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Estimates of soil carbon concentration in tropical and temperate forest and woodland from available GIS data on three continents

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ABSTRACT

Aim Concern about climate change, with the subsequent emergence of carbon markets and policy initiatives such as REDD (reducing carbon emissions by decreasing deforestation and forest degradation), have focused attention on assessing and monitoring terrestrial carbon reserves. Most effort has focused on above-ground forest biomass. Soil has received less attention despite containing more carbon than above-ground terrestrial biomass and the atmosphere combined. Our aim was to explore how well soil carbon concentration could be estimated on three continents from existing climate, topography and vegetation-cover data.

Location Peru, Brazil, Argentina, Australia, China.

Methods Soil carbon concentration and leaf area index (LAI) as well as GIS-derived climate and topography variables for 65 temperate and 43 tropical, forest and woodland ecosystems, were either directly measured or estimated from freely available global datasets. We then used multiple regressions to determine how well soil carbon concentration could be predicted from LAI, climate and topography at a given site. We compared our measurements with top soil carbon estimates from the Food and Agriculture Organization of the United Nations (FAO) harmonized world soil map.

Results Our empirical model based on estimates of temperature, water availability and plant productivity provided a good estimate of soil carbon concentrations ($R^2 = 0.79$). In contrast, the values of topsoil carbon concentrations from the FAO harmonized world soil map correlated poorly with the measured values of soil carbon concentration ($R^2 = 0.0011$).

Main conclusions The lack of correlation between the measured values of soil carbon and the values from the FAO harmonized world soil map indicate that substantial improvements in the production of soil carbon maps are needed and possible. Our results demonstrate that the inclusion of freely available GIS data offers improved estimates of soil carbon and will allow the creation of more accurate soil carbon maps.

Keywords
Carbon accounting, climate, forest, geographic information systems, leaf area index, REDD, soil carbon, voluntary carbon standards, woodland.

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INTRODUCTION

Concern about global climate change has focused attention on the stocks and flows of the global carbon cycle. Financial incentives for reducing carbon emissions by decreasing deforestation and forest degradation (REDD) are the focus of political consideration as a potential means to reduce CO_2 emissions and slow climate change. REDD and the various emerging voluntary carbon standards (Merger *et al.*, 2011) could also help pay for biodiversity conservation (Bekessy & Wintle, 2008; Venter *et al.*, 2009). However, soil carbon has received little attention in these discussions (van Noordwijk & Akon-Minang, 2009). This is problematic because soils contain two to three times more carbon than the global vegetation pool and atmosphere combined and this large carbon pool is vulnerable to land-use change and management (Houghton, 2007; Trumbore, 2009).

The use of remote-sensing tools and geographic information systems to predict soil carbon has focused on grasslands (Yang *et al.*, 2008). Soil carbon has been omitted in most efforts at up-scaling (spatial extrapolation from point measurements) in forest and woodland because simple, robust and reliable methods to assess these stocks are lacking (Gibbs *et al.*, 2007; Baccini *et al.*, 2008). This absence of an approach reflects the recognition that many different factors influence soil carbon content in forests and woodlands, e.g. plant productivity and functional traits (Cornwell *et al.*, 2008; Vivanco & Austin, 2008), soil texture (Jobbagy & Jackson, 2000), climate (Liski *et al.*, 2003) and terrain (Stallard, 1998; Rosenbloom *et al.*, 2006). The apparent inability to estimate soil carbon limits the rigorous quantification of soil carbon pools in forests and woodlands. For example, the soil carbon pool at a given site/region is typically estimated as simply twice the size of the above-ground terrestrial biomass (after Bol *et al.*, 1999; Lal, 2004). These limitations matter because soil carbon, like biomass, is vulnerable to losses and degradation via physical and biotic processes, and should be protected in any comprehensive efforts to reduce CO_2 emissions (Veldkamp, 1994; Solomon *et al.*, 2007; Don *et al.*, 2011; Powers *et al.*, 2011; Zummo & Friedland, 2011).

Theory suggests that terrestrial plant productivity and soil carbon are likely to be related, at least in undisturbed forest or grassland ecosystems (Gibbs *et al.*, 2007; Yang *et al.*, 2008). There is localized evidence that soil carbon is indeed influenced by ecosystem productivity (Jobbagy & Jackson, 2000; Yang *et al.*, 2008; Kunkel *et al.*, 2011). Yet scarcity of suitable data poses a serious challenge to the examination of these relationships at the macro scale, especially for tropical ecosystems (Powers *et al.*, 2011). Nonetheless there are various site-level data on carbon concentration in the very upper soil horizons in forests and woodlands at different locations around the world where measurements of various above-ground ecosystem parameters have also been made, e.g. in the network of long-term ecological research sites in the USA (Gosz *et al.*, 2010). Such topsoil measures offer a basis for clarifying whether soil carbon reserves can be effectively estimated from more easily accessible site attributes. The objective in this study is to determine the degree to which soil carbon concentration can be effectively estimated using free GIS data for climate and topography and vegetation cover with a dataset that includes a wide diversity of tropical and temperate forest and woodland ecosystems on three continents.

METHODS

We identified or generated suitable data from 65 temperate and 43 tropical primary forest and woodland ecosystems in which no human impacts were apparent (Fig. 1). These communities, located in Peru, Brazil, Argentina, Australia and China, spanned a wide range of site productivities and other characteristics: for example, the average canopy height ranged from 2 to 40 m (see

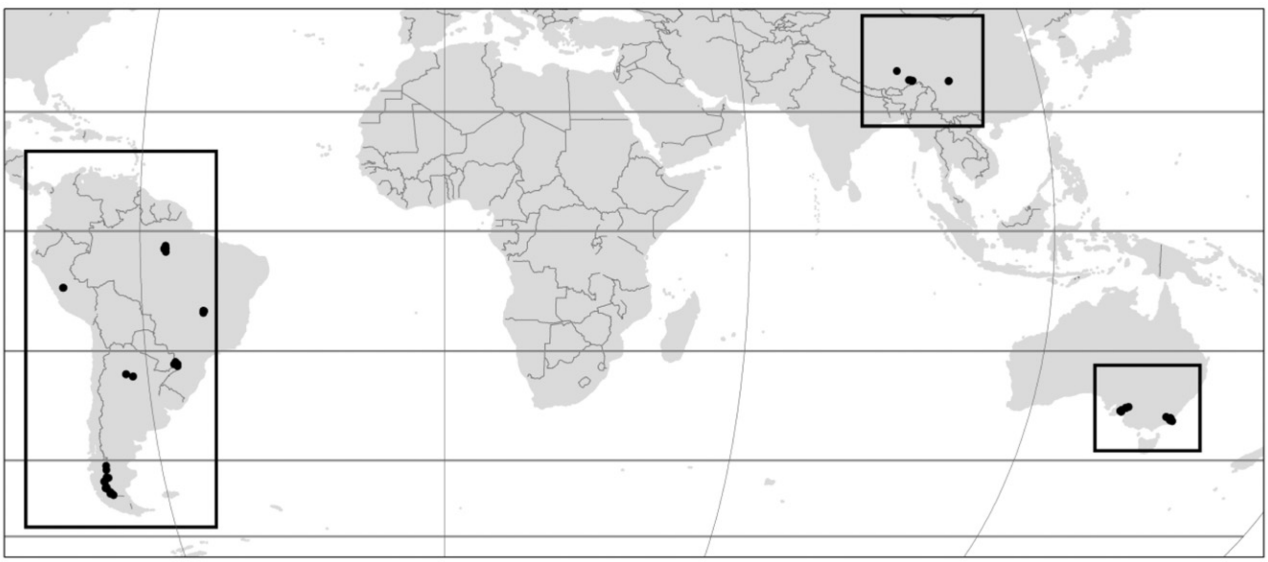

Figure 1 Locations of sample sites considered in this analysis, with data from Williams *et al.* (2002), Silva *et al.* (2008), Ladd *et al.* (2009), Luo *et al.* (2009) and Silva *et al.* (2010).

Table 1 Summary statistics for the sampled biomes.

		LAI ($m^2\ m^{-2}$)			MAT (°C)			MAP (mm)		
Ecosystem	n	Min.	Med.	Max.	Min.	Med.	Max.	Min.	Med.	Max.
Temperate forest/ woodland	65	0.25	1.93	12.41	–1.7	7.2	18.3	279	630	1787
Tropical drought-deciduous savanna	8	1.62	2.28	2.44	20.4	20.5	20.9	583	685	640
Evergreen savanna	3	0.42	0.625	0.75	20.6	21.15	22.7	1420	1546	1652
Subtropical rain forest	8	3.26	4.56	5.05	18.2	19.1	20.3	1681	1829	1914
Cloud forest	6	5.4	6.12	7.9	20.75	21.4	21.4	1433	1751	1906
Tropical rain forest	17	1.97	6.06	7.0	20.6	25.2	26.4	1420	1847	2013

LAI, leaf area index; MAT, mean annual temperature; MAP, mean annual precipitation; n, sample size; Min., minimum; Med., median; Max., maximum.

Table 1 and Appendix S1 in Supporting Information for further details). These data (see Appendix S1) include a synthesis of existing studies that report measurements of soil organic carbon (SOC) concentration in topsoil (10 cm depth) where the following requirements were fulfilled: coarse root debris > 2 mm had been removed by sieving, leaf area index (LAI) had been recorded, and the reported geo-referenced coordinates were accurate enough to allow for spatial analyses (Williams *et al.*, 2002; Silva *et al.*, 2008, 2010; Ladd *et al.*, 2009; Luo *et al.*, 2009). We focus on soil carbon concentration, as opposed to stocks, due to the availability of suitable data. We also collected additional samples from subtropical rain forests, semi-arid deciduous woodlands and cloud forests to improve their representation in our dataset (Appendix S1). Our own measurements of soil carbon concentration, including those described in Ladd *et al.* (2009), derive from the dry combustion (induction furnace) method. When appropriate, we cross-referenced soil carbon measurements against soil pH measurements to ensure that the soil samples were free of soil inorganic carbon and thus composed of SOC (after Donato *et al.*, 2011). Soil samples were collected from nine randomly selected points within a 20 m × 40 m quadrat using a hand auger (10 cm depth). To reduce the number of chemical analyses we pooled individual soil samples into combined samples. From the nine samples collected within each quadrat we created three composite samples so that each composite sample contained an equal proportion of soil from three auger holes ($n = 3$ for each site). The additional samples were collected from existing networks of permanent plots, using the methods described by Ladd *et al.* (2009). In Peru, for example, we sampled cloud forests that are part of the Salvias network of long-term forest plots (http://www.salvias.net). In Argentina we sampled subtropical rain forest and tropical semi-arid woodland located on research stations operated by the Instituto Nacional de Tecnología Agropecuaria (INTA). Additional information on all the data collection protocols can be found in Appendix S1 and papers cited therein.

Spatial data – climate and topography

The climate parameters for each site (Fig. 1) were estimated from the WorldClim dataset (Hijmans *et al.*, 2005). WorldClim contains geographic surfaces for 19 different climatic parameters that describe rainfall, temperature and variation in those parameters at a resolution of 0.008333° (approximately 1 km) (see Table 2). Solar radiation (W m^{-2}) was calculated from the solar radiation tool in ArcGIS version 9.3.1 (ESRI, CA, USA), with topography data from the 3″ resolution NASA Shuttle Radar Topography Mission digital elevation model (SRTM DEM) of the globe (Jarvis *et al.*, 2008). We also calculated 'climatic water balance' (W^*, a composite variable that integrates rainfall and radiation data) for use in statistical analyses. W^* integrates climatic variables in a form judged relevant to plant productivity (Ladd *et al.*, 2009), which may in turn have a direct impact on soil carbon through litter and rhizo deposition (Yang *et al.*, 2008; Kunkel *et al.*, 2011):

Table 2 A description of the WorldClim parameters (further detail available at http://www.worldclim.com, and in Hijmans *et al.*, 2005).

Parameter	Description
BIO1	Annual mean temperature
BIO2	Mean diurnal range [mean of monthly (max. temp.–min. temp.)]
BIO3	Isothermality (BIO2/BIO7) (× 100)
BIO4	Temperature seasonality (standard deviation × 100)
BIO5	Max. temperature of warmest month
BIO6	Min. temperature of coldest month
BIO7	Temperature annual range (BIO5–BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

$$W^* = [\mathrm{MAP} - (Q/rL)] + 4000 \quad (1)$$

where MAP is mean annual precipitation (mm $year^{-1}$), Q is mean annual solar radiation (J m^{-2} $year^{-1}$), r is the density of liquid water at 25 °C (1000 kg m^{-3}) and L is the latent heat of evaporation of water at 25 °C (2.5×10^6 J kg^{-1} H_2O) (after Wynn *et al.*, 2006).

A set of 11 topographic variables was derived from the SRTM DEM using an approach that is relatively unconstrained by the spatial resolution of the input DEM (Wood, 1996; Wang *et al.*, 2010). In summary, a quadratic function was fitted to the elevation values within a 500-m diameter circular sample window around each sample location, and a set of indices was calculated from this surface to describe the topography around each sample location. In our preliminary analyses we also calculated the topographic variables using a 1000-m analysis window – but all our initial analyses showed that the two levels of spatial resolution differed little in predictive power and therefore we only report results derived using the 500-m analysis window.

Topographic variables were derived to represent slope, aspect, longitudinal curvature, cross-sectional curvature, fuzzy memberships of the morphometric classes of ridges, valleys, pits, peaks and passes, the compound morphometric terrain index (CMTI) and the R^2 of the fitted quadratic function (Wang *et al.*, 2010). Longitudinal curvature represents the rate of change of elevation along a channel or ridge. Cross-sectional curvature is the rate of change of elevation across the valley or ridge, and can be used to identify steep-sided valleys or ridges. The fuzzy memberships of each morphometric class were calculated as a function of the distance of the processing location to that feature within the sample window (e.g. the axis of a ridge), divided by the radius of the sample window. Memberships are zero when the feature class is not found in the sample window. CMTI is an index derived from the fuzzy memberships of 'ridge' (positive) and 'valley' (negative) classes. Values of 1 are ridge tops, values of –1 are in valley centres, while values of 0 are along planar slopes at the scale analysed. Intermediate values between zero and the extremes have partial membership in the set of ridges or valleys and approximate upper, middle and lower slope positions. The R^2 acts as a measure of terrain complexity and roughness within the sample window as it measures the deviation of the observed terrain from the fitted quadratic function. Finally, estimates of topsoil carbon concentration were extracted from the Food and Agriculture Organization of the United Nations (FAO) harmonized world soil map (FAO *et al.*, 2009). This map consists of 16,000 soil mapping units represented as choropleths in raster format at a resolution of 30″ (*c.* 1 km).

Data analysis

We used a step-wise procedure to identify and remove explanatory variables that were collinear with other explanatory variables in the dataset, following the method described by Fox (2002). Firstly, we calculated variance inflation factors (VIFs) for the complete set of independent variables. We then began an iterative process in which we deleted the explanatory variable with the highest VIF score, recalculated VIF scores for the remaining explanatory variables and then repeated this process until all remaining explanatory variables had VIF scores of less than 10 (after Quinn & Keough, 2002). Through this iterative process we identified 20 explanatory variables free from collinearity. The explanatory power of these 20 variables on soil carbon concentration was then assessed using multiple linear regression (Appendix S2). Before proceeding with the regression analyses, soil carbon concentration was log transformed ($\log_{10}$) because the data were right skewed, and because the measured values of soil carbon concentration varied by orders of magnitude across sites (Quinn & Keough, 2002). Note also that mean annual rainfall and radiation were integrated into a climatic water balance model (W^*) and were not included as separate, explanatory variables in the regression analyses.

Table 3 Summary statistics for the multiple regression model with the best Akaike information criterion ranking (n = 108).

Source	d.f.	SS	F	Pr > F	η^2
LAI	1	0.29	84.3	< 0.0001	17
BIO8	1	0.70	203.4	< 0.0001	41
BIO15	1	0.07	20.8	< 0.0001	4
BIO18	1	0.22	63.4	< 0.0001	13
BIO19	1	0.06	18.8	< 0.0001	4
Error	101	0.35			

d.f., degrees of freedom; SS, sum of squares; Pr, probability; η^2, percentage of variation of the R^2 explained by each independent variable (see Plaistow *et al.*, 2006); LAI, leaf area index; BIO8, a temperate-related variable; BIO15, -18, -19, precipitation-related. See Table 2 for further description of the climate parameters. See Appendix S2 for a comparison of AIC values across 20 different regression models.
F = 65.2, d.f. = 6, 101; P < 0.0001, R^2 = 0.79. Model: $\log_{10}(\%C) = 0.40 + (2.24 \times \mathrm{LAI}) - (1.15 \times \mathrm{BIO8}) + (9.93 \times \mathrm{BIO15}) + (2.95 \times \mathrm{BIO18}) - (1.37 \times \mathrm{BIO19})$.

The parsimony of 20 different regression models that varied in complexity [i.e. the number of independent variables ranged from 1 to 20 was assessed using the Akaike information criterion (AIC)]. The regression model with the best AIC ranking contained five variables. The relative importance of these five variables was then assessed by partitioning the sum of squares from the regression analysis (the η^2 values of Table 3). We then drew individual plots of these five variables versus soil carbon concentration. The statistical power of the regression calculations was assessed using the Van Wijngaarden–Dekker–Brent algorithm (Brent, 1973). Finally, we performed simple linear regression of measured soil carbon concentration versus estimates of soil carbon concentration from the FAO harmonized world soil map. All statistical analyses were performed using XL-stat (Addin Soft, Paris, France).

RESULTS

A multiple regression model with five variables that integrated data on plant productivity and climate was able to predict the

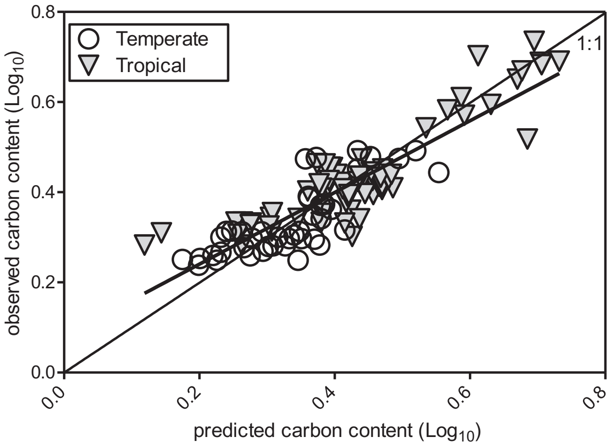

Figure 2 The relationship between modelled and measured values of carbon concentration in soil at a depth of 10 cm for both tropical and temperate forest and woodland ($y = 0.79x + 0.08$, $R^2 = 0.79$). See Table 3 for further details on the statistical model. The thin line indicates 1:1. Note that carbon data were $\log_{10}$ transformed prior to analysis.

major pattern of variation in soil carbon concentrations represented in our 108 sites ($R^2 = 0.79$), but had a slight tendency to underpredict at low levels of soil carbon, and slightly overpredict at high levels of soil carbon concentration (Fig. 2). The climatic variables and the plant productivity variable (LAI) were strong predictors of soil carbon concentration (see Table 3 and Appendix S2). The topographic variables had little predictive power (see Table 3 and Appendix S2). The regression model with the best AIC ranking had five independent variables (Fig. 2) and accounted for 79% of the variance in soil carbon concentration (Table 3, Figs 2 & 3). The AIC calculations indicated that regression models with six and seven independent variables had comparable parsimony, but the increase in predictive power (R^2) was marginal at less than 1% (see Appendix S1). The five explanatory variables in the regression model with the lowest AIC were: LAI, BIO8 (= mean temperature of wettest quarter), BIO15 (= precipitation seasonality, coefficient of variation), BIO18 (= precipitation of warmest quarter), BIO19 (= precipitation of coldest quarter) (see Table 2 for further description of the variables). The η^2 values (Table 3) are a measure of the percentage variation of the R^2 of the regression model that is explained by each variable. The η^2 values confirmed that all five independent variables contributed predictive power to the regression model (see Table 3 for further details, Appendix S2 for further details on the results of the regression analysis and Fig. 3 for individual plots of the five environmental variables versus the $\log_{10}$ of soil carbon concentration). Inspection of the residuals from the multiple regression analyses indicated no systematic bias (see Appendix S2). The analysis of statistical power for the regression analysis using the Van Wijngaarden–Dekker–Brent algorithm demonstrated that 28 replicate measurements would have given the regression analysis adequate power (Appendix S3), i.e. there was a one chance in ten of committing a Type II error. The actual sample size for this study ($n = 108$) was about 3.8 times larger than the required minimum, indicating that our analyses were robust.

There was no correlation between measured soil carbon concentration in our dataset and estimates of soil carbon concentration from the FAO harmonized world soil map (FAO *et al.*, 2009) (Fig. 4; $y = -0.0001x + 0.4043$, $r^2 = 0.0011$).

DISCUSSION

A regression model with five explanatory variables was sufficient to estimate 79% of the variation in the carbon concentration of soil samples from three continents. In contrast, there was a complete absence of correlation between our field measured values and those derived from the FAO harmonized world soil map (FAO *et al.*, 2009). The FAO map and presumably others like it do not reliably predict variation in local soil carbon. However, our analyses suggest that such large-scale predictions are feasible. The inclusion of GIS-derived climate and plant productivity variables in the up-scaling process, as in our regression model, would allow for predictive mapping at a fine spatial resolution and would significantly improve the accuracy and value of soil carbon maps.

The correlates of soil carbon concentration

The links between soil carbon and plant community characteristics have not yet been established across a broad range of ecosystems (Jobbagy & Jackson, 2000; Trumbore, 2009). Our results suggest that any such generalizations must integrate a diversity of influences. The individual plots of soil carbon concentration versus the environmental variables identified as important by the multiple regression analysis and the calculation of AIC values revealed relatively weak correlations (Fig. 3). This underlines the implications of the multiple regression analyses: while many variables have an influence, it is likely that no single explanatory variable determines the concentrations of soil carbon.

Nevertheless temperature was highlighted by our analysis, probably due the fact that higher temperatures accelerate decomposition and lower temperatures impede it (Liski *et al.*, 2003). Note, however, that the inhomogeneous variance with respect to mean temperature of wettest quarter precludes concrete inference from this correlation. Plant productivity too was important, explaining 17% of soil carbon concentration variability (Table 3). The finding that LAI was also a useful predictor is consistent with previous studies conducted at more regional spatial scales (Yang *et al.*, 2008; Kunkel *et al.*, 2011). Remote sensing of above-ground attributes of plant communities (e.g. Asner *et al.*, 2010; Ryan *et al.*, 2012) holds promise for improved assessments of soil carbon.

The links between water availability and soil carbon concentration were more complex. On the one hand, there was a positive correlation between soil carbon concentration and precipitation in the warmest quarter (Fig. 3d), which may reflect a positive synergy between water availability and high temperatures on plant growth that subsequently leads to

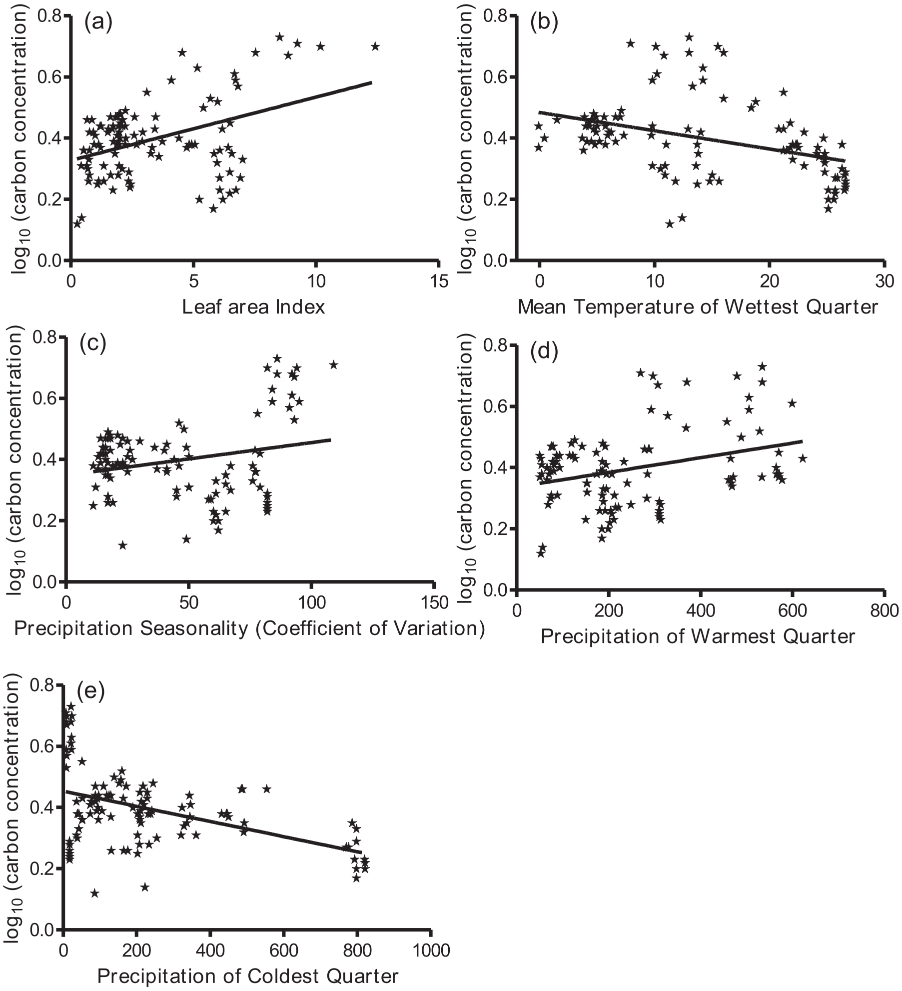

Figure 3 Individual plots of the five environmental variables included in the regression model with the best Akaike information criterion ranking versus $\log_{10}$ soil carbon concentration. (a) $r^2 = 0.17$, (b) $r^2 = 0.15$, (c) $r^2 = 0.06$, (d) $r^2 = 0.10$, (e) $r^2 = 0.21$.

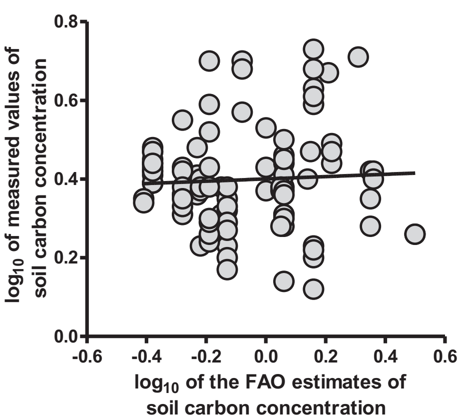

Figure 4 Soil carbon concentrations from the FAO harmonized world soil map versus measured values of soil carbon concentration.

higher rates of litter deposition (Sala *et al.*, 1988). However, there was a negative correlation between soil carbon concentration and precipitation in the coldest quarter (Fig. 3e). In this instance also, inhomogeneous variance precludes concrete inference. In contrast to climate and plant productivity, the topographic variables emerged as not significant in our analysis. This could be because climatic effects dominate at the macro scale considered in this analysis. However, we believe it is premature to dismiss the relationship between topography and SOC, which can be very important at local scales (Rosenbloom *et al.*, 2006; Kunkel *et al.*, 2011). An important challenge for the future is to develop indices that can capture this relationship between topography and soil carbon at the macroecological scale.

Implications for the assessment of carbon stocks across continents

Aside from a few specific advocates, soil carbon has not been addressed in on-going discussions about the monitoring and control of global carbon stocks (as in REDD) (van Noordwijk &

Akon-Minang, 2009). The principal reason for this neglect has been the lack of effective and affordable methods for large-scale assessment and monitoring. We believe that this obstacle can be addressed and that there are good reasons for doing so. A main challenge to estimating carbon stocks at the macro scale has been the use of different measurement protocols at different sites and on different projects (Gibbs *et al.*, 2007). Our approach indicates the possibility of obtaining reliable estimates of soil carbon using a standard method across biomes. Correctly valuing ecosystems, including their carbon values, should boost and facilitate the effective use of conservation resources (Miles & Kapos, 2008).

Geo-referenced data have been used to accurately estimate above-ground biomass in forest and woodland (Baccini *et al.*, 2004; Asner *et al.*, 2010; Ryan *et al.*, 2012). Our analyses show that this approach can be extended to soil carbon. Estimating carbon in tonnes per hectare will require that soil bulk densities are measured or derived from other variables (see Bol *et al.*, 1999; Don *et al.*, 2011; Saiz *et al.*, 2012). Accurate estimates of the soil carbon inventory in forest ecosystems will also require greater attention to soil depth (Kaiser *et al.*, 2001; Guo *et al.*, 2006). A significant percentage of the soil carbon inventory is found below the topsoil (Jobbagy & Jackson, 2000; Guo *et al.*, 2006). These deep soil carbon pools might also be vulnerable to land-use change and may thus also contribute to atmospheric carbon dioxide when forests are cleared and/or degraded (Fontaine *et al.*, 2007). Jobbagy & Jackson (2000), for example, suggest that measurement to a depth of 3 m may yield estimates of soil carbon about 1.5 times larger than inventories to a depth of 1 m. To date few studies have measured soil carbon inventories and properties at such a depth in forest and woodland ecosystems. Thus, we propose that future efforts to improve the assessment of soil carbon stocks and properties should not be restricted to the topsoil. We recognize that the effort required for very deep sampling is a practical limitation and concern, and would probably slow adoption and thus reduce coverage. Assessment to *c.* 1 m depth appears a defensible and pragmatic standard given the data already available to this depth (Don *et al.*, 2011; Powers *et al.*, 2011).

Our evaluation did not include many localized forest types such as the peat forests of Southeast Asia (Jaenicke *et al.*, 2008). More research is required to assess whether the environmental correlates considered in this study are applicable to such forests. We have also excluded mangroves and other forms of swamp forest – vegetation types that can be associated with considerable carbon in soils and sediments (Donato *et al.*, 2011). We acknowledge that disturbances of many kinds can influence soil carbon (Veldkamp, 1994; Solomon *et al.*, 2007; Don *et al.*, 2011; Powers *et al.*, 2011). Our results apply to primary forest and woodland in the regions under study. Nevertheless, our results are an important first step towards establishing a potential reference for assessing net change in non-pristine systems and the gains that may be made by allowing vegetation recovery.

Finally, the monitoring of global carbon stocks requires that changes in soil C stocks are quantifiable. This poses major challenges at present but practical solutions should be possible by an extension of our approach. Freely available global data that can be used for local climate (i.e. WorldClim) and plant productivity estimates (i.e. MODIS imagery), are based on measurements that have been repeated through time. MODIS imagery, for example, has been collected continuously since the year 1999. This opens possibilities for modelling changes in carbon stocks through time. Further data collection and analyses will be needed to develop these approaches. Given their promise in monitoring the global carbon stocks these approaches require a major international investment.

CONCLUSIONS

We have shown that the carbon concentration of topsoil from tropical and temperate forests and woodlands is influenced by many variables, but that these influences are consistent and predictable. Variables related to climate, like temperature (i.e. mean temperature of the wettest quarter) and water availability (e.g. precipitation in the warmest and coldest quarters), as well as plant productivity (approached via measurements of LAI) all influence soil carbon concentration. While the relationships are complex they are not unwieldy. Topographic indices did not improve the estimation of local soil carbon concentrations.

A benefit of our approach is that all the necessary variables can be derived from freely available datasets, including LAI which can, for example, be estimated from the NASA Landsat-5 Thematic Mapper imagery (Kunkel *et al.*, 2011).

To turn our carbon concentration estimates into tonnes per hectare, and to facilitate their inclusion in REDD or similar schemes, requires additional work on soil bulk density and clarification and agreement concerning relevant soil depths. We also strongly advocate for better coverage of regions, such as Africa, that are poorly represented in the current global database.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's web-site.

Appendix S1 Raw data.
Appendix S2 Statistical output from the multiple regression.
Appendix S3 Statistical output from the post hoc power analysis of the multiple regression statistics.

BIOSKETCH

Our research team includes a terrestrial ecologist (B.L.), a spatial analyst (S.W.L.), a soil scientist (W.A.), an ecophysiologist (P.L.P.), a tropical forest ecologist (D.S.), a biogeochemist (L.C.R.S.), a policy expert from the conservation, not-for-profit sector (P.G.), an evolutionary ecologist (S.P.B.) and an applied ecologist (M.N.).

Author contributions: B.L., P.L.P. and M.N. all contributed to the field work. L.C.R.S. contributed data from Brazil. S.W.L. performed the spatial analyses. The central idea for this manuscript was developed through discussions at the University of Bonn (W.A. and B.L.). D.S. and P.G. were largely responsible for making clear the policy implications of this research. All co-authors contributed to the writing of this manuscript.

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