Global Self-Similar Scaling of Terrestrial Carbon With Aridity

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Key Points:
- Key statistics of terrestrial carbon stocks scale with the hydroclimatic regime via a universal exponent
- The carbon stock distributions in each hydroclimatic regime, when normalized by their averages, collapse onto a single curve
- Self-similar scaling predicts carbon loss of 7.3 Pg C for 1% increase of global aridity

Abstract While it is well known that water availability controls vegetation growth and soil microbial activity, how aridity affects ecosystem carbon patterns is not completely understood. Toward a more quantitative assessment of terrestrial carbon stocks, here we apply dimensional analysis and scaling to the global joint distribution of terrestrial carbon stock, obtained from international survey data and harmonized global maps. The results show a remarkable self-similar behavior of the global carbon stock with dryness index, whereby the key statistics (e.g., mean, quantiles, and standard deviation) of carbon stock tend to scale with the hydroclimatic regime (i.e., aridity) via a universal exponent. Such a scaling reflects the strong coupling between the hydrological cycle and biogeochemical process and enables robust predictions of carbon stocks as a function of aridity only. When normalized by its averages in the corresponding hydroclimatic regime, the carbon stock distributions collapse onto a single double Pareto lognormal distribution, often used in economics to describe income. The presence of this distribution in completely different physical contexts, such as biogeochemistry and economics, hints at generating mechanisms that transcend the details of the specific stock being considered.

Plain Language Summary Water is essential to plant growth and soil microbial communities, which control the amount of total carbon stored over the land in the form of biomass and soil organic carbon. Yet, the global carbon patterns are still not very clear, especially with regard to the statistics in different ecosystems. Here by analyzing international survey data and harmonized global maps of carbon stocks we find a new relationship between terrestrial carbon storage and the aridity index, a quantity commonly used to quantify the local soil water availability. The carbon storage distributions for the same aridity index have similar shapes with relatively large probabilities of both extremely high or low carbon stocks across all terrestrial ecosystems. Such features allow us to gain information on future carbon stocks and inform climate mitigation planning.

1. Introduction

Due to its critical role in supporting cellular structure, water is a necessary ingredient for life (Hohmann-Marriott & Blankenship, 2011). The amount of water in the soil controls the terrestrial stock of soil organic carbon and biomass (Mu et al., 2011; Zhao & Running, 2010). Dry climates with lower plant productivity are prone to land degradation and are threatened in terms of biodiversity, while wet environments with fertile soils are susceptible to shift from carbon sinks to sources in changing climates (Brando et al., 2020; Hutjes et al., 1998; Jung et al., 2017). Water availability is expected to change in response to global warming (Held & Soden, 2006) but the projections remain uncertain (Byrne & O’Gorman, 2015; Greve et al., 2014). Such uncertainties propagate into the global biogeochemical cycles, posing great challenges not only for high-resolution Earth system modeling (Bradford et al., 2016; Canadell et al., 2021) but also for nature-based approaches to climate-change mitigation (Bastin et al., 2019; Wang & D’Odorico, 2019).

The role of aridity on ecosystem processes has received significant research attention recently, highlighting the nonlinear dependence of the biogeochemical process and plant dynamics on water availability (Berdugo et al., 2020; Lasslop et al., 2016; Maestre et al., 2015; Porporato et al., 2003). However, such studies typically focused on a limited range of aridity for specific types of ecosystems (see a brief review of these studies in Table S1 in Supporting Information S1) or only analyzed average ecosystem attributes without exploring their full statistical distributions. Extending the analysis to the entire spectrum of aridity, from wetlands to forests and deserts, is crucial to achieve global estimations of carbon stocks and predict their future distributions.
Toward this goal, here we used global survey and remote sensing data sets to systematically quantify the impacts of water availability on carbon stocks of terrestrial ecosystems. We stress that our goal is not to obtain a detailed fit of the data, which explicitly accounts for the particular controls on terrestrial carbon storage, but to provide robust—if approximate—statistics that emerge at the global scale. Our hypothesis that aridity provides a major control of global carbon stock is formalized by means of dimensional analysis. This explicitly brings out the control by the dryness index and suggests the possibility of a self-similar scaling. The global observations confirm such a scaling, revealing the critical control of the hydrological process on the global carbon cycle. As will be seen, once rescaled to account for aridity, the carbon-stock statistics collapse onto a universal distribution, which reflects the stochastic balance of assimilation and respiration losses, acting in space and time besides the hydroclimatic control.

2. Hypotheses, Dimensional Analysis, and Scaling

Consistent with our hypothesis of a dominant hydroclimatic control on terrestrial carbon, we started by formulating a physical law (Porporato, 2022) for the long-term carbon stock (aboveground and belowground), in units of areal density of carbon, as a generic function $g$ of the main governing quantities

$$ C = g(C^*, \alpha, \lambda, T^*, E_{max}, w_0, T, ...) $$

where $C^*$ is a reference carbon stock (units of areal density of carbon) to be defined later (see Equations 4 and 5), $\alpha$ is the mean rainfall depth per event (units of length), $\lambda$ is the rainfall frequency (inverse of time), $T^*$ is a reference temperature, $E_{max}$ is the potential evapotranspiration rate (length over time), $w_0$ is the soil storage capacity (length), and $T$ is ambient temperature. The choice of these governing quantities is guided by considerations of the main processes impacting the plant dynamics and soil water and carbon balance of a region. Considering $C^*, \alpha, \lambda, T^*$ as dimensionally independent quantities, the II theorem (Barenblatt, 1996; Porporato, 2022) allows us to reformulate the previous hypothesis in terms of fewer dimensionless groups

$$ \frac{C}{C^*} = \varphi \left( \frac{E_{max}}{\alpha \lambda}, \frac{w_0}{\alpha}, \frac{T}{T^*}, \ldots \right) = \varphi(D_I, \gamma, \tau, ...) $$

(2)

where the dryness index, a well-known aridity indicator, is defined as the ratio of long-term average rates of potential evaporation, $E_{max}$, to precipitation, $R = \alpha \lambda$,

$$ D_I \equiv \frac{E_{max}}{R} $$

(3)

This dimensionless index has been used in hydrology for partitioning precipitation into evaporation and runoff (Budyko, 1974; Daly et al., 2019; Porporato, 2022; Porporato et al., 2004; Zhang et al., 2004) and is also widely used in ecology to characterize ecosystem functioning (Berdugo et al., 2020; Wang et al., 2014; Zhou et al., 2019). Furthermore, we also consider a hypothesis of incomplete self-similarity (Barenblatt, 1996; Porporato, 2022) with respect to the dryness index

$$ \frac{C}{C^*} = D_I \psi(\gamma, \tau, ...) $$

(4)

The existence and degree of validity of such a scaling relationship are tested with global data next.

3. Geographic Patterns of Carbon Stocks and Aridity

We analyzed the monthly potential evapotranspiration and precipitation data from the Climate Research Unit (CRU TS v 4.04, https://crudata.uea.ac.uk/cru/data/hrg/), which is a widely used climate data set obtained by interpolating climate variables from global networks of weather station observations (Harris et al., 2014). The dryness index was calculated as the ratio of the long-term averages of potential evapotranspiration and precipitation as defined in Equation 3.

To find the global carbon stocks, we summed the harmonized global maps of above and belowground biomass (HGMB, https://doi.org/10.3334/ORNLDAAC/1763) and Harmonized World Soil Database (HWSD, https://daac.ornl.gov/SOILS.guides/HWSD.html). The former is the most up-to-date biomass data sets integrated from
several remote sensing data sets and other ancillary maps (Spawn et al., 2020); the latter is one of the most complete soil data sets developed by the Food and Agriculture Organization in collaboration with multiple international soil research centers (Hiederer & Köchy, 2011). The global biomass is estimated to be 409 Pg C and global soil carbon is 1417 Pg C, for a total of $C_t = 1826$ Pg C global terrestrial carbon stocks. Note that HWSD estimates soil carbon stocks only up to 1 m depth of soil, which may neglect certain deep soil carbon, for example, in some peatlands (Dargie et al., 2017; Jackson et al., 2017).

As shown in Figure 1, even by simple inspection, the global distribution of total carbon stock, defined as the sum of biomass and soil organic carbon, already appears related to that of the dryness index. The wet and carbon-rich regions are located in the tropics and at high latitudes, such as the Amazon rainforest, Indonesia, and the peatlands in Canada and Siberia; as well known, deserts such as Sahara and Atacama, some of the driest regions in the world, are also lowest in carbon content. While the carbon stock is also influenced by various factors associated with photosynthesis and soil respiration processes, these biotic and abiotic factors are highly interconnected and associated with the local aridity (see Figure S1 in Supporting Information S1), thus leading to a dominant control of the dryness index on carbon stocks.

4. Self-Similar Behaviors of the Global Carbon Stocks

To precisely quantify the carbon-aridity relationship shown in Figure 1, we analyzed the statistics of carbon stocks as functions of the dryness index, as suggested by Equation 4. These carbon and climate data were interpolated into the same equal-area grids with 0.05° resolution in the equator and uniform latitudinal spacing (Malkin, 2019), facilitating the estimation of statistics without treating the different geodetic zonal weights in any grid points. We also excluded urban areas and lands with snow/ice/water cover (see the hatched area in Figure 1) using the land cover information from Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover

![Figure 1. Comparison between dryness index and total carbon stocks.](image-url)
Climate Modeling Grid Product (modis.gsfc.nasa.gov/data/dataprod/mod12.php). These pairwise carbon-aridity data sets were used to quantify the statistics of carbon stocks conditional on the dryness index as reported below.

4.1. Mean Carbon Stocks

The results reported in Figure 2a show that, within each hydroclimatic regime (i.e., conditionally on dryness index), the mean total carbon, \( \mu_C \), can be well approximated as a power-law function of dryness index. This means that looking at Equation 4, the mean carbon for a given dryness index can be written as

\[
\mu_C = C^* D_I^b
\]

provided that the function \( \psi \) is chosen to have a unit average. This thus serves as the definition for the reference carbon \( C^* \), which was left unspecified in Equation 1, as the mean carbon at dryness index equal to one. The data fit results in an exponent \( b = -0.4 \) (−0.44, −0.40), \( C^* = 145 \) (141.8, 150.6) Mg ha\(^{-1} \), and the coefficient of determination is 0.98 (brackets indicate the 95% confidence bounds). Although subject to some scatter, this trend is fully consistent with the hypothesis of self-similarity with respect to the dryness index.

Quite surprisingly, while we would have expected the self-similarity to be specific to some asymptotic range of the dryness index, the data show a relatively good fit across the entire range of observations. Compared to the scale-dependent power laws in climatology (Lovejoy, 2015; Markonis & Koutsoyiannis, 2016; Nilsen et al., 2016), the deviations around \( D_I = 1 \) and 5 are less abrupt, which may result from heterogeneities in the photosynthetic rates and biogeochemical processes (e.g., Berdugo et al., 2020). While it is expected that more detailed models (e.g., piecewise power-law functions) provide a better fit (see Supplementary Text and Figure S2 in Supporting Information S1), compared to more precise but possibly less informative models, the parsimonious scale-invariant assumption allows us to robustly estimate global carbon stocks, moving across different hydrological regimes.

From a biogeochemical point of view, the dominant control of aridity on global mean carbon stocks may be understood as the combined effect of vegetation and soil microbial response to water availability in controlling the photosynthesis and decomposition rates. On the one hand, the increase in carbon input through photosynthesis increases with soil moisture, but tends to plateau in wet conditions (Porporato & Yin, 2022). On the other hand, the carbon loss due to decompositions is linked to soil microbial activity, which instead declines with anoxic conditions, thus favoring the accumulation of carbon (Moyano et al., 2013). At regional scales or with smaller sample sizes, the carbon-aridity relationships tend to deviate more from the power-law scaling and to...
4.2. Variances of Carbon Stocks

The relationship (Equation 4) suggests that not only the mean but also the higher-order statistics might exhibit the same self-similarity. Indeed, the data analysis confirmed that also the variance of the carbon stock distributions (see the shaded area in Figure 2a) exhibits a scaling behavior similar to the mean. Specifically, the standard deviation in each hydroclimatic regime ($\sigma_c$, see red triangles in Figure 2a) is well represented by

$$\sigma_c = \sigma_0 D_i^b$$  

(6)

where $\sigma_0 = 76 \ (73.4, 84.4) \text{ Mg ha}^{-1}$ and $b = -0.4 (−0.43, −0.35)$, which is basically the same as for the mean when rounded to one decimal figure (coefficient of determination is 0.91 and the brackets indicate the 95% confidence bounds). As for the mean, this power-law scaling is only approximate (see alternative fits in Figure S9 in Supporting Information S1). Combined with Equation 5, however, it produces a coefficient of variation (obtained by dividing Equation 6 by 5), which is approximately constant and equal to 0.55, across all terrestrial ecosystems. This signifies that the relative dispersion of carbon stocks is invariant in each hydroclimatic regime.

This global pattern also seems to be invariant across different spatial scales. While, as expected, upscaling grid data reduces the spatial heterogeneity and thus lowers the variances of carbon in each hydroclimatic regime (see red triangles in Figures S10a–S10c in Supporting Information S1), the corresponding mean carbon stocks still scale with dryness index with nearly identical exponent for data at different spatial resolutions (see black circles in Figures S10a–S10c in Supporting Information S1). Even in the extreme case of lumping the data across different Köppen-Geiger climate zones, this power-law relationship remains valid (see Figure S10d in Supporting Information S1), pointing to the robustness of this self-similar scaling behavior.

4.3. Distributions of Carbon Stocks

Looking at the full distributions of carbon stocks in each hydroclimatic regime, a final remarkable result emerges: when normalized by their conditional averages with respect to the dryness index ($c = C / \mu_C$) according to Equation 5, the data collapse onto a single distribution, as seen in Figure 2b. This means that one may link formally the normalized carbon distribution to Equation 4 as a derived distribution of the remaining environmental variables ($\gamma, \tau, \ldots$) impacting the carbon stock besides $D_i$ as (Au & Tam, 1999)

$$f_c(c) = \int \delta(c - \psi(\gamma, \tau, \ldots)) f_{\gamma,\tau,...}(\gamma, \tau, \ldots) d\gamma d\tau \ldots$$  

(7)

where $\delta$ is the Dirac delta function and $f_{\gamma,\tau,...}(\gamma, \tau, \ldots)$ is the joint distribution of ($\gamma, \tau, \ldots$). This result emphasizes the strong deterministic control of the environmental variables on terrestrial carbon, resulting in a probabilistic structure in greatest part imposed by environmental variability.

Focusing directly on the empirical distribution of $c$, Figure 2b shows that it displays two distinct power-law tails connected by a smooth, bell-shaped curve. This behavior is well fitted by a Double Pareto Lognormal, a distribution which recently has been used quite extensively in economics and the physical sciences (Reed & Jorgensen, 2004). Its probability density function can be expressed as

$$\tilde{f}_c(c) = \frac{a \beta}{\alpha + \beta} c^{-a-1} \exp\left(\alpha v + \alpha^2 \tau^2 / 2\right) P_a\left(\frac{\ln c - v - \alpha \tau^2}{\tau}\right) + \frac{a \beta}{\alpha + \beta} c^{-b-1} \exp\left(-\beta v + \beta^2 \tau^2 / 2\right) \left[1 - P_a\left(\frac{\ln c - v + \beta \tau^2}{\tau}\right)\right].$$  

(8)

where $P_a$ is the cumulative distribution function of the standard normal distribution, $\alpha$ and $\beta$ define the upper and lower tails, $v$ and $\tau$ define the lognormal distribution in the body part. This distribution with maximum likelihood estimation of parameters $a = 4$, $\beta = 2.7$, $v = -0.01$, and $\tau = 0.2$ is compared with the empirical distributions in Figure 2b (solid black lines) as well as graphically compared in quantile-quantile plots in Figure S5 in Supporting Information S1.
The collapse of the distributional tails, with their algebraic (i.e., not exponential) decay, reveals another self-similar behavior, which is indicative of a wide distribution with large probabilities of both extremely high or low carbon stocks, regardless of the ecosystem type and hydrologic regime. Such a universal behavior is noteworthy, especially in view of the many factors controlling the soil-plant carbon dynamics, and points to a common, fundamental way in which regional heterogeneities in aridity impact the local carbon stocks.

Besides the global soil survey data used in the above analysis, we also checked the scaling behavior in other model-based soil mapping data and different aridity data. The soil carbon data sets use state-of-the-art machine learning models to link soil carbon as functions of climate, landscape, land use/cover, and other related variables, and also include soil carbon in deeper soils; potential evapotranspiration in Equation 3 for aridity can be calculated from Priestley-Taylor equation (Priestley & Taylor, 1972). The results show that the power-law scaling is still valid, but with slight deviations in the extreme wet or dry regimes (see Figures S11–S14 in Supporting Information S1). The distribution of the normalized carbon stocks again collapses onto a single curve although the upper tails seem to have a somewhat faster decay (i.e., exponential). It should be noted that the carbon-aridity relationship obtained from these model-based data sets reflects the features of the training samples (which do not cover the entire globe) and could be influenced by model structures.

5. Discussion

The emergence of an approximate, but apparently robust scaling of carbon stock with aridity at the global scale may have significant practical implications. Given the strong controls of aridity on soil nutrient availability, plant growth, and carbon fluxes, identified by CO₂, the carbon cycle evolves quasi-statically and the expected carbon stocks will be scaled with 〈k〉. In an Earth-greening scenario (Zhu et al., 2016) of 1% decrease in dryness index for all land cover, the carbon gain would be 0.4% of total terrestrial carbon stocks (i.e., C, (1–0.99〈k〉) = 7.3 Pg C), while assuming a global drying (Sherwood & Fu, 2014) of the same magnitude one would have approximately the same amount of carbon loss.

Albeit approximate, the global scaling with aridity covers the entire range of aridity with a simple mathematical law with few parameters. This may appear surprising, given the well-known threshold-like nonlinearities which are known to impact ecohydrological and biogeochemical processes at small spatial and temporal scales (Berdugo et al., 2020; Manzoni & Porporato, 2009). The global averaging, combined with random heterogeneities in space and time, smears out some of these more abrupt changes and nonlinearities, producing a smoother behavior, similarly to the simplification of soil moisture loss function at large space-time scales (Porporato & Yin, 2022 and references therein) and the global soil microbial response to aridity (Manzoni et al., 2012).

It is also noteworthy that similar universal distributions have been found in other contexts, notably in economics to model income distributions. There, the presence of a Double Pareto Lognormal distribution has been attributed to a statistical behavior introduced by competition of geometric Brownian motions of gains and losses, subject to random renewals (Luckstead & Devadoss, 2017; Reed, 2003; Reed & Jorgensen, 2004; Toda, 2017). The presence of similar laws in such a completely different physical context seems to point out a universal generating mechanism, which transcends the details of the particular stock being considered. Further investigations along these lines are certainly warranted.

In conclusion, the global scaling of carbon stocks unveiled here allows us to link aridity projections to soil-plant carbon stocks, providing quantitative estimates of carbon storage trends for ecosystems attaining different aridity conditions. While of course the details of future carbon storage are also related to the speed at which such
different dryness indices are achieved, quasi-static estimates based on the obtained distributions may be useful to inform climate-mitigation strategies and to provide benchmarks for global simulations. Future work should focus on the genesis and justification of the global self-similarity behavior found as well as on the effects of dynamic changes in dryness index on transient changes in carbon storage; upscaling these dynamics, from the pulsing dynamics at the local scales to the global and multi-decadal scales of climatic interest (Austin et al., 2004), remains a crucial open problem for future carbon-storage predictions.

Conflict of Interest
The authors declare no conflicts of interest relevant to this study.

Data Availability Statement
The original data sets for CRU (https://crudata.uea.ac.uk/cru/data/hrg/), HGMB (https://daac.ornl.gov/VEGETATION/ guides/Global_Maps_C_Density_2010.html), HWSD (https://daac.ornl.gov/VEGSOILS/guides/HWSD.html), MCD12C1 (https://modis.gsfc.nasa.gov/data/dataprod/mod12.php) are available at the corresponding data servers. Derived data and computer codes for this study are available at figshare (https://doi.org/10.23.196/m9.figshare.20744767).

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