGB of African closed-canopy tropical forests may be particularly sensitive to future precipitation and temperature changes.

1. Introduction

Comparative studies of the above-ground biomass (AGB) of tropical forests exist for South America [1–3] and Asia [4] but not for Africa. Thus, some ostensibly simple questions remain unanswered: how much AGB does an average structurally intact African tropical forest store? Where in Africa is biomass lower or higher; and what controls this spatial variation? How do African forest AGB values compare with those on other continents? Here, we collate standardized AGB data from across tropical Africa to provide a first answer to these broad questions.

Understanding the spatial patterns of biomass in African forests is important on at least four counts. First, to provide insights into how tropical forests function. Africa provides a useful contrast with Amazonia in terms of separating possible causal factors underlying AGB variation, as unlike Amazonia, Africa does not possess a strong east-west gradient in soil fertility that coincides with other gradients such as mean annual air temperature [1,3,5]. Therefore, studying African forests may assist in developing a more coherent understanding of tropical biomass variation and the relative contributions of climate, soils and disturbance. Additionally, recent work suggests some systematic neo- versus palaeotropical differences in forest structure (i.e. South American versus Africa/Asia forests; [6]), and perhaps AGB varies similarly, as some recent analyses suggest [7]. Second, biomass estimates provide information on ‘emissions factors’ for estimating carbon losses from deforestation and forest degradation [8]. Third, they can assist calibrating and validating carbon mapping exercises [9]. Fourth, modelling tropical forests requires data to both develop and test representations of African forests and their response to a changing environment [10].

The live biomass density of a tropical forest is the sum of the biomass of all living organisms per unit area. This is determined by both the rate of fixation of carbon into root, stem, branch and leaf material per unit area, and how long that fixed material is resident as living mass in each of those biomass pools. Hence, both the net primary productivity (NPP) and the biomass residence time ($\tau_W$, 1/biomass turnover rate) determine a forests’ AGB. In practice, for old-growth forests the turnover times of fine root and leaf material are much shorter (approx. 1–2 years) than that of woody biomass (approx. 50–100 years), and hence total AGB is almost entirely determined by the rate of production of woody biomass (NPP$_{wood}$; some 20–40% of NPP [11]) and its residence time. Thus, all other things being equal, a forest with higher NPP$_{wood}$ should have greater AGB. Similarly, a forest with a greater $\tau_W$ will accumulate NPP$_{wood}$ over more years, leading to greater AGB. Thus, a priori, resource availability should affect AGB via NPP$_{wood}$, and the size–frequency distribution of disturbance events should affect AGB via $\tau_W$. These disturbance events may be endogenous, for example, related to species life-history traits, soil physical characteristics or biotic interactions (from plant disease to foraging elephants), or exogenous, for example via climatic extremes, or some combination of the two. A third possible class of effect is associated with the species pool available in a given forest that may systematically elevate or depress AGB via effects on either NPP$_{wood}$ or $\tau_W$. This may be important given evidence of the relationship between geology and free species distributions [12,13], and contribute to the high AGB in Southeast Asian forests dominated by Dipterocarpaceae [4,6]. These factors may be non-linear (soil depth beyond a certain level may have no effect on $\tau_W$), co-correlated (precipitation and soil fertility [14]) or interacting (species growing on high-fertility soils may have shorter lifespans, shortening $\tau_W$ [3]). A recent evaluation of Amazonian AGB patterns...
The evidence for the effects of individual drivers of spatial differences in AGB within tropical forests is limited, but allows hypotheses to be articulated. Each forest grows on a particular soil under a particular climatic regime. In terms of climate, theory suggests that AGB will be lower when NPP is reduced in forests experiencing a dry season where growth is reduced or ceases owing to a limit in water availability, as has been documented [1,2,4]. Although when accounting for the spatial autocorrelation, this effect on NPP appeared much reduced for Amazon forests [3]. Conversely, extremely wet forests have lower AGB than moist forests [15], perhaps attributable to a lower NPP owing to the cloudiness associated with high rainfall reducing incoming insolation rates [14,16,17]. Hence, high wet-season rainfall may be associated with low AGB. However, simple wet/dry season comparisons are more complex in Africa as the movement of the intertropical convergence zone generates two wet and two dry seasons annually over much of Central Africa, and tropical forests across Africa are on average drier than those in the Americas of Asia [18].

Low air temperature may restrict the efficiency of photosynthesis, hence higher air temperatures in the coolest part of the year may be associated with higher AGB. By contrast, forests growing under higher air temperatures may have higher respiration costs, and if photosynthesis is not higher (or reduced because of higher atmospheric water vapour pressure deficits [19]), NPP may be lower and hence AGB—other things being equal—would be lower. Therefore, forests growing under very high air temperature may be generally associated with a lower AGB. Although Amazonian AGB was not significantly related to mean annual air temperature, wood production was, however, negatively associated with it [3], and in Asia most of the best models relating AGB to environmental conditions do not include temperature [4], suggesting any AGB–temperature relationship may be relatively weak, or is being masked by other covarying factors. We therefore consider both temperature and precipitation as potential drivers of spatial variation in AGB.

The impact of soils on AGB is likely to be complex. Developmentally older soils tend to provide fewer of the nutrients plants require than do younger soils, and hence are poorer substrates for plant growth, but conversely are often deeper and structurally provide improved water retention, and hence are better for plant growth and biomass support [5,14]. Thus, a separation of plant-relevant soil physical and chemical characteristics is necessary to disentangle the likely opposing impacts of nutrient availability on AGB via NPPWOOD and physical soil characteristics via \( \tau_w \). Additionally, it is uncertain whether it is phosphorus and/or other nutrients that are the most important fertility-related soil parameters affecting NPPWOOD. Furthermore, soil data are often unavailable for forest inventory plots, and methods of soil analysis may also be different: all of which complicate analyses of soil effects on tropical forest function. Based on available evidence, we predict structurally poor soils, including coarse-textured sandy soils, to be associated with lower AGB. The predicted response to the higher availability of soil nutrients is ambiguous, as NPPWOOD is likely to be higher, hence higher AGB might be expected, yet such forest stands may become dominated by species with low wood mass density (WMD) which tend to have shorter life spans (shorter \( \tau_W \)), and hence a lower AGB. Positive AGB–nutrient relationships from Borneo imply the increase in NPPWOOD dominates there [4], whereas in Amazonia, the decline in \( \tau_w \) appears to dominate [1,3]. A Central African study suggests that higher NPPWOOD and lower \( \tau_w \) likely balance each other in terms of their impact on AGB [20].

The role of exogenous disturbance events in determining AGB is also difficult because such events are difficult to characterize ex post facto. However, we may get insights in three ways. First, stem density provides insights as low disturbance rates over preceding decades are likely to result in greater biomass allocated to fewer stems, because when exogenous disturbance events are rare, larger older trees should dominate, shading out and thus reducing the growth rates and survival probability of smaller trees (‘self thinning’). Second, habitat fragmentation may elevate disturbance rates, altering AGB patterns in remaining forest [21]. Third, community-average WMD should be lower in more frequently disturbed and hence dynamic forests comprising greater numbers of earlier successional species [22]. Therefore, we report on all of AGB, basal area (BA), stand WMD and stem density for our 260 forest monitoring plots encompassing West, Central and East Africa, also investigating their relationship with soil, climate and fragmentation variables. Analytically, we use a series of statistical techniques to attempt to build a synthetic understanding of the likely controls on forest AGB across tropical Africa.

2. Methods

(a) Data collection and processing

Forest inventory plot data, collected and collated as part of the African Tropical Rainforest Observatory Network (AfriTRON; www.afritron.org), were selected for analysis when conforming to the following criteria: closed-canopy tropical forest; geo-referenced; all trees greater than or equal to 100 mm diameter measured; greater than or equal to 0.2 ha; majority of stems identified to species; old-growth and structurally intact, i.e. not impacted by recent selective logging or fire; mean annual air temperature greater than or equal to 20°C and greater than or equal to 1000 mm mean annual precipitation (from WorldClim [23]). Three remaining plots previously characterized by researchers as ‘montane’ forest were excluded. In all plots, tree diameter was measured at 1.3 m along the stem from the ground, or above buttresses, if present. The 260 plots (total, 312.5 ha) that conformed to the criteria comprised 132,899 stems, of which 85% were identified to species and 96% to genera. Further details are given in the electronic supplementary material.

For each plot, we calculated (i) stem density greater than or equal to 100 mm diameter per ha; (ii) the BA (sum of the cross-sectional area at 1.3 m, or above buttresses, of all live trees in \( m^2 \) ha\(^{-1} \)); (iii) BA-weighted wood mass density (WMD\(_{BA}\), i.e. the mean of the WMD of each stem weighted by its BA, where WMD is dry mass/fresh volume in g cm\(^{-3} \)). The best taxonomic match wood density of each stem was extracted from a global database [24,25] following a well-established procedure [26]; (iv) AGB (including stem, branches and leaves) was calculated using the Chave et al. [15] ‘moist forest’ equation to estimate the AGB of each tree in the plot, using diameter, WMD and tree height, with height estimated from diameter using the recommended regional equations for West (region west of the Dahomey gap), Central (Congo–Ogoué Basin and contiguous forest) and East (east of Congo Basin) Africa, as defined in [7],

\[ AGB = \frac{WMD_{BA} \cdot BA}{1.56 \cdot \tau_w} \]
and expressed dry mass as Mg ha$^{-1}$ (= metric tonnes ha$^{-1}$). The stem density BA, WMD, WMDBA and AGB values were calculated using the http://www.forestplots.net/ data management facility [27]; version 13 April 2013 [28]. The locations of the study plots are shown in figure 1.

Average mean annual temperature ($T_{A}$), mean monthly maximum air temperature ($T_{\text{max}}$), mean monthly minimum air temperature ($T_{\text{min}}$), mean temperature in the warmest and coldest quarters ($T_{WARMQ}$, $T_{COLDQ}$), temperature seasonality (coefficient of variation; $T_{CV}$) and average mean annual precipitation ($P_{A}$), mean monthly maximum precipitation ($P_{\text{max}}$), mean monthly minimum precipitation ($P_{\text{min}}$), precipitation in the wettest and driest quarters ($P_{\text{WETQ}}$, $P_{\text{DRYQ}}$) and precipitation seasonality (coefficient of variation; $P_{CV}$) were extracted from the WorldClim database at the finest resolution available (30'; [23]), giving mean long-term climate data (approx. 1950–2000) for each plot location (see the electronic supplementary material for further details).

Detailed information on soils was not available for most plots, but the soil class or type was often known or estimated from data outside the plot, local knowledge, local soil or geology [29]. For each plot, we therefore had a notional soil type, and where necessary this information was converted to a standard classification and soil variables extracted (for 0–30 cm and 30–100 cm depth) for the corresponding soil type at or closest to the plot location from the FAO Digital Soil Map of the World dataset [29]. This provides a method of incorporating consistent soil information, while avoiding the possible problem of incorrectly assigning plots overlying non-dominant soil types, or averaging data from plots on differing soil types within the same interpolated soil map grid square. Hence, plots within the same landscape on differing soil types are assigned corresponding differing soil parameters. The soil data are to be treated with caution, as they are not in situ data, particularly as soil geographers sometimes use vegetation characteristics themselves as an aid to their mapping of soil [30], giving rise to a potential tautology. Nevertheless, our approach taken here incorporates the in situ data available and avoids some common pitfalls of using gridded soil data allowing for a first-order analysis of any likely edaphic effects on the studied stand properties.

To test for soil-related effects, we used (i) principal components analysis (PCA) on the soil-structure-related data (0–100 cm), giving a sand–clay axis (PC1 sand; low values are high sand content) and a silt axis (PC2 clay–silt; high values are clay-rich, low values silt-rich; loadings in the electronic supplementary material); (ii) sum of exchangeable bases (0–30 cm), in cmol kg$^{-1}$ ($\Sigma_{B}$), the most relevant to tree growth cation-related plant nutrition variable in the FAO dataset; (iii) C:N ratios as a surrogate for plant available phosphorus. Phosphorus availability is likely to be very important for tree growth but is not reported in the FAO or other large-scale soil datasets. However, soil C:N ratio (0–30 cm) has been shown to be strongly negatively correlated with total extractable phosphorus across in Amazonia [5], and unpublished African in situ soil data also support this notion (S. Lewis et al., unpublished data). Additionally, we also define soil classes based on pedogenetic development, following the scheme in reference [31]: all soils younger than alisols (in this dataset cambisols and histosols), score 1; all soils younger than ferralsols but older than alisols, score 2; all ferralsols, score 3.

Habitat fragmentation indices were devised using Google Earth Pro. We measured the distance from the plot centre to (i) the nearest forest edge (any absence of forest cover greater than or equal to 1 ha), giving a distance to edge (fragment edge in km, $F_{E}$) and (ii) the nearest edge of a clearing greater than or equal to 1 ha in eight directions every 45$^\circ$ from north, from which we estimated fragment size by summing the areas of the eight triangles generated (fragment area in km$^2$, $F_{A}$).

(b) Statistical analysis

The dataset is complex with explanatory variables spatially autocorrelated. Furthermore, some of the soil types are rare, and temperature- and precipitation-related variables also correlate. As there is no single statistical method that can account for all of these aspects of the dataset, our approach was to use a series of statistical techniques, each with its own limitations, to build a synthetic understanding of the controls on AGB.

We first investigate the continuous variables, presenting Spearman’s correlation coefficients, accounting for spatial autocorrelation using Dutilleul’s method [32]. For categorical soil variables, we use ANOVA to assess their potential impacts on response variables. We then take an information-theoretic approach, testing all possible combinations of the climate, fragmentation and soil variables, selecting the best model on the basis of the lowest Akaiki’s information criterion, corrected for finite sample sizes (AIC$_{C}$). We assume all of the ordinary least-squares (OLS) models within two AIC$_{C}$ units of the lowest AIC$_{C}$ model are plausible alternatives in terms of explaining variation in the dataset [33,34]. Extensive preliminary analysis showed which pairs of variables had the most explanatory power $T_{\text{min}}$ or $T_{\text{WARMQ}}$, $T_{\text{max}}$ or $T_{\text{COLDQ}}$, $P_{\text{min}}$ or $P_{\text{WETQ}}$, $P_{\text{max}}$ or $P_{\text{DRYQ}}$. We selected $T_{\text{min}}$, $T_{\text{WARMQ}}$, $P_{\text{min}}$ and $P_{\text{WETQ}}$ for inclusion in the models to better allow comparisons of models across response variables. Following this, the low AIC$_{C}$ models were checked for parameter redundancy by removing redundant variables that are the same sign (i.e. if $T_{A}$ and $T_{\text{WARMQ}}$ are included and of the same sign, then one is removed based on importance values), and the full suite of models was run again.

Figure 1. Above-ground biomass (AGB), basal area (BA), basal area-weighted wood mass density (WMDBA), and stem density for 260 plots in closed-canopy tropical forest. Green represents ‘closed forest’ and ‘flooded forest’ categories from the 300 m resolution European Space Agency Globcover (v. 2.3) map for the year 2009. (Online version in colour.}

[43x445]mean monthly minimum precipitation (\(\text{forest}.\) Green represents ‘closed forest’ and ‘flooded forest’ categories from the 300 m resolution European Space Agency Globcover (v. 2.3) map for the year 2009. (Online version in colour.)
minus these redundant terms (see the electronic supplementary material for further details). Removing redundant terms aids the interpretation of the results and avoids the possible problem of over-fitting sometimes associated with larger datasets [34]. We then account for spatial autocorrelation in our OLS models. As there is no definitive technique to account for spatial autocorrelation [35], we follow the recent example of Quesada et al. [3] who used eigenvector-based spatial filtering (extracted by principle component of neighbour matrices [36,37]) on a similar dataset from Amazonia, which aids cross-continental comparisons.

We identify the spatial filters significantly correlated with the residuals from the OLS model, and re-run the identical explanatory variables as in the OLS model plus the selected filters, termed spatial eigenvector mapping (SEVM) models. We computed other less stringent filtering methods, but as these inform more on the underlying structure of the variables rather than addressing our specific hypotheses we omit them for brevity (see [3]). We used spatial ecology in macroecology, version 4.0 [37] for the analysis.

3. Results

(a) General patterns

The mean stem density of the 260 plots was 425.6 stems ha⁻¹ greater than or equal to 100 mm diameter (95% CI: ± 11.1; figure 1). The mean BA was 30.3 m² ha⁻¹ (CI: ± 0.77; figure 1). The mean WMD was 0.645 g cm⁻³ (CI: ± 0.0063) on a stems basis, with WMD BA (BA-weighted WMD) being 0.633 g cm⁻³ (CI: ± 0.0080). The mean above-ground live biomass was estimated at 395.7 Mg dry mass ha⁻¹ (CI: ± 14.3; figure 1). The relationships between AGB and three possible proximate causes of variation, stems ha⁻¹, BA and WMD BA differ from strong (BA) to non-significant (stems ha⁻¹; figure 2). There was a strong significant convex relationship of AGB with latitude (p < 0.001), with AGB tending to be greatest near the equator, alongside more moderate significant relationships with BA and WMD BA (p < 0.001 and p = 0.02), but not for the number of trees per hectare (figure 3). Quadratic fits thus suggest that, on average, forests on the equator have high AGB (452 Mg dry mass ha⁻¹), relatively high BA (72.7 m² ha⁻¹), and relatively high WMD BA (0.64 g cm⁻³; figure 3). Surprisingly, Tₘ does not show a clear convex relationship with latitude (see the electronic supplementary material). Countertuitively, many lower latitude plots have lower temperatures because they are at a higher altitude. Similarly, there is no latitudinal relationship with Pₐ. This is because P₂ uses convexly related to latitude, whereas P₁ is concavely related, obviating any latitudinal trend in Pₐ (see the electronic supplementary material). Average soil development age also peaks at the equator, where heavily weathered ferralsols dominate, as does fragment size and distance to the nearest clearing. These correlations imply that lower Tₘ, consistent moderately high Pₐ, a lack of habitat fragmentation, and attributes associated with highly weathered soils may promote the highest AGB. The values for all plots are provided in the electronic supplementary material.

The different forest types had different AGB and other structural parameters. The five swamp locations had lower AGB, 322.2 Mg dry mass ha⁻¹ (not significantly so, p = 0.16), and significantly lower BA (24.2 m²; p = 0.03) than the terra firme plots. This was attributable to fewer large diameter stems in such forests, as the total number of stems was not lower (428 ha⁻¹) and WMD BA was much higher than for the non-swamp plots (0.728 g cm⁻³). These data confirm the outlier status of the swamp plots, which were therefore excluded from the final information-theoretic analysis. Monodominant forests, dominated by Gilbertiodendron dewevrei, are a common occurrence in Central Africa (n = 23) and were found to have significantly higher AGB than non-Gilbertiodendron-dominated forests (514.9 versus 384.1 Mg dry mass ha⁻¹; ANOVA, p < 0.001), but not BA (32.2 versus 30.2 m²). They also had significantly lower stem density (340 versus 434 stems ha⁻¹; p < 0.001) and significantly higher WMD BA (0.696 versus 0.627 g cm⁻³; p < 0.001).

(b) Relationships with single variables

AGB was found to be positively spatially autocorrelated over distances to approximately 700 km, with similar values for BA (approx. 500 km), and less for WMD BA (approx. 300 km), but no clear pattern for stem density (see the electronic supplementary material). Considering bivariate relationships first, although the signs of the AGB relationships with Pₐ, Pₐ min (positive), Pₐ WET and Pₐ CV (negative), and all temperature variables (negative) were as predicted,
only $T_{CV}$ and $P_{CV}$ were significantly negatively correlated with AGB after adjustment of the effective degrees of freedom to account for spatial autocorrelation (figure 4). The soil variable $\Sigma B$ was, however, significantly negatively correlated with AGB, and PC2 (clay) significantly positively correlated, even after accounting for spatial autocorrelation (figure 4). The results for BA show significant negative relationships with only $T_A$ and $T_{\text{WARMQ}}$ (after accounting for spatial autocorrelation), although $\Sigma B$ was marginally significant ($p = 0.06$). For WMD$_{BA}$, only PC2 (clay) was significantly related, suggesting clay-rich soils have higher WMD$_{BA}$ than silt-rich soils. Note that the $\Sigma B$ and C:N correlations are strongly influenced by the histosol soils which often occur beneath swamps. For stem density, none of the studied variables was found to be significantly correlated after accounting for spatial autocorrelation. No edge or fragment size variables were significantly correlated with AGB, BA, WMD$_{BA}$, or stem density. Correlation coefficients before and after accounting for spatial autocorrelation plus bivariate plots are in the electronic supplementary material.

The 260 plots were located on 17 major soil types, within eight major classes. The most common soil class was ferralsols ($n = 94$), and most common type orthic ferralsols ($n = 74$). An ANOVA on the plots overlying common soil classes ($n \geq 5$ plots) showed that AGB on cambisols, nitosols and acrisols (373, 358 and 320 Mg ha$^{-1}$, respectively) was significantly lower than that on ferralsols and arenosols (436 and 444 Mg ha$^{-1}$, respectively; see electronic supplementary material for full results). That is, the relatively fertile and developmentally younger soils had lower AGB than either the sandier and lower fertility arenosols, or deeply weathered but nutrient-poor ferralsols. For BA, the only significant difference was the lower values on acrisols (27.5 m$^2$ ha$^{-1}$) compared with ferralsols (32.0 m$^2$ ha$^{-1}$). The plots on arenosols, cambisols and nitosols all had similar BA (30.7, 30.3, 30.2 m$^2$ ha$^{-1}$, respectively). Developmentally younger and relatively fertile acrisols and cambisols have significantly lower WMD$_{BA}$ (0.609 and 0.617 g cm$^{-3}$) than arenosols (0.660 g cm$^{-3}$) or histosols, which at 0.728 g cm$^{-3}$ were significantly higher than all other soil classes. For stem density, nitosols were significantly higher (477 stems ha$^{-1}$) than either ferralsols or arenosols (423 and 395 stems ha$^{-1}$, respectively). Analysis of soil types showed similar results to the soil class ANOVAs. For example, developmentally younger soils had lower AGB, with xanthic ferralsols having the highest AGB (463 Mg ha$^{-1}$), double that of the lowest class (chromic cambisols, 232 Mg ha$^{-1}$). Of three within-soil class comparisons (e.g. ferric versus orthic acrisols), the more fertile soil type had lower AGB in each case. All ANOVA results are in the electronic supplementary material.

(c) Relationships considering all variables

The lowest AIC$_C$ OLS model for AGB included $P_A$, $P_{\text{WETQ}}$, $T_A$, $T_{\text{WARMQ}}$, C:N, $\Sigma B$ and PC2 (silt–clay continuum) soil variables and explained 32.4% of the variation in the dataset (table 1). $P_A$ was positively related to AGB, higher by 1.3 Mg dry mass ha$^{-1}$ for each 10 mm increment of rainfall, unless precipitation in the wettest quarter was higher, when this would reduce AGB. Put another way, precipitation in the nine drier months is positively related to AGB, whereas it is negatively related in the wettest three months. Similarly, $T_A$ was positively related to AGB and $T_{\text{WARMQ}}$ negatively related. Taken together, this implies a net AGB difference of approximately $-11.7$ Mg dry mass ha$^{-1}$ (approx. 3% of AGB) for each degree Celsius of higher temperature. C:N ratio was negatively related to AGB, i.e. higher phosphorous availability is related to higher AGB (if the assumption that C:N is a surrogate for plant available phosphorus, as we argue in the methods, holds). Conversely, higher $\Sigma B$ was negatively related to AGB; clay-rich soils (PC2) were positively related. Standardized regression coefficients show that soil and temperature effects are larger than the precipitation effects. There were 10 other models within two AIC$_C$ units, and therefore plausible, with each model removing one or more of $\Sigma B$, C:N and $P_{\text{WETQ}}$, and/or adding a negative $F_E$ term (i.e. lower AGB farther from edges). Overall, there are opposing sign temperature ($T_A$, $T_{\text{WARMQ}}$), precipitation ($P_A$, $P_{\text{WETQ}}$) and soil

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**Figure 3.** Above-ground biomass (AGB), basal area (BA), basal area-weighted wood mass density (WMD$_{BA}$), and stem density for 260 plots versus latitude in decimal degrees. Quadratic fits are $\text{AGB} = 451.6 - 3.57 \times \text{latitude}^2$ ($r^2 = 0.31$, $p < 0.001$); $\text{BA} = 32.7 - 0.150 \times \text{latitude}^2$ ($r^2 = 0.18$, $p < 0.001$); WMD$_{BA} = 0.641 - 0.00051 \times \text{latitude}^2$ ($r^2 = 0.02$, $p = 0.02$). (Online version in colour.)
fertility (C : N, Σ B) terms affecting forest AGB. The models’
did not show strong spatial structure (see the electronic
supplementary material). Excluding the 23 *Gilbertiodendron-
dominated plots does not alter any conclusions.

The lowest AICc model after applying the SEVM filters
was similar to the OLS models, including $P_A$, $P_{WETQ}$ and
PC2 but no longer with any temperature or soil fertility vari-
ables (table 1). Eight other low AICc models were identified
as plausible: these were without PC2 (five models), or added
Σ B or C : N in some combination, in common with the OLS
models. In one model, temperature terms are retained, but
these are not positive. Thus, the main impact of the filters
was to remove the overall negative temperature effect.
However, this result should be treated cautiously, because
the SEVM residuals models are very similar to those from
the OLS models (see the electronic supplementary material).

Given the importance of high temperature impacts for
the future of tropical forests as well as the ambiguity of the
results, we re-ran the models including only the warmest
forests: those plots less than 500 m. All the low AICc OLS
models again included a negative relation with temperature,
as did 10 of 11 low AICc SEVM models. Overall, among the
warmest African forests, if temperature variation has an
impact on AGB variation, then it is negative.

The lowest AICc OLS model for BA was similar to the
AGB OLS models, but with the two soil fertility terms not
included, and an added negative $F_E$ term; this model explained
24.6% of the variation in the dataset (table 1). Twelve other low
AICc models were identified, adding to the best model nega-
tive Σ B and/or C : N terms, adding a positive $T_A$ term or
removing $P_{WETQ}$ or $F_E$ in some combination. Thus, the low
AICc BA and AGB models were collectively similar. Adding
the SEVM filters retained similar results, but removed the precip-
citation terms and reduced the magnitude of both the
negative $T_{WARMQ}$ and positive PC2 terms (table 2). The five alternative
low AICc models include the missing $P_A$ and
$P_{WETQ}$ terms and/or the C : N term. Hence, for BA, the temper-

erature relationship is negative and larger than that for AGB
(approx. 3–5% lower BA in forests growing under higher air
temperature). The spatial residuals were improved using the
SEVM filters over the OLS models.

The lowest AICc OLS model for WMDBA included posi-
tive effects of $P_{init}$ positive $T_A$ impact, positive PC2 (clay)
plus negative C : N relationship, PC1 (sand) and $F_A$ terms.
The model explained 15.0% of the variation in the dataset
(table 1). There were three alternative low AICc models, in-
volving an additional negative term Σ B, negative $T_{min}$ or
without the $F_A$ term, respectively. The lowest AICc SEVM
model retained only a strong positive relationship with tem-
perature, PC2 and the negative $F_A$ terms. Seven alternative low
AICc models included an additional PC1, C : N, and/or $T_A$
term or dropped PC2 in various combinations. Overall,
there is a strong increase in WMDBA with higher air tempera-
ture, a likely decrease with C : N, and an increase in sandy-
or clay-rich soils. The precipitation and fragmentation terms are
weak in comparison with the temperature and soil effects.
The spatial residuals were improved over short distances
when using the SEVM filters.

The lowest AICc OLS model explained only 7.1% of the
variation in stems ha$^{-1}$; the model included a positive
relationship with $P_{WETQ}$ and PC2, a stronger negative $T_A$
term and a negative $F_E$ term (i.e. more stems closer to forest
edges; table 1). The 12 alternative low AICc models differed
from the other dependent variables analysed, as models of

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**Figure 4.** Bivariate plots of AGB and (a) temperature (top; mean annual temperature, temperature coldest month, temperature in warmest quarter, temperature of coefficient variation, left to right), (b) rainfall (middle; mean annual rainfall, rainfall in driest month, rainfall wettest quarter, rainfall coefficient of variation, left to right) and (c) soil and fragmentation (bottom; PCA axis two, silt to clay texture, sum of bases in topsoil, carbon to nitrogen ratio in topsoil, distance to nearest forest edge and clearing, left to right; note log scale). Dashed regression lines indicate a significant relationship before accounting for spatial autocorrelation, solid lines after accounting for spatial autocorrelation (full details and equivalent graphs for BA, WMDBA and stem density in electronic supplementary material). CV is coefficient of variation.
Table 1. Lowest AICc model fits ($\beta$) and p-values for above-ground biomass (AGB), basal area (BA), BA-weighted wood mass density (WMD BA) and stem density (SD) without (OLS) and with (SEVM) spatial filters to account for the spatial structure in the dataset. $T_a$, average mean annual temperature; $T_{\text{min}}$, minimum monthly temperature; $T_{\text{WARMQ}}$, warmest quarter temperature; $P_a$, precipitation per annum; $P_{\text{min}}$, precipitation in the driest month; $P_{\text{WETQ}}$, precipitation in the wettest quarter; C : N, carbon : nitrogen ratio; $\sum B$, sum of bases; principal components analysis first two axes on soil structure, PC1 relating to sand content, and PC2 clay–silt content; $F_E$, distance to the nearest forest edge; $F_A$, area of forest fragment (numbering of the spatial filters is inconsequential).

<table>
<thead>
<tr>
<th>variable</th>
<th>AGB, OLS model</th>
<th>AGB, SEVM model</th>
<th>BA, OLS model</th>
<th>BA, SEVM model</th>
<th>WMD_BA, OLS model</th>
<th>WMD_BA, SEVM model</th>
<th>stem density, OLS model</th>
<th>stem density, SEVM model</th>
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<td>constant</td>
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<td>332.65</td>
<td>&lt;0.001</td>
<td>64.12</td>
<td>&lt;0.001</td>
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<td>$P_a$</td>
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<td>0.16</td>
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<td>0.006</td>
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<td>$P_{\text{min}}$</td>
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<tr>
<td>$P_{\text{WETQ}}$</td>
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<td>0.062</td>
<td>-0.33</td>
<td>&lt;0.001</td>
<td>-0.007</td>
<td>0.065</td>
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<td>$T_a$</td>
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<td>0.002</td>
<td>-1.54</td>
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<td>$T_{\text{min}}$</td>
<td>0.01007</td>
<td>0.008</td>
<td>0.01021</td>
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<td>&lt;0.001</td>
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<td>C : N ratio</td>
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<td>-0.00599</td>
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<tr>
<td>$\sum B$</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>PC1 sand</td>
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<td>PC2 clay</td>
<td>20.68</td>
<td>0.043</td>
<td>14.20</td>
<td>0.122</td>
<td>1.95</td>
<td>&lt;0.001</td>
<td>1.32</td>
<td>0.013</td>
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<td>$F_E$</td>
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<td>-0.20</td>
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<td>0.01136</td>
<td>0.045</td>
<td>0.00943</td>
<td>0.09</td>
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<td>-0.00013</td>
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<td>13.17</td>
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<td>-21.53</td>
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<td>filter no. 6</td>
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<td>-197.36</td>
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</tr>
<tr>
<td>filter no. 12</td>
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</tbody>
</table>
Table 2. Mean environmental parameters for forest inventory plots in West, Central and East Africa. Alt, altitude; \( T_1 \), \( T_2 \), \( T_3 \), mean, warmest, warmest quarter temperature; \( T_{\text{min}} \), minimum monthly temperature; \( T_{\text{max}} \), maximum monthly temperature; \( T_{\text{mean}} \), mean monthly temperature; \( T_{\max} \), maximum daily temperature; \( T_{\min} \), minimum daily temperature; \( T_{\text{mean}} \), mean daily temperature; \( T_{\text{wet}} \), mean daily temperature in the wettest quarter; \( T_{\text{dry}} \), mean daily temperature in the driest quarter; \( T_{\text{dev}} \), deviation from the mean daily temperature; \( T_{\text{cv}} \), coefficient of variation of temperature; \( T_{\text{cv}} \), coefficient of variation of precipitation; \( T_{\text{cv}} \), coefficient of variation of soil development index; \( T_{\text{cv}} \), coefficient of variation of sand content; \( T_{\text{cv}} \), coefficient of variation of stem density; \( T_{\text{cv}} \), coefficient of variation of AGB; \( T_{\text{cv}} \), coefficient of variation of BA; \( T_{\text{cv}} \), coefficient of variation of WMD. Different letters indicate significant differences following Tukey’s tests following ANOVA. 

\( \Delta 2 = 0.0 \) (owing to missing values due to cloud in satellite imagery). 

4. Discussion

African tropical forests are characterized by relatively high AGB, at 395.7 Mg dry mass ha\(^{-1}\), which in Central Africa—where the majority of the area is covered by closed-canopy forest—is much higher than in other regions. In Central Africa, AGB is typically higher than in other regions, especially in the tropical moist forests of Borneo at approximately 445 Mg dry mass ha\(^{-1}\). These higher values are due to the high temperature and humidity conditions in Central Africa, which favor the growth of large trees. In contrast, the forests in West Africa have AGB values of 176 Mg dry mass ha\(^{-1}\), which are still significantly higher than those in Central Africa. However, the forests in East Africa have AGB values of 280 Mg dry mass ha\(^{-1}\), which are significantly lower than those in Central Africa. This suggests that the forests in East Africa are generally lower in AGB, which is likely due to the lower temperature and humidity conditions in this region. Overall, the results suggest that the forests in Central Africa are characterized by the highest AGB, followed by those in West Africa, and then those in East Africa. These differences are likely due to the differences in climate, soil, and other environmental factors that affect forest growth.
Table 3. Cross-continental comparisons of forest structure from networks of intact old-growth closed-canopy tropical forest for the largest biogeographic regions from Africa, Asia and the Americas.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Central Africa</th>
<th>Borneo, Asia</th>
<th>Central/east Amazonia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Above-ground biomass, Mg dry mass ha⁻¹</td>
<td>429a</td>
<td>445b</td>
<td>341c</td>
</tr>
<tr>
<td>Basal area, m² ha⁻¹</td>
<td>31.5a</td>
<td>37.1b</td>
<td>29.0d</td>
</tr>
<tr>
<td>Wood mass density, g cm⁻³</td>
<td>0.65a</td>
<td>0.60b</td>
<td>0.66c</td>
</tr>
<tr>
<td>Stem density, ≥ 100 mm diameter, ha⁻¹</td>
<td>425a</td>
<td>602b</td>
<td>597d</td>
</tr>
<tr>
<td>Mean tree size, m²</td>
<td>0.074</td>
<td>0.062</td>
<td>0.049</td>
</tr>
<tr>
<td>Mean tree height, stem 100 mm diameter, m</td>
<td>13.3a</td>
<td>11.9b</td>
<td>10.6c</td>
</tr>
<tr>
<td>Mean tree height, stem 400 mm diameter, m</td>
<td>30.8a</td>
<td>30.3b</td>
<td>28.1c</td>
</tr>
<tr>
<td>Mean tree height, stem 1000 mm diameter, m</td>
<td>43.5a</td>
<td>46.0b</td>
<td>39.0c</td>
</tr>
</tbody>
</table>

aThis study.
bFrom [4].
cFrom [22].
dFrom [38].
eFrom [7].

WMD measurements) plus more extensive sampling of tropical forests will help refine future estimates.

The high AGB in African forests is coupled with a very low stem density, 426 stems greater than or equal to 100 mm ha⁻¹, compared with 602 ha⁻¹ in Borneo [4] and 592 in Amazonia [38]. Low stem density is therefore the signature structural feature of African tropical forest compared with other continents. It then follows that mean tree size is greater in Africa than elsewhere in the tropics (table 3). WMD in Africa (0.65 g cm⁻³) is similar to that in central and eastern Amazonia (0.66 g cm⁻³; [22]) but higher than forests in Borneo (0.60 g cm⁻³; [4]) or western Amazonia (0.56 g cm⁻³; [22]). This result points towards African forests being dominated by relatively low-frequency disturbance regimes over at least recent decades allowing trees time to grow large and stands to self-thin. This point is reinforced by the relatively common occurrence in Central Africa of monodominant stands, dominated by a single tree species (e.g. *Gilbertiodendron dewevrei*, *Cynometra alexandri*), compared with the rarity of monodominance in Amazonia or Southeast Asia [40]. These stands, which can cover tens to thousands of hectares, lack obvious edaphic or climatic controls, occur instead in areas that appear to lack disturbance over long-term [40–43]. The even lower stem density, higher AGB and higher WMDBA and slower dynamics of these forests, compared with nearby mixed-species stands, provides further support for this view [40–43]. On the other hand, the extremely low stem density in African forests may relate to the very high large animal biomass: elephants (*Loxodonta africana cyclotis*), gorillas (*Gorilla gorilla gorilla*) and other large herbivores such as bongos (*Tragelaphus eurycerus*) may keep the density of small trees very low [44]. This view is reinforced by a recent paper from Southeast Asia showing a large increase in sapling density when the large animal fauna is extirpated [45].

Our results, in conjunction with recent studies across Borneo [4] and Amazonia [2,3] and pan-tropical analyses [6,7], thus provide some evidence that the three major continental groupings of tropical forest differ in their basic structural parameters, with African forests being tall stature, high AGB, low stem density and high WMD; Borneo characterized by tall stature, high AGB, high stem density and lower WMD, and Amazonian stands associated with shorter stature, lower AGB, high stem density and across most of Amazonia high WMD (table 3). The implication is that there are either (i) major cross-continental allocation differences or (ii) NPP is greater across the palaeotropics, or (iii) biomass residence times are longer (i.e. disturbance rates are lower) in the palaeotropics. The low stem density in African forests points towards Amazon–Africa differences being more likely a result of different biomass residence times, with Africa–Borneo differences being more likely based on NPP differences (high AGB, but not low stem density, and low WMDBA suggesting higher NPP). A recent pan-tropical analysis of biomass residence times is consistent with these conclusions despite few data from the palaeotropics [31]. Alternatively, the differences may relate to the history and biogeography of the different regions, particularly the dominance of the Dipterocarpaceae across Southeast Asia.

Spatially, our results show clear patterns such as the relationship with latitude, with the highest AGB forests near the equator. Here, we briefly consider the impact of soil parameters, rainfall, temperature and forest fragmentation, in turn, followed by conclusions on the possible causes of difference among the sampled plots in Central, West and East Africa.

The soil data derive from a gridded global database rather than from the plots themselves and thus must be treated cautiously. Furthermore, the analyses were sensitive to outlier soil types (leading to the exclusion of swamp plots on histograms from the latter analyses). The AGB–soil fertility results were, however, partially consistent with both our stated hypotheses. First, we hypothesized that higher resource availability increases NPP increasing AGB. Higher C:N ratios were associated with lower AGB; and because C:N is negatively related to total extractable phosphorus [5], this implies that it might be higher phosphorus availability that is associated with higher AGB. This accords with studies that show that phosphorus can limit tree growth in tropical forests, and consistent with those from Amazonia, where AGB is positively linked with total soil phosphorus (see [3] and references therein). Second, and counter to this, faster-growing forest stands may become dominated by low WMD species with shorter lifespans (lower $\tau_W$), and hence lower AGB. Consistent with this, when $\Sigma B$ was included in low AIC$_C$. 

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Consistent with this, when $\Sigma B$ was included in low AIC$_C$. 

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http://rstb.royalsocietypublishing.org/ Downloaded from on June 25, 2017
models, it was strongly negatively associated with AGB. Again, this is accords with results from Amazonia where AGB is negatively related to exchangeable soil potassium [3]. However, considering WMD\textsubscript{DA}, the results are not as clearly interpretable, as the lowest AIC\textsubscript{C} SEVM model includes no soil fertility terms. While some alternative models do include negative $\Sigma B$ terms, when included C:N terms imply a positive phosphorus–WMD\textsubscript{DA} relationship, counter to predictions. Our working hypothesis to account for these results is that a greater supply of limiting nutrients leads to higher AGB, because higher NPP levels more than offset any lowering of WMD\textsubscript{DA} and thereby $\tau_W$, whereas greater supplies of non-limiting nutrients lead to lower AGB, because $\tau_W$ is lower and NPP is not increased. The data on soil physical variables are too limited to make robust deductions, as soil depth and other physical conditions remain unknown. AGB was, however, positively associated with developmentally older soils, and with clay-rich soils compared with silt-rich soils (PC2), suggesting that deep well-structured clay-rich soils may be of benefit to trees in attaining a large size. Interestingly, the PC2 term was usually a stronger term in the analyses suggesting impacts on $\tau_W$ may be a more important driver of differences in AGB, BA and WMD than soil fertility terms. In situ sampling is required to elucidate the impacts of the physical and chemical characteristics of soils on AGB and its component drivers.

Biome relationships with rainfall were likewise broadly consistent with a priori expectations. In all OLS and SEVM analyses, the low AIC\textsubscript{C} models included terms in which higher rainfall outside of the wettest quarter increased AGB, implying increased NPP owing to higher water availability. The results are broadly consistent with those from Amazonia where precipitation in the dry season is positively associated with variation in AGB [3], and across Borneo where $P_A$ is positively associated with AGB [4], and wider syntheses [46]. Our results differ from some previous reports in that more rainfall in the wettest part of the year was correlated with lower AGB. However, our results are consistent with the limited data showing than ever-wet forests tend to have lower NPP [14,16,17] and AGB [15]. This implies that the excess rainfall either reduces NPP (owing to more clouds, or perhaps soil saturation effects) or elevates mortality, thereby shortening AGB residence times.

The results of the possible impact of the temperature-related variables on AGB were complex. Bivariate plots and the low AIC\textsubscript{C} OLS models both showed that high $T_{\text{WARMQ}}$ was associated with low AGB. By contrast, only one of eight SEVM low AIC\textsubscript{C} models included a negative net temperature term. This suggests that after accounting for the spatial structure in the temperature data the negative effect of temperature is removed (but note that the SEVM filters did not substantially improve the residuals in the model, see electronic supplementary material). The cause of the difference is due to filter 1 in the SEVM analyses, which is deeply concave with distance. This is driven by a preponderance of higher elevation plot locations around the eastern and western periphery of the Congo Basin, giving long-distance temperature symmetry in the dataset. Thus, when plots from only Central Africa are retained the same shaped SEVM filter 1 is retained, whereas when only plots less than or equal to 500 m are retained in the analysis (i.e. higher altitude east and west Central Africa region plots are removed), the negative temperature effect from the OLS model is retained in most low AIC\textsubscript{C} models. A negative relationship between temperature and AGB could arise through a variety of mechanisms (e.g. higher respiration costs; midday declines in photosynthesis [19]) and is consistent with a demonstrated negative relationship of $T_A$ with wood productivity in Amazonia [3]. Such temperature effects have not, in general, been detected in the past [3,4,46], but it is worth noting that previous AGB studies have analysed smaller sample sizes than in this study.

The lowest AIC\textsubscript{C} OLS model predicts that forests have 11.7 Mg dry mass ha$^{-1}$ lower AGB for each higher degree of temperature (3% of AGB). Recent model results give divergent projections of the magnitude of temperature impacts on tropical vegetation biomass. For example, our results are about 20–40% of the impact predicted by one recent model [47]. However, a more recent result suggests that approximately 8 Mg C ha$^{-1}$ is lost at equilibrium per degree of warming from the tropical land surface, of which about half is related to vegetation (and half to soils; [48] and P. Cox 2013, personal communication). Thus, assuming biomass is approximately 50% carbon, and 75% of this vegetation biomass is above-ground, the model-predicted difference is approximately 6 Mg dry mass ha$^{-1}$ for AGB across all tropical vegetation types. Thus, our results appear, given our focus on forests with high AGB, broadly similar to the model results in [48].

Considered another way, if we substitute space for time, and assume that air temperature is rising by 0.26°C per decade [18], this would equate to a loss of approximately 0.3 Mg dry mass ha$^{-1}$ yr$^{-1}$ for contemporary forests (0.08% of AGB). Such a decline has not been detected in African forests, indeed, a much larger increase of 1.2 Mg dry mass ha$^{-1}$ yr$^{-1}$ has been documented [26]. This is has been attributed, in part, to higher atmospheric CO$_2$ concentrations, an interpretation consistent with theory and model results [49] and the observation that increasing forest AGB is a general, long-term and global phenomena [50]. Thus, if there is a negative impact of temperature on tropical AGB currently, then it is being overwhelmed by other positive effects such as increasing CO$_2$. If CO$_2$ effects saturate in the future, then any negative impact of temperature should become apparent.

A further surprising temperature effect was the strong positive relationship of WMD$_{DA}$ with $T_A$ (table 1). For each higher degree, WMD$_{DA}$ increases by 0.01 g cm$^{-3}$ (approx. 1.5%). Combining this with the WMD$_{DA}$–AGB relationship in figure 1 suggests each higher degree increases AGB by 7.6 Mg dry mass ha$^{-1}$ purely related to higher wood density in these forests. The same strong positive temperature–wood density relationship is shown across Amazonia [3,51] and larger-scale analyses across the Americas [52] and China [53]. The positive WMD–$T_A$ relationship is thought possibly to be a necessary adaptation to the effect of increases in temperature reducing the viscosity of water [54] and the generally higher vapour pressure deficits encountered by trees living in warmer climates, which, all things being equal, may benefit higher WMD trees as they tend to have increased drought tolerances. This effect has been shown in experiments [55]. Thus, in terms of AGB, the strong negative BA–temperature relationship is somewhat offset by the positive WMD–temperature. Additionally, in global change terms, hypothesized decreases in WMD of forest stands caused by better conditions for growth [26] may be somewhat offset by the increase in WMD from higher air temperatures.

The habitat fragmentation results are a difficult to interpret. This may be related to the relatively weak indices derived for distance from the nearest edge and fragment area. Reduced
BA and lower stem density further from edges could be related to a lower density of elephants and other large herbivores, and the known thickening of vegetation very close to forest edges. However, the lower WMDBA in larger fragments does not fit this pattern. Much finer scale analyses with better metrics of distance from edges, including different types of edge [56], will be necessary to ascertain the true effects of fragmentation on forest biomass. More generally, the stem density models explained a much lower proportion of the variation in the data (7%) compared with the AGB, BA and WMDBA models. The large number of low AICc models and their very different structure suggest that stem density is not primarily controlled by the factors we measured. However, there was a strong impact of temperature, with each greater degree Celsius associated with 10 stems fewer per hectare. We know of no reason for such a relationship. Given that the plots were selected as ‘old-growth’, and density is uniformly low across the continent, this suggests that stem density is primarily an emergent property of the long-term disturbance regime, and this has been relatively low across the African tropical forests over recent decades.

We suggest that the lower AGB in West African forests compared with Central African forests is likely to be caused by a complex mix of factors. First, the low WMDBA of the West African forest, but not WMD, compared with Central African forest, suggests a species composition difference, with large trees having lower WMD in West Africa. This may be caused by the removal of elephant populations over the past few hundred years, and a generally more depauperate fauna, leading to a lack of dispersal of larger seeded species that tend to be associated with higher WMD. Second, the two key environmental differences that may account for the lower West African AGB are the high C : N ratio (likely associated lower phosphorus levels), and higher average air temperatures. By contrast, the lower AGB in forests of East Africa appears to be related to developmentally younger soils, with high $\sum B$, and therefore lower WMD for all size classes of stems. This is reinforced by the evidence of the relatively low stature of East African forests, with trees being significantly shorter than elsewhere in Africa [7,39,57]. Differences in forest structure correlated with soil age from central to eastern Africa may be similar to the east–west Amazon differences related to soil development age; if so, then we would expect to see similarly high stem turnover and shorter $\tau W$ in East compared with Central Africa when recensuses of these inventory plots are completed. While both East and West Africa are also more fragmented than Central Africa, our OLS results do not point to this being a major factor in their lower AGB. However, our findings clearly show that there are multiple combinations of environmental conditions that lead to lower AGB.

Overall, our results, combined with others, suggest pantropical AGB–environment consistencies. These have potential implications for the future behaviour of tropical forests within the changing Earth system. While space for time substitutions must be treated with caution, especially in the light of the inevitable spatial and temporal autocorrelations, the results suggest that the physiological effects of higher air temperature may to some degree offset ongoing increases in AGB expected to flow from NPP enhancements associated with increased atmospheric CO$_2$ concentrations (as models show [43,58]). Perhaps more importantly, the influence of rainfall may be large but difficult to quantify, with precipitation in the driest nine months is positively related to AGB, whereas precipitation in the wettest three months is negatively associated with AGB. This potential future change appears underappreciated by the global change community, which has focused significant attention on the impacts of droughts [59], but not the implications for forests of wet-season rainfall increases. Higher temperature and concomitant decreases in water viscosity will also probably lead to a shift towards higher WMD species, countering any shift to lower WMD species from either increasing forest dynamism [60,61], or from growth increases from higher resource availability which have been hypothesized to benefit lower WMD species [26,38,49]. Such conclusions are necessarily tentative, because the underlying NPP and biomass residence time parameters need to be analysed across the environmental space that tropical forests occur to more robustly test for possible generalizations. Once identified, such patterns and processes can then be incorporated into predictive models of the future. This will be possible if emerging pan-tropical networks are well-distributed, long-term, and efforts are made to ensure that monitoring sites incorporate site-specific soil analyses and local climate data.

Acknowledgements. We are indebted to the many organizations and people who made the numerous expeditions to collect the data analysed possible. We thank Christian Amani (University of Bukavu), M. Sindani (University of Kisangani), Olivier J. Hardy, Jean Lejoly (Brussels Free University) and Commission Universitaire pour le Développement grant to J.V. (Kisangani plots), Pierre Ploton and Narcisse Kamdem (Dend Deng plots), Mike D. Swaine (Kade plots), Sophie Allain (Dja plots), Jeannete Sonké (Dja, MDC, NGI, CAM, BIS plots), Raymond Lumumbano, Bruno Peredaean, American Mopanga, Ngamba Mongama and Palu Eyianyo (WWF-DRC; Malebo plots), and FRIA grant (FNRS) to J.F.B. (Malebo plots), C.E.B. and Armand Boubady (C.E.B., Miele plots), Rouger Gabon (Haut-Abanga, Leke/Moyabi plots), C.B.C. (Mayumba, Rabi-Mandji plots), BELSPO for funding and WWF, UNIKIS and INERA for logistic support (Yangambi plots), Leroy Gabon and Yves Issembé (CENAREST; LOT and Makende plots), Jonathan Dabo, Kwaku Duah, Yaw Nkrumah, Alfredo Justice Godwin, Raymond Votere (Ghana Forestry Commission plots), Government of Gabon (Gabon plots), for access to field sites, field data, logistical support and funding. S.L.L. thanks E. Mitchard for assistance with figure 1.

Funding statement. USAID/CIFOR (to S.L.L. and T.S.), GECOCARBON (to S.L.L. and B.S.) and European Research Council (to O.L.P., S.L.L. and B.S.), NERC (New Investigators award to S.L.; TROBIT Consortium award to J.L.T.W., S.L.L. and Y.M.), Leverhulme award to J.L. and S.L.L.), Gordon and Betty Moore and David and Lucile Packard Foundations (to L.J.T.W., S.L.L. and Y.M.), NERC (New Investigators award to S.L.; TROBIT Consortium award to J.L.T.W., S.L.L. and Y.M.), Leverhulme Trust (to S.L.L.), Missouri Botanical Garden (to M.L.), Royal Society joint project (to T.R.F and E.F.) and Royal Society University Research Trust (to S.L.L.), and European Research Council (to O.L.P., S.L.L. and B.S.) and European Research Council (to O.L.P., S.L.L. and B.S.). We are indebted to the many organizations and people who made the numerous expeditions to collect the data analysed possible. We thank Christian Amani (University of Bukavu), M. Sindani (University of Kisangani), Olivier J. Hardy, Jean Lejoly (Brussels Free University) and Commission Universitaire pour le Développement grant to J.V. (Kisangani plots), Pierre Ploton and Narcisse Kamdem (Dend Deng plots), Mike D. Swaine (Kade plots), Sophie Allain (Dja plots), Jeannete Sonké (Dja, MDC, NGI, CAM, BIS plots), Raymond Lumumbano, Bruno Peredaean, American Mopanga, Ngamba Mongama and Palu Eyianyo (WWF-DRC; Malebo plots), and FRIA grant (FNRS) to J.F.B. (Malebo plots), C.E.B. and Armand Boubady (C.E.B., Miele plots), Rouger Gabon (Haut-Abanga, Leke/Moyabi plots), C.B.C. (Mayumba, Rabi-Mandji plots), BELSPO for funding and WWF, UNIKIS and INERA for logistic support (Yangambi plots), Leroy Gabon and Yves Issembé (CENAREST; LOT and Makende plots), Jonathan Dabo, Kwaku Duah, Yaw Nkrumah, Alfredo Justice Godwin, Raymond Votere (Ghana Forestry Commission plots), Government of Gabon (Gabon plots), for access to field sites, field data, logistical support and funding. S.L.L. thanks E. Mitchard for assistance with figure 1.

Funding statement. USAID/CIFOR (to S.L.L. and T.S.), GECOCARBON (to S.L.L. and B.S.) and European Research Council (to O.L.P., S.L.L. and Y.M.), NERC (New Investigators award to S.L.; TROBIT Consortium award to J.L.T.W., S.L.L. and Y.M.), Leverhulme Trust (to S.L.L.), Missouri Botanical Garden (to M.L.), Royal Society joint project (to T.R.F and E.F.) and Royal Society University Research Fellowship (to S.L.L.) grants all part-funded AfriTRON (www.afriron.net) and this work. ForestPlots.net development is funded by the Gordon and Betty Moore Foundation, NERC, The University of Leeds, European Research Council and the Royal Society.

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