

Better estimates of soil carbon from geographical data: a revised global approach

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Better estimates of soil carbon from geographical data: a revised global approach

Abstract

Soils hold the largest pool of organic C on Earth, yet, we are unable to include the soil organic carbon (SOC) reservoir into climate change mitigation strategies, because our database for ecosystems where human impacts are minimal is still fragmentary. The aim of this study is to provide a tool for generating a global baseline of SOC stocks. We use partial least square (PLS) regression on measured SOC and freely available geographic datasets that describe climate, topography, productivity and soil C across biomes. The accuracy of the model was determined by the root mean square deviation (RMSD) of predicted SOC against 100 independent measurements. The best predictors were primary productivity, climate, topography, biome classification and soil type. The largest C stocks were found in boreal forests and tundra, averaging 254 ± 14.3 and 310 ± 15.3 t ha⁻¹ in the top 1m of soil, respectively. Deserts had the lowest observed C stocks (53.2 ± 6.3 t ha⁻¹). Solar radiation, potential evapotranspiration, and mean annual temperature were negatively correlated with SOC stocks, whereas soil water content was positively correlated with SOC stocks. RMSD (0.68) represented approximately 14% of observed soil C stock variation with overestimation for extremely low C stocks and underestimation for extremely high C stocks. Using PLS regression can provide baseline predictions of SOC stocks, which may serve for estimating the maximum SOC that may be sequestered across biomes.

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25 **Keywords:** soil organic carbon; geographic information systems; climate; global;
26 pristine ecosystems; baseline

27 Introduction

28
29 Scientists and policy makers recognise that conservation of ecosystems – where
30 historical anthropogenic land use change is minimal – hereafter “pristine
31 ecosystems” - offers an effective means for preserving terrestrial carbon stocks
32 and abating greenhouse gas emissions (Ladd and Peri 2013; Stockmann et al.
33 2013; Scharlemann et al. 2014). As a result, initiatives to reduce greenhouse gas
34 emissions from deforestation and enhance ecosystem carbon stocks such as
35 REDD+ (reducing emissions from deforestation and forest degradation in
36 developing countries) have gained increasing traction, providing financial
37 incentives for the protection of existing terrestrial carbon stocks in conservation
38 and production forests (UN-REDD 2016). However, such initiatives focus primarily
39 on aboveground carbon stocks (Scharlemann et al. 2014), for which precise
40 geospatial data are being produced (Asner et al. 2010; Ryan et al. 2012; Ladd and
41 Peri 2013). Much larger amounts of carbon, however, are stored in soil.
42 It is estimated that the amount of C stored in soils (1500- 2400 Pg) is three times
43 larger than that found aboveground biomass (450 – 600 Pg) (Houghton 2014,
44 Scharlemann et al. 2014). Nevertheless, soil organic carbon (SOC) stocks are
45 notoriously difficult to predict, especially in pristine ecosystems, which are often
46 difficult to access. Carbon storage depends on the existing interactions between all
47 processes in the soil-vegetation-atmosphere system (Silva 2017). Therefore, soil
48 organic C stocks vary depending on i) carbon inputs resulting from ecosystem
49 factors such as climate, soil, and vegetation and ii) mechanisms controlling C
50 mean residence times (Jobbagy and Jackson 2000; Lützow et al. 2006; Laganriere

et al. 2010; Don et al. 2011; Kögel-Knaber and Amelung 2014). In pristine ecosystems mean residence times of C stored in plant biomass depends on the vegetation type (Mahli and Grace 2000; Galbraith et al. 2013) while in soils mean residence times are C-pool specific and may span decades or even centuries (Kuzyakov 2006; Schmidt et al. 2011). Therefore, it is not surprising that SOC has become a focus for climate change mitigation policy. For example, the recent COP21 initiative aimed at increasing SOC stocks to reduce atmospheric CO₂ concentration by 4 parts per mill per year (URL: <http://4p1000.org>, Minasny et al. 2017). On the other hand, other strategies to mitigate climate change such as REDD+ still lack a consideration of soils. A major challenge for preserving or achieving SOC enhancement goals is the paucity of reliable data on current carbon stocks of pristine ecosystems. Therefore, this study was designed to improve our understanding and ability to predict SOC stocks in pristine ecosystems across biomes.

Quantifying SOC stocks of natural systems requires several challenges to be overcome. Accurately quantifying SOC stocks at landscape level is difficult because landscapes are heterogeneous, dynamic, and multiple factors interact to impact both formation and degradation of SOC (Bui et al. 2009; Don et al. 2011; Powers et al. 2011; Ladd et al. 2013; Manning et al. 2015). In addition, a precise estimation of SOC stocks is challenging, particularly in pristine ecosystems that are remote and difficult to access (Scharlemann et al. 2014). However, these ecosystems are expected to store large SOC pools at a long-term steady state equilibrium maximum (Sanderman et al. 2017). This provides target baseline values for the amount of SOC

that could be sequestered in soils. Already Minasny et al. (2017) point out, as also discussed by many other authors (e.g., Post and Kwon 2000; Lal 2004b; Lam et al. 2013; Sanderman et al. 2010), that it is mostly managed agricultural lands that provide potential for sequestering SOC, yet, certainly not more than the equilibrium value than exists under climax vegetation in pristine environments (Lal 2004b). Only when knowing this maximum amount of C stored in soils, policy makers may have a clue to value or quantity of soil C that any attempt for mitigating climate change through better soil management could achieve.

To address the difficulties of accurately quantifying SOC stocks, global maps of SOC have been developed. For example, the maps developed by the European Union, and the International Soil Reference and Information Centre (ISRIC, SoilGrids products) (Hiederer and Köchy 2011; Hengl et al. 2014; Hengl et al. 2017). The European Union's global SOC map is largely based on the FAO system of soil taxonomy (Hiederer and Köchy 2011). This taxonomy is limited as it accounts for soil forming processes, but it does not integrate climatic controls on SOC stabilization in a quantitative manner. In contrast, the SoilGrids products (at 1 km and 250m resolution) are based on automated mapping and machine learning techniques and consider the CLORPT soil forming factors (i.e., Climate, Organisms, Relief, Parent material, and Time; Jenny, 1941). This approach has the drawback that it calculates SOC from soil properties, such as bulk density, soil organic matter, and particle distribution, which has much higher uncertainty than SOC calculated directly from empirical data (Hengl et al. 2014; Hengl et al. 2017). Yet another drawback is that these maps were developed to predict current SOC stocks without

considered degree of human impact, leaving the question of predictions for pristine ecosystems, which could be used as baseline C reference, aside.

To address these important limitations of previous SOC mapping efforts, here we propose a solution or complementary approach that considers both CLORPT soil formation factors and uses empirical SOC data to refine SOC stock predictions at large scales. Specifically, this study predicts global SOC stocks for the top 1 m of the soil profile, by using freely available geographic data sets [climate, topography, primary productivity (indicated by normalized difference vegetation index: NDVI), and soil characteristics] on SOC measurements in pristine ecosystems across biomes. Our objective was to ease the challenge of predicting and assessing SOC baselines; this may help guide land management and restoration efforts, e.g. in pursuit of Land Degradation Neutrality (LDN), where SOC is one of the LDN indicators (Lal 2016; Cowie et al. 2018).

Materials and methods

The SOC stock dataset

A database of SOC stocks in pristine ecosystems was compiled from peer-reviewed publications. Data were obtained from 38 sources (see appendix S1) compiled with electronic search engines (i.e. Google Scholar and ISI web of science) and by reference to relevant meta-analyses (Don et al. 2011; Powers et al. 2011; Deng et al. 2016). In addition a subset of sites from the ISRIC-WISE international soil profile dataset were included in this study (Batjes 1995). To ensure the best coverage of the globe, we also included sites from the National Soil Survey Center (NSSA, www.nrcs.usda.gov), which is operated by the United States Department of

Agriculture (USDA), and comprises a large dataset of soil properties in several sites across the globe. For the sites derived from the NSSA, we calculated the C stocks using the following equation:

$$C = \%C \times \delta a \times h \times C_m$$

Where C is the C stocks in t ha^{-1} , $\%C$ is the percentage of C in soil, δa is the bulk density (g cm^{-3}), h is the depth of measurement (in cm) and C_m is the correction for coarse fraction measured for each soil pit (Soil Survey Staff 2011).

For this compilation we only included data when SOC stocks were measured to 1 m depth. And, as the aim of the study was to generate a baseline for C stocks, we only included sites that could represent pristine ecosystems, i.e., where no information indicated that they had been used for arable cropping in the past or which showed unusual climax vegetation. Hence, we equate these sites as pristine, i.e., with minimal anthropogenic impacts. Therefore, all observed sites are considered to approximate SOC stock at equilibrium. Assessing the effects of land use on SOC stocks was not the objective of this study.

The final dataset included 1346 observations of SOC stocks in pristine ecosystems, plus an independent dataset of 100 sites for validation (Figure 1). The 1346 sites represent adequately every biome (Figure 2) and are distributed across all 5 ice-shield free continents (Figure 1). Moreover, the 100 sites used for model accuracy assessment are also distributed across the 5 continents and 11 of the 12 biome classes used for the analysis. The only biome type that was not represented in the

validation dataset was tropical conifer forests, however, this is the biome with the lowest coverage on Earth (0.3%, Figure 2).

Data sources used to compile the GIS-derived independent variables

The selection of freely available, GIS-derived, independent variables was guided by the state factor model (Dokuchaev 1879; Jenny 1941), where soils are described as a function of Climate, Organisms, Relief, Parent material and Time (CLORPT, see introduction and discussion).

Estimates of climate parameters and solar radiation for each site (i.e. 1346 observed sites for modelling and 100 sites for accuracy calculation) were derived from the WorldClim data set (Hijmans et al. 2005; Fick and Hijman 2017). See Table 1 for a description of the WorldClim parameters and columns H to Z in appendix S1 for parameter estimates. WorldClim contains geographic surfaces for 19 different climatic parameters that describe rainfall, temperature and variation in those parameters at a resolution of 30 arc seconds (approximately 1 km² at the equator). The second version of WorldClim (Fick and Hijman 2017) contains monthly values of solar radiation (in kJ m⁻² day⁻¹) at a spatial resolution of approximately 1 km² at the equator. We used ArcGIS 10.1 to obtain estimates of the mean yearly values (column AA, appendix S1).

Global potential evapotranspiration and aridity index (Trabucco and Zomer 2009) were downloaded from the CGIAR-CSI GeoPortal (<http://www.csi.cgiar.org>) at a spatial resolution of 30 arc seconds (~1 km²) (columns AH and AI in appendix S1).

The period for this dataset corresponds to 1950-2000. Soil water balance (SWB) variables (Columns AE to AG in appendix S1) for the 1346 sites were also downloaded from the CGIAR-CSI GeoPortal (<http://www.csi.cgiar.org>). These variables also have a spatial resolution of approximately 1 km² (30 arc seconds) (Trabucco and Zomer 2010).

Biome classification was obtained either from the source publications (column AL in appendix S1) or from the Global terrestrial ecoregions map, based on the World Wildlife Fund biome classification (<https://www.worldwildlife.org>). Biome classifications have proven useful as a variable for modelling global ecological processes (Prentice et al. 1992).

Primary production at each site was approximated using normalized difference vegetation index (NDVI). We used the global map of the European Space Agency (ESA), (<http://maps.elie.ucl.ac.be>, see their Land Surface Seasonality products). This map provides NDVI values for the period 1999-2012 at 1 km² spatial resolution divided in two measurements: Aggregated Mean (AggMean: greenness dynamic over a period of 7 days) and standard deviation (Std of the mean NDVI, representing the variability of NDVI over a 7 day period) (columns AB and AC in appendix S1).

Elevation data (column AD, appendix S1) were downloaded from the SRTM30 project at approx. 1 km² resolution (<https://dds.cr.usgs.gov/srtm/>). They comprise a combination of data from the Shuttle Radar Topography Mission and the U.S. Geological Survey's GTOPO30 data sets.

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193 Information on the geology was obtained from the world geologic maps available
194 from the USGS database (<http://energy.usgs.gov>) to determine geologic units and
195 age (columns AJ, AK and AS in appendix S1). The geochemical, mineralogical, and
196 physical properties of rocks (column AR in appendix S1) for the 1346 sites were
197 derived from the Global Lithological Map (Hartmann and Moosdorf 2012).

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199 Soil taxonomic class of the soil at each site (Column AM, appendix S1) was obtained
200 directly from the source publication whenever this information was provided. When
201 this information was not reported we extracted soil types from the SoilGrids soil
202 taxonomy map at 250m of spatial resolution, based on the World Reference Base
203 (WRB) (Hengl, et al. 2017). Global Landform Classification data (Columns AN to AQ,
204 appendix S1) were downloaded from the European Commission
205 (<http://eusoils.jrc.ec.europa.eu>). These maps provide information on relief classes,
206 steepness, soil texture and local convexity following Meybeck et al. (2001) and
207 Iwahashi and Pike (2007) at a spatial resolution of 1 km².

208

209 *GIS processing*

210 The extraction and calculation of the required GIS-derived independent variables
211 was done using ArcGIS 10.1 (Redlands, California). All processed geographical
212 datasets were uploaded to ArcGIS. Using the extraction tool of ArcGIS, we
213 extracted the corresponding pixel value for each observed site, or nearest neighbor
214 pixel if the corresponding pixel of target site was not indexed, and added them to
215 the raw dataset (Appendix S1). For the NDVI values, we obtained estimates of the

mean values (of the 7 day-period) for the AggMean and Std of the NDVI per pixel, developing new raster images. Then, we extracted the value per site. Annual average values of solar radiation, were calculated based on the monthly average for each pixel, and then the corresponding value was extracted. Finally, we calculated the total area of each biome.

Analyses

The dependent variable, SOC stock to 1 m depth, was natural log transformed prior to analysis to reduce the influence of outliers (Quinn and Keough 2002). The resulting dataset was analysed using Partial Least Squares (PLS) Regression (XlStat, AddinSoft, Paris) because this type of analysis allows the inclusion of both quantitative and categorical independent variables (see appendix S2). This analysis transforms the original variables to new ones (or components), which are linear combinations from the originals. To evaluate the strength of correlation between our observed SOC stocks and the model predictions, we performed a linear regression (XlStat, AddinSoft, Paris) on the naturally log transformed values of the observed and the predicted SOC stock values (appendix S2).

To determine the relation between the most representative variables and the naturally log transformed values of the observed SOC stocks, we performed linear regressions and ANOVA (XlStat, AddinSoft, Paris).

To estimate the accuracy of the model, we calculated the predicted values (using the model equation) for the dataset of 100 sites, then, used root mean square deviation ($\text{RMSD} = [\sum(\text{observed} - \text{predicted})^2 / n]^{1/2}$) (Figure 1, appendix S1).

Results

The values of SOC stocks (to 1 m depth) in published literature ranged from 3 to 3069 t ha⁻¹ and varied considerably across biomes: boreal forests (253.6 ± 14.3 all values in t ha⁻¹ ± standard error), deserts (53.2 ± 6.3), Mediterranean forests (141.5 ± 20.4), montane grass and shrubs (99.1 ± 6.5), temperate broadleaf and mixed forests (151.6 ± 15.4), temperate conifer forests (220.9 ± 23.7), temperate grasslands (104 ± 4.6), tropical and subtropical coniferous forests (93.9 ± 20.6), tropical and subtropical dry forests (130.7 ± 40.5), tropical and subtropical grasslands (100.9 ± 10), tropical and subtropical moist forests (143.1 ± 9), tundra (310.2 ± 15.3) (see also appendix S1 for further detail).

The model derived from the PLS regression proved effective in predicting measured SOC (Figure 3, $y = -0.09 + 1.01x$, $R^2 = 0.49$, appendix S2). The predictive model included all the independent variables (qualitative and quantitative) (see appendix S2, cell B7099). From the 100 independent sites used to evaluate the accuracy of the model, we found that the RMSD (0.68) represented approximately 14% of the average observed C stock values. However, it overestimated values for extremely low C stocks (e.g. deserts) and underestimated values for extremely high C stocks (e.g. tundra or boreal forests) (Figure 3).

The PLS regression analysis indicated that the 10 most important variables in the model were solar radiation, the standard deviation of normalized difference vegetation index (i.e. NDVI-std), potential evapotranspiration, soil water balance variables (i.e. soil water content and aridity stress on vegetation), biome classification, landform, soil type and temperature-related climate variables (i.e.

mean diurnal range and mean annual temperature) (Figure 4); see appendix S2 for statistical details of the PLS regression analysis and model. The further evaluation of the effect of solar radiation, potential evapotranspiration, soil water content, biome classification and mean annual temperature on soil C stocks is shown in Figure 5. Linear regressions for the quantitative variables and the ANOVA for biome classification gave the following results. Higher values of solar radiation ($y = 6.4 - 0.0001x$, $R^2 = 0.27$, Figure 5a), potential evapotranspiration ($y = 5.33 - 0.001x$, $R^2 = 0.10$, Figure 5c) and mean annual temperature ($y = 4.86 - 0.02x$, $R^2 = 0.09$, Figure 5e) were related to low C stocks. However, high soil water content ($y = 3.95 + 0.01x$, $R^2 = 0.12$, Figure 5b) was related to high C stocks. Further, the highest stored C stocks in the top 1m were found in boreal forests and tundra, with no detectable statistical difference between these biomes. Temperate conifer forests and mediterranean forests were statistically similar to both tundra and boreal forests, but also similar to temperate broadleaf and mixed forests. All tropical and subtropical forests (i.e. moist, dry and coniferous) had no detectable statistical difference. Tropical and subtropical grasslands were similar to both temperate grasslands and montane grass and shrub, although the latter were statistically different from each other. In contrast, deserts had the lowest observed C stocks and were statistically different from all other biomes (Figure 5d).

Discussion

Our results show that baseline SOC stocks can be reasonably well predicted from freely available geographic and climatic datasets. Using a combination of

environmental variables. Across 100 different pristine ecosystem locations we found that 49% of average variance in SOC stocks across biomes was predicted. The most powerful predictive variables in our model were: solar radiation, variability in plant productivity as approximated by NDVI-std, temperature-related variables, soil water balance, landform, soil type and biome classification. Sanderman et al. (2017), who developed two predictive models, one for historical and one for current soil C stocks (i.e. prior to and after land use changes), also found that the most important variables in these models (historical and current C stocks) were related to climate and topographic attributes, such as temperature, elevation, landform and precipitation.

Within and across biomes, variation in aboveground biomass is known to be positively correlated with variations in temperature and precipitation (Sala et al. 1988; Chapin et al. 2002). We also found that these variables affected SOC stocks, though not necessarily in the same simple direction (Figure 5e). Specifically, our PLS analysis indicated that SOC stock was negatively correlated with solar radiation, potential evapotranspiration and temperature, but was positively correlated with soil water content and primary productivity. This is explained by the fact that beside primary productivity (see above), soil temperature and moisture also control the rate of litter decomposition and soil C accumulation (Stockmann et al. 2013). High temperatures increase microbial activity and decomposition rates, releasing C from soil to the atmosphere (Chapin et al. 2002; Gilmanov et al. 2007) at rates that depend on interactions between microbial and plant communities (Winsome et al. 2017). On the other hand, low temperatures decrease both primary productivity and

decomposition, explaining why cold environments preserve ancient C-rich soil horizons under conditions that currently limit plant growth (Adams et al. 2011). We also found that elevated soil water content correlated with elevated C stocks. This relationship could again be explained by the increase in primary productivity due to higher soil moisture and higher precipitation values, lower soil temperatures at elevated water supply, and enhanced SOC storage where water stagnates, e.g., in depressions (e.g., Batjes 1996; Chapin et al. 2002; Doetterl et al. 2013; Adhikari et al. 2014). In any case, we were able to describe significant predictable relationships that show how SOC stocks might change with climate.

The key driver behind soil temperature and moisture is solar radiation. It generally promotes plant productivity (Chapin et al. 2002; Gilmanov et al. 2007; Ladd, et al. 2009; Ladd, et al. 2014) and therefore soil C inputs, in ecosystems that are not water-limited. The negative effect of solar radiation on SOC levels could, in part, be related to the role of solar radiation in the decomposition of surface litter (Austin and Vivanco 2006; Borchard et al. 2014) or to litter quality, which may change with primary production (Bouwman 1990). Beside temperature and geography, litter quality (e.g. nutrients, C:N ratio or lignin:N ratio) is a key regulator of initial surface litter decomposition rates (Zhang et al. 2008) and thus likely also for formation of stable organic matter (Neff et al. 2002).

Variability in primary productivity (i.e NDVI-std) was an important predictive variable but this may be due to vegetation characteristics influenced by topography instead of primary productivity itself (Mulder et al. 2011). For example, in Argentinean

Nothofagus forests, evergreen species (i.e. less variability in primary productivity) are more common in lowlands, near lakes and locations with alluvial soils, while upland forests are generally deciduous (i.e. more variability in primary productivity; Peri et al. 2012). Similarly, Brazilian Cerrado evergreen forests are typically found on alluvial and riparian sites whereas drought deciduous species occur in dryer upland Cerrado sites (Silva et al. 2008). Because SOC tends to accumulate in depressions (Roman-Sanchez et al. 2018, Figure 1S Appendix) and because plant productivity is more stable in these same locations, this may mean that continuous growth and less variability in primary productivity, leads to a positive correlation between NDVI-std and SOC. More research is required to elucidate causal relationships and the mechanisms that determine them across the globe. However, despite the questions related to mechanisms the data do clearly show that it is possible to predict SOC storage from freely available climatic and GIS data, thus offering scientist and policy makers a tool for valuing the success of conservation measures or for estimating the potential of a given degraded biome to sequester C; i.e. up until the baseline in pristine ecosystems is reached.

Implications for large-scale C mapping

We have shown that using now readily available geographic datasets can lead to a good ability to model, predict and assess SOC stocks that could in turn provide better targeting of habitat protection to help maximise both carbon storage and conservation of nature (Sheil et al. 2016). Our analysis provides a clear demonstration of a strategy that could help improve the current generation of global SOC maps in pristine ecosystems and also shows that independent variables that

can be derived simply, such as simple ecosystem classifications, can add significant power to empirical models that aim to predict soil C stocks.

As the quality and availability of geospatial and satellite data that relate to the mechanistic factors that drive soil formation (Climate, Organisms, Relief, Parent material and Time; i.e. CLORPT, see first paragraph of methods) (Dokuchaev 1879; Jenny 1941) advance, more accurate predictions should become possible (Ladd et al. 2014). Additionally, advances in GIS capability, data handling and statistical methods, mean that we are now in a position to develop a quantitative version of the CLORPT model that allows accurate prediction of SOC stocks in pristine ecosystems on a large scale. With better resolution of NDVI, soil and topographic data within a given landscape, producing highly resolved SOC maps at catchment scale is then feasible based on advanced statistical or machine learning tools like random forest regression (e.g., Grimm et al. 2008; Wiesmeier et al. 2014; Hounkpatin et al. 2018). Here, we found that within the biomes mean standard deviation ranged from 36 t C ha⁻¹ in tropical and subtropical coniferous forests to 277 t C ha⁻¹ in tundra biome, thus tropical and subtropical coniferous forest were the least represented biome both in the dataset (N=3) and of biomes in general, representing only 0.3% of the total ice free-terrestrial surface. While tundra, was the best represented biome (N=325) and also the one with the largest area (~40%) of the total ice free terrestrial surface (Figure 2). This could indicate that larger biome coverage means more variability in C stocks.

Yet, large difference between C stocks across extreme biomes, for example, the ones existing between tundra or boreal forests and deserts, includes the risks of an

overestimation and underestimation of extreme values (very low and high SOC stocks) in our model, thus calling for even more sophisticated non-linear learning algorithms for potential improvements to achieve more exact SOC estimations for extreme environments.

Implications for conservation and management strategies

The development of a global C stock baseline can facilitate efforts to include SOC in schemes such as REDD+ that aim to conserve ecosystems and their carbon stocks and for achievement of Land Degradation Neutrality (Cowie et al. 2018). Including SOC in such schemes with the aim of increasing SOC stocks, could favour better land management practices. These practices include conservation, biological farming and the use of compost and eventually biochar (Adams et al. 2011; Ladd et al. 2018). Although these practices can increase SOC stocks, there are several limitations in adopting them. These limitations include negative impact on food security (from lower yields of organic systems and from the conversion of agricultural lands to woodlands), limited biomass resources for compost and biochar, limited economic resources of land, among other limiting factors (Adams et al. 2011; Poulton et al. 2017). Additionally, soil management strategies should also focus on the restoration of degraded ecosystems and desertified landscapes, restoration and improved productivity of grasslands, and reforestation (Lal 2004a; Adams et al. 2011; Lal 2013), which in some cases have been shown to increase SOC beyond levels found in the most productive terrestrial ecosystems (Silva et al. 2013; Silva et al. 2015). Also, when developing management or conservation strategies changes in species composition across biomes should be taken into

account. This is because such variations cause shifting ecosystem C fixation and water balance, having important consequences for SOC stocks and groundwater recharge (Maxwell et al. 2018).

In our study, we do not include the effects of anthropogenic land use change (LUC) on SOC stocks, since we focus on pristine ecosystems. However, LUC have been linked to important C stocks variations, especially in transitioning from pristine ecosystems to cropping (Smith et al. 2008; Berhongaray et al. 2013; Rabbi et al. 2015; Sanderman et al. 2017). Recent work has shown that combining LUC and freely available GIS data may also predict changes in SOC stocks in croplands (e.g., Sandermann et al. 2017; Hounkpatin et al. 2018), thus providing an option to rate former SOC losses against baseline SOC levels as assessed here – which is basically the inverse of estimating the maximum amount of SOC that might potentially be re-sequestered. Yet, all these changes depend on time, and while changes in SOC losses may be rapid, occurring within a few years to decades (Dalal and Mayer 1986; Solomon et al. 2007), it may take decades until SOC levels restore, frequently not to the level of the pristine environment (Robles and Burke 1998; Post and Kwon, 2000; Lal 2004b; Preger et al. 2010). For future Earth system modelling it will likely be needed to augment the statistical modelling approach used here with process-based models to gain mechanistic insight and facilitate prediction and analysis of possible future scenarios.

Conclusion

We have shown that SOC stocks of pristine ecosystems can be accurately predicted using available data. Further, 49% of average variance for pristine

ecosystems across biomes was predicted. Our model provides a theoretical baseline for accurately identifying sites with a high potential for C storage through restoration and rehabilitation of degraded land. Additionally, it shows where the highest SOC stocks are in pristine ecosystems, and where efforts can be best made to conserve soil C. And perhaps most importantly, this information can be used in conjunction with estimates of current SOC stocks (obtained from other sources, e.g. current SOC stocks from Sanderman et al. 2017) to identify sites with the greatest gap between current and potential SOC stocks. This could help guide the selection of sites for restoration, to achieve maximum negative emissions, through carbon sequestration in soil.

Supplementary material

Data to this article can be found online at:

http://www.unpa.edu.ar/cecyt/1876/grupo/forestal_silvopastoril/actividades

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Additional information

Conflict of Interest: The authors declare that they have no conflict of interest.

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Table legends

Table 1 A description of the WorldClim parameters (i.e. climatic variables) extracted with ArcGIS 10.1 (Redlands, California) for each observed site used for the development of the model (further detail available at <http://www.worldclim.com>, and in Hijmans *et al.* 2005)

Table 1

Parameter	Description
BIO1	Annual mean temperature
BIO2	Mean diurnal range [mean of monthly (max. temp.–min. temp.)]
BIO3	Isothermality (BIO2/BIO7) (x 100)
BIO4	Temperature seasonality (standard deviation x 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

Figure legends

Fig. 1 The global distribution of the 1346 soil pits that were geo-referenced and used to measure SOC stock (t ha^{-1}) to 1-meter depth and the 100 sites used for validation of the model obtained with partial least square (PLS) regression analysis. Raw data and source publications from which the data were obtained are provided in appendix S1

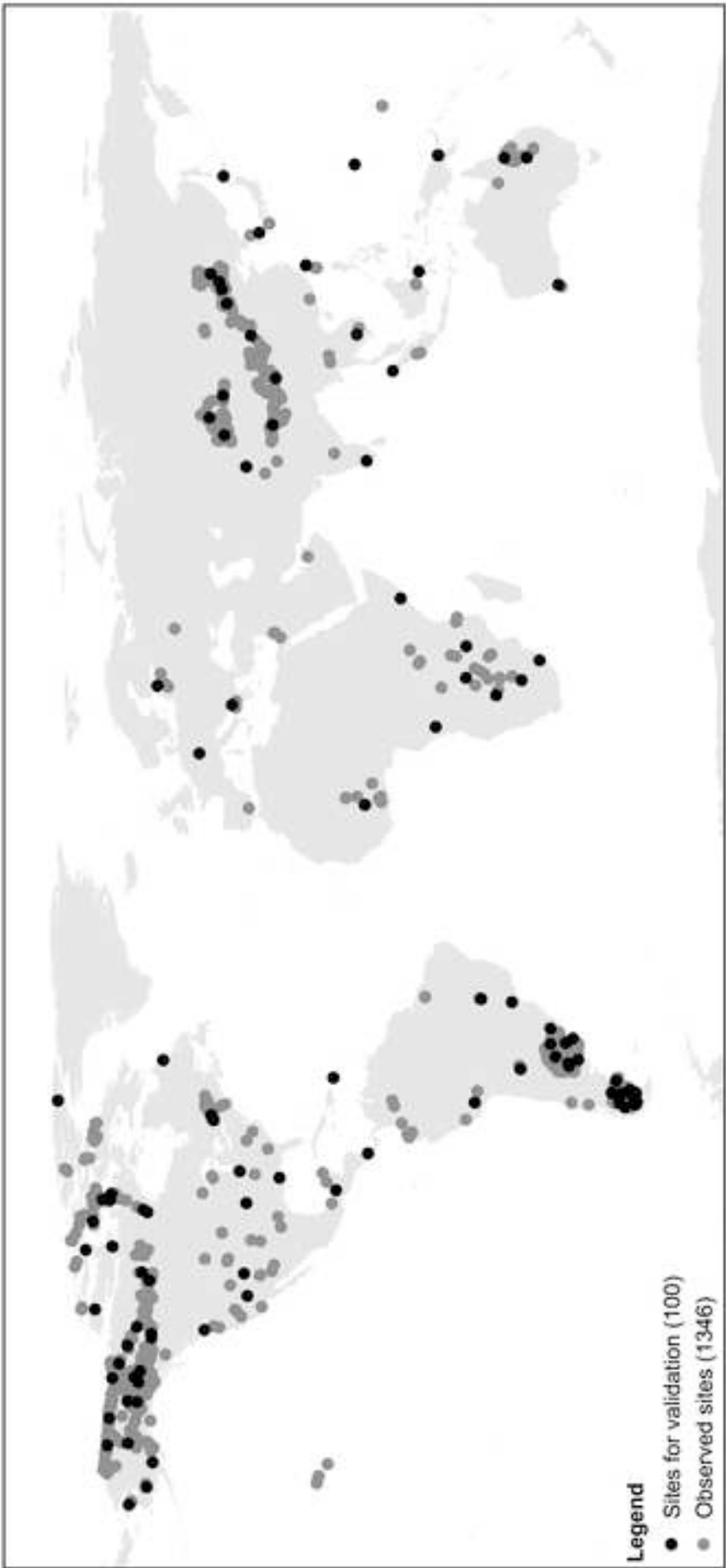
Fig. 2 Number of observations of C stocks according to each biome classification (following the WWF terrestrial biome classification) and the area (millions of km^2)

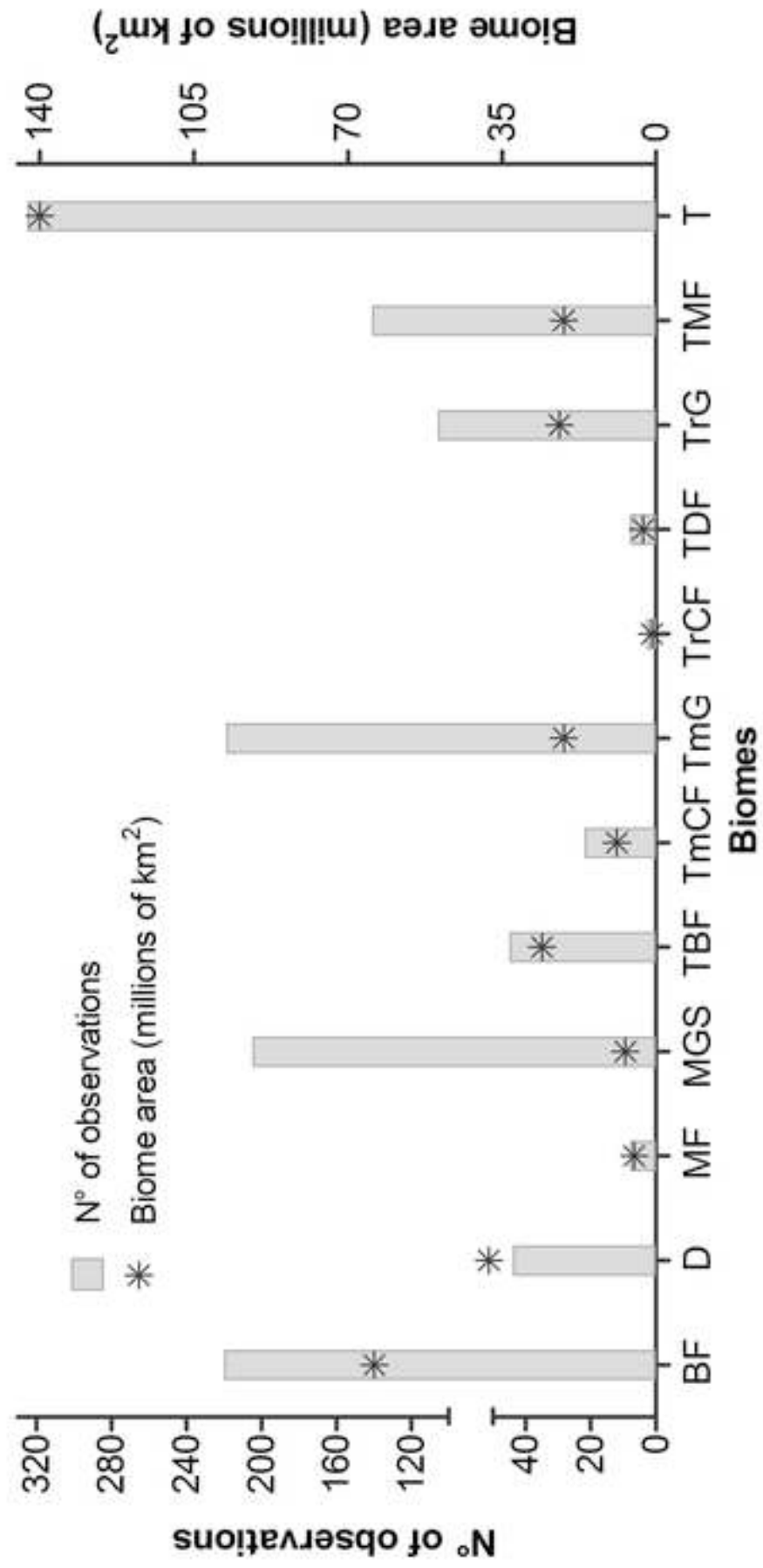
that each biome represent in the globe. BF= boreal forests, D= deserts, MF= Mediterranean forests, MGS= montane grass and shrub, TBF= temperate broadleaf and mixed forest, TmG= temperate grasslands, TrCF= tropical and subtropical coniferous forests, TDF= tropical and subtropical dry forests, TrG= tropical grasslands, TMF= tropical and subtropical moist forest, T= tundra

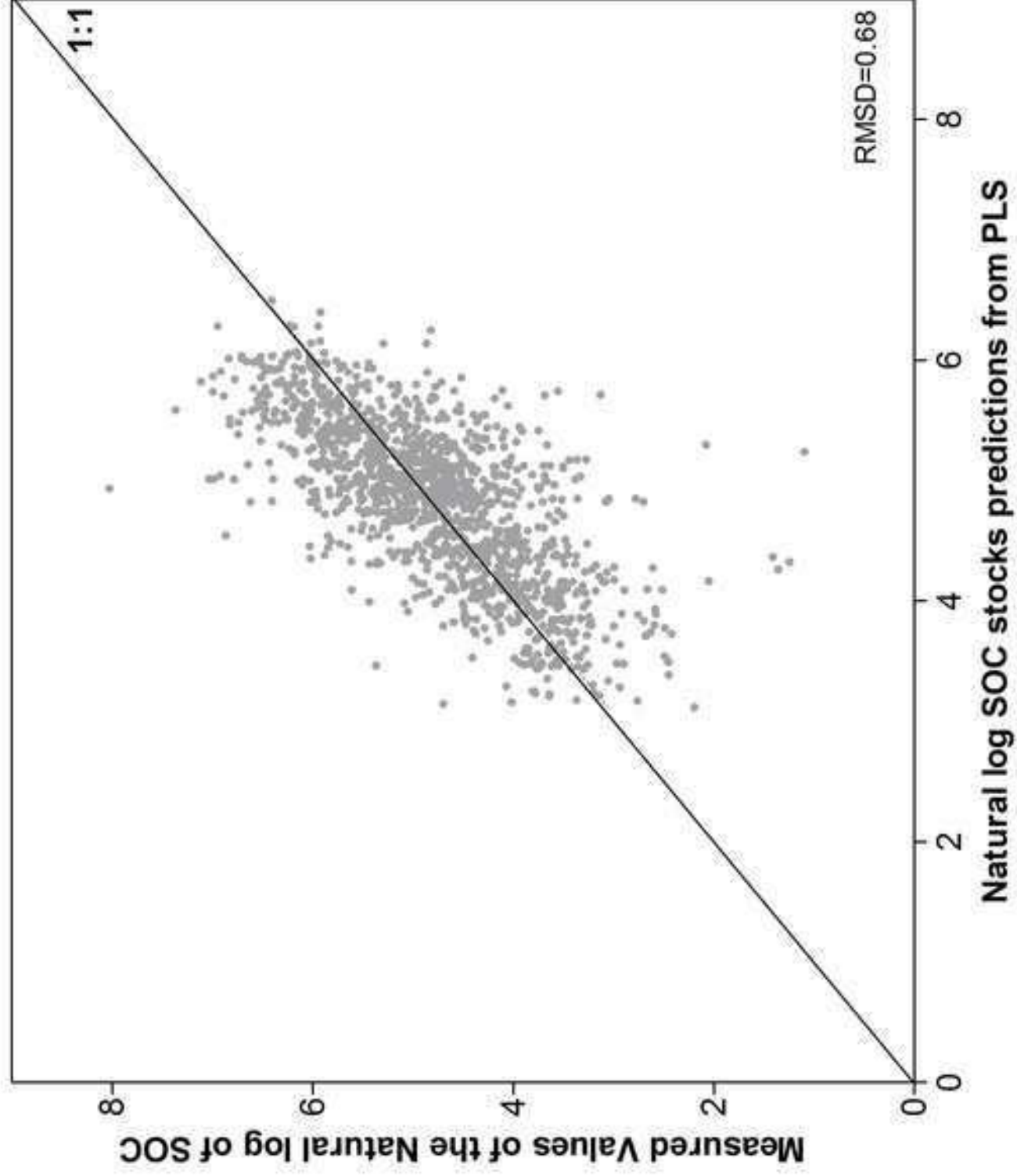
Fig. 3 The correlation between predictions of the natural log of SOC stocks derived from the PLS regression model constructed with independent variables derived from freely available geographic datasets and the same measured (natural log transformed) values of SOC stock obtained from the peer reviewed literature ($y = -0.09 + 1.01x$, $R^2 = 0.49$). See appendix S2 for further statistical detail of the partial least square (PLS) regression model. RMSD: root mean square deviation

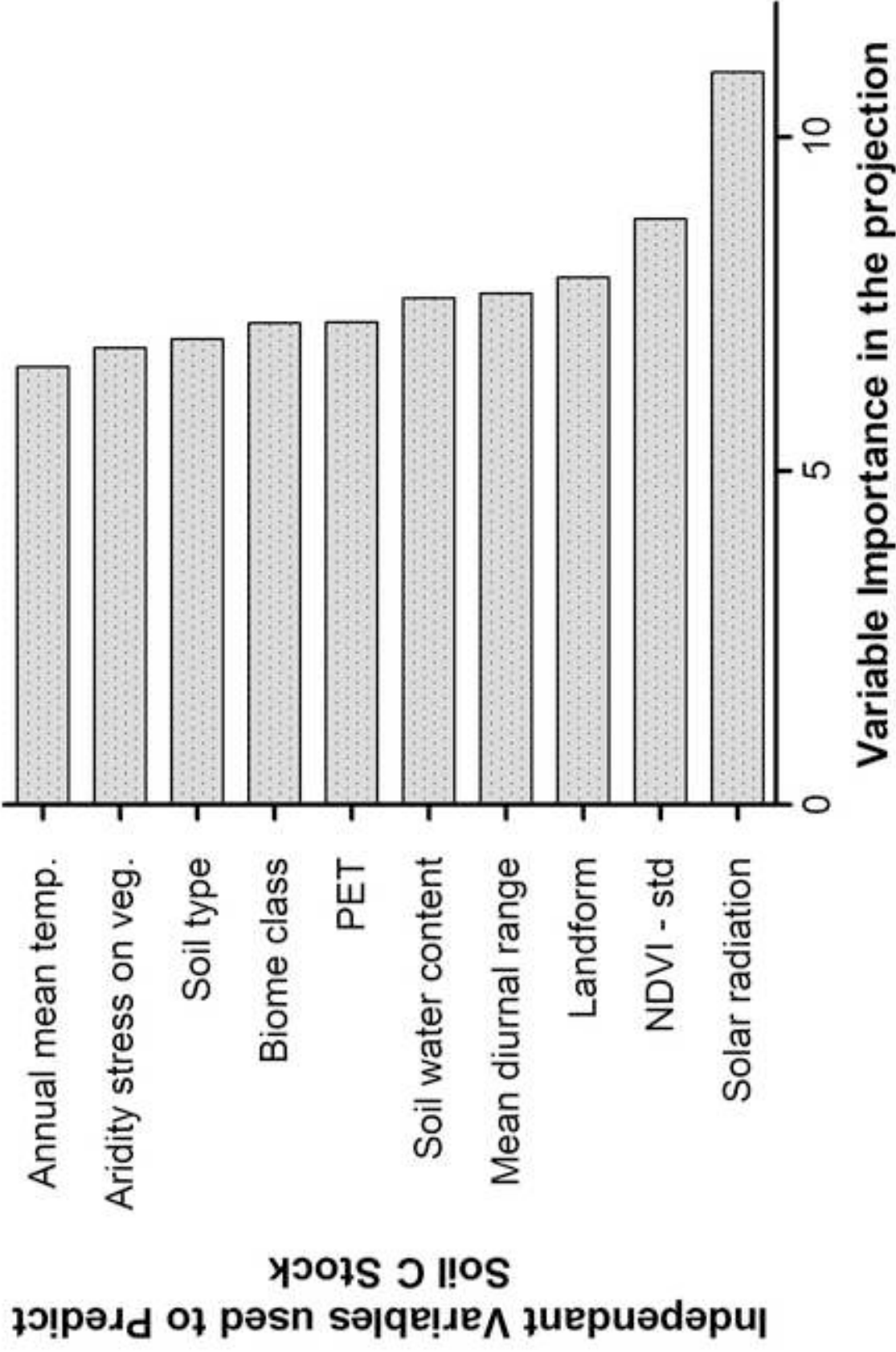
Fig. 4 The top ten variables for SOC stock prediction, based on node frequencies from the PLS regression analysis (see appendix s2 for details). Solar radiation (kJ m^{-2}) for the period 1970-2000, NDVI = Normalized Difference Vegetation Index, in this case the mean value of the standard deviation of the recorded values between 1999 and 2012, Landform = relief class (e.g. lowlands, plains, high altitude mountains, etc.), soil water content in and aridity stress on vegetation for the period 1950-2000. PET is Potential Evapotranspiration (1950-2000), soil type according to WRB classification and biome classification (e.g. tundra, boreal forest, temperate grasslands, etc.)

Fig. 5 Relation between observed C stocks and the most representative variables in the projection. Obtained from the PLS regression model for the 1346 sites with measured C stocks (t ha⁻¹). a) Solar Radiation (kJ m⁻²) vs. log transformed C stocks, b) Soil water content (%) vs. log transformed C stocks, c) Potential evapotranspiration vs. log transformed C stocks, d) ANOVA for C stocks according to biome classification (Fisher LSD test, $\alpha=0.99$), different letters mean statistical differences. BF= boreal forests, D= deserts, MF= Mediterranean forests, MGS= montane grass and shrub, TBF= temperate broadleaf and mixed forest, TmG= temperate grasslands, TrCF= tropical and subtropical coniferous forests, TDF= tropical and subtropical dry forests, TrG= tropical grasslands, TMF= tropical and subtropical moist forest, T= tundra. e) Annual mean temperature (°C) vs. log transformed C stocks









line figure

