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# Climatic and edaphic-based predictors of Normalized Difference Vegetation Index in tropical dry landscapes: A pantropical analysis



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# Climatic and edaphic-based predictors of Normalized Difference Vegetation Index in tropical dry landscapes: A pantropical analysis

**Running title:** Climate and edaphic predictors of NDVI


## Abstract

**Aim:** Spatial patterns in resource supply drive variability in vegetation structure and function, yet quantification of this variability for tropical dry forests (TDF) remains rudimentary. Several climate-driven indices have been developed to classify and delineate TDF globally, but differences among the now classic indices result in overlapping but distinct geographic coverages for this important biome. Needed is a statistical climo-edaphic synthesis of these indices to assess and delineate TDF extent.

**Location:** Pantropical

**Time period:** Modern

**Major taxa studied:** Vascular plants

**Methods:** We assembled most known prior descriptions of TDF into a single data layer and statistically assessed how the TDF biome, what we call tropical dry landscapes (TDL) composed of forest and non-forest vegetation, varied with respect to normalized difference vegetation index (NDVI) sensed by MODIS (250 m pixel resolution). We examined how NDVI varied with respect to mean annual temperature (MAT) and rainfall (MAR), precipitation regime, evapotranspiration, and the physical, chemical, and biological properties of TDL soils.


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**Results:** Overall, NDVI varied widely across TDL, and we were able to identify five principal NDVI categories occurring at the following statistically determined (unitless) thresholds: (*i*) 0.23, (*ii*) 0.43, (*iii*) 0.50, (*iv*) 0.61 and (*v*) 0.71. A tree statistical modeling captured 90% of NDVI variation across TDL with 14 climate and soil metrics as predictors. The model was then pruned to use only three strongest metrics. These included the Lang Aridity Index, total evapotranspiration (ET), and MAT, which aligned with identified NDVI thresholds and accounted for 70% of the variation in NDVI. We found that across a global TDL distribution, ET was the strongest positive predictor and MAT the strongest negative predictor of NDVI.

**Main conclusions:** The remote sensing-based approach described here provides a comprehensive and quantitative biogeographical characterization of global TDL occurrence and the climatic and edaphic drivers of these landscapes.

**KEYWORDS**

climate, continental scale, MODIS, prediction, remote sensing, soil, tropical forest biome

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# 1 INTRODUCTION

The structure and function of tropical forests are strongly constrained by climatic and edaphic conditions, of which interannual and seasonal variation in rainfall and temperature and soil nutrient supply are viewed as being most important (Baldocchi et al., 2001; Law et al., 2002; Litton & Giardina, 2008; Zhao & Running, 2010; Doughty et al., 2015; Zhang et al., 2016; Ballantyne et al., 2017; Green et al., 2019; Sullivan et al., 2020; Muller-Landau et al., 2021). Spatial and temporal variation in rainfall is widely viewed as a central determinant of tropical dry forests (TDF) occurrence, with 3 to 10 months of annual drought characterizing the TDF biome (Chidumayo & Gumbo, 2010; FAO 2012). The intra-annual amount and distribution of rainfall strongly modulate TDF structure and function, especially the carbon (C) cycle (Campo & Merino, 2016; Mendes et al., 2020; Rojas-Robles et al., 2020), with interannual variation in rainfall providing secondary controls (Allen et al., 2017; Huang et al., 2021). Additionally, the TDF biome is associated with high land use intensities that create dynamic mosaics of forest, land under agricultural uses, and land supporting other human practices (Blackie et al., 2014; Banda-R. et al., 2016). These uses often alter TDF composition, structure, and function and for this reason, we describe the TDF biome as comprising both forest and non-forest vegetation that together form tropical dry landscapes (TDL). As TDF and savannas can co-occur in a range of environmental conditions (Staver, Archibald, & Levin, 2011; Moncrieff, Hickler, & Higgins, 2015), large savanna matrices encompass surround patches of TDF in some TDL resulting in a mix of TDF and fire-dependent grass and shrub dominated ecosystems.

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The strong sensitivity of TDL to spatial and temporal variation in rainfall is reflected in the dominant indicators of TDF and landscapes, including mean annual rainfall (MAR), mean annual temperature (MAT), and the number of sequential dry months in the dry season (Supporting Information Table S1). Typically, TDF is characterized by a MAT higher than 17 °C, an MAR range of 250 mm to 2,000 mm, and an annual ratio of potential evapotranspiration (PET) to MAR that exceeds unity (Murphy & Lugo, 1986). The most important driver of TDF structure and function is pronounced intra-annual variation in rainfall amount, with each dry season month receiving less than 100 mm of rainfall (Pennington, Lavin, & Oliveira-Filho, 2009).

Spatial variation in plant primary production and associated C process rates are driven by climate and soil properties (Schlesinger & Bernhardt, 2020), and broad-scale relationships between climate and forest productivity reveal strong effects of moisture and temperature (Luyssaert et al., 2007; Litton & Giardina, 2008). In TDF, the amount of dry season rainfall relative to atmospheric demand (i.e., the evapotranspiration that would be achieved from a well-aerated soil/ plant surface at field water-holding capacity; Schwartz, Litner, Feng, & Powers, 2020) appears to be a strong predictor of ecosystem productivity (Stan et al., 2021). Remote sensing is a central tool for monitoring C stocks and fluxes at regional to global scales (Ssemmanda, Gelorini, & Verschuren, 2014; Cao, Li, Liu, Chen, & Wang, 2018), with satellite derived normalized difference vegetation index (NDVI) providing highly temporally resolved data for understanding dynamics of vegetation greenness at planetary scales. Particularly relevant for

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TDL analyses are NDVI responses to MAT, MAR, and both inter and intra-annual climate variation (Walther et al., 2002; Yu, Price, Ellis, & Shi, 2003; Zeng, Collatz, Pinzon, & Ivanoff, et al., 2013; Zhou et al., 2014; Pan et al., 2018; Linscheid et al., 2020). Globally, NDVI-based analyses reveal that warmer temperatures in combination with lower rainfall amounts reduce greenness, thus productivity, with these relationships being strongest in low latitude forests (Allen et al., 2010; Becknell, Kucek, & Powers, 2012). Finer scale patterns within TDL are less well understood, limiting efforts to accurately model TDF responses to climate change.

Here, we build on previous work (Mallegowda, Rengaian, Krishnan, & Niphadkar, 2015; Corona-Núñez, Campo, & Williams, 2018) to examine how variation in climate and soils relate to NDVI across a global range of TDL sites. Specifically, we: (*i*) constructed a comprehensive data base of all published TDF ecoregions; (*ii*) conducted spatial and temporal analyses of the relationships between NDVI and diverse climatic and edaphic variables for these ecoregions; and from this (*iii*) established a generalized climo-edaphic statistical model to characterize global TDL. To achieve these goals, we analyzed 80 globally distributed and biogeographically defined TDF ecoregions (Figure 1). The specific objectives of this research were to: (1) evaluate how the variables most used to describe TDF are related to NDVI for previously identified TDL in Afrotropic, Australasian, Indo-Malayan, Neotropic and Oceanian biogeographic regions; (2) use climatic and edaphic variables to assign TDL to NDVI-based ecological groups; and (3) quantify how variation of these NDVI-based ecological groups relates to interannual climate variation.

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# 2 METHODS

## 2.1 Categorization and selection of biogeographic regions and ecoregions

To robustly characterize global variation in TDL, we identified five broad biogeographic regions where this ecosystem is distributed: Afrotropic, Australasian, Indo-Malayan, Neotropic, and Oceanian. Each of these biogeographic regions is characterized by a physical environment (e.g., climate) and geological history that defines the ecosystem processes and prominent species distributions. Across these five regions, we identified 80 ecoregions based on three criteria that correspond to polygons generated by World Wildlife Fund for Nature: (1) whether the site was identified as TDF by Olson et al. (2001) and revised by Dinerstein et al. (2017); (2) whether a site was described as TDF by authors who have focused their efforts and research on the description of this ecosystem within each of the five biogeographic regions (Supporting Information Table S1); and (3) whether sites were described as TDF in the FAO (2012) assessment of TDF (Supporting Information Table S2). We unavoidably included disturbance driven vegetation types such as savanna and geomorphologically determined vegetation types such as riparian forests, which transition into adjacent TDF that shape TDL dynamics (Dexter et al., 2018). To refine our understanding of environmental controls on TDF, we compiled diverse climatic and edaphic information with which to quantify variation in NDVI across the five major biogeographic regions and the 80 ecoregions. We excluded the following TDF types. Australia was excluded from the Australasian region because, for the scale of this analysis it did not

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contain representative coverage of TDF. We also excluded a small island TDF from Oceanic biogeographic region: Yap Tropical Dry Forests because this ecoregion was missing data needed to assess NDVI.

## 2.2 Selection of sample points

We created a 1 $km^2$ grid for each of the five biogeographic regions and identified the centroid of each cell of the grid, which we used as a sample point. We selected 100 sample points in a random block design from the full population of centroids for a given ecoregion and repeated this for each of the 80 studied ecoregions. We then used the HILDA+ Global Land Use Change layer (HILDAplus_vGLOB-1.0; Winkler, Fuchs, Rounsevell, & Herold, 2021) to evaluate the land use types for the resulting grid of 8,000 points. The HILDA+ layer contains land cover information from 1960 to 2019, which allowed us to mask points defined as urban, cropland, ocean, water, or as missing data. We used the remaining unmasked points, defined as forest, shrubland, pasture, rangeland, or unmanaged grassland, in our analyses. These latter categories containing perennial TDL vegetation made up the 5,831 sample points used in our analyses. We used a randomized block design to assess relationships between NDVI and climatic and edaphic variations found across TDL (Figure 1). All spatial analyses were conducted in ArcGIS 10.2.1. We assumed some level of homogeneity within a given ecoregion with respect to soils, climate, flora and fauna, and other factors to examine ecological patterns across each of the 80 ecoregions (Olson et al., 2001; Dinerstein et al., 2017).

For Peer Review

### 2.3 Normalized difference vegetation index

We used 12 years (2005 to 2016) of NDVI data (250 m pixel resolution) collected with Moderate Resolution Imaging Spectroradiometer (MODIS) instruments aboard US NASA's Terra and Aqua satellites. The MODIS product was used because of its longevity, resolution, and frequent observations. Data analyses relied on 12-yr mean NDVI conditions for each of the 80 ecoregions sampled here. While data are collected sub-weekly, we used averaged monthly data to calculate mean annual NDVI for the 12-yr period. NDVI is dimensionless and ranges from -0.1 to 0.9, with higher values associated with denser vegetation and lower values associated with sparser vegetation. The lowest values represent bare ground.

### 2.4 Climatic and edaphic metrics

For each sample point, we obtained rainfall, temperature, and evapotranspiration data from repositories including: NASA Earth Observations (https://neo.gsfc.nasa.gov/); Climatic Hazards Center - UC Santa Barbara (www.chc.ucsb.edu/about); Numerical Terradynamic Simulation Group (NTSG)-University of Montana (www.ntsg.umt.edu/); Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) for Biogeochemical Dynamics (www.daac.ornl.gov/); and SOILGRID (www.soilgrids.org/). We examined a total of 17 climate variables: four temperature metrics, 10 precipitation metrics, an evapotranspiration metric, and two aridity metrics that integrate annual precipitation and temperature measures (Table 1). All

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climate variables were summarized into mean annual averages representing from 1 up to 12 years of available data (Table S3). We also considered 17 edaphic metrics involving physical, chemical and biological properties of soils (Table 1). These were all represented by a single point in time measurement, and so have no temporal averaging component. Each of the 34 metrics was processed and normalized to standard units. Detailed information on the time frame, scale, units and reference sources of each of the 34 variables used are specified in Table S3.

### 2.5 Data analyses

We explored mean annual NDVI variation against mean annual precipitation, number of dry months and mean annual temperature. We used multiple regression models to relate these metrics to NDVI. Our assessment was comprehensive with respect to global distribution of TDF biome, but we did not evaluate the effects of forest successional age or ecological condition.

To identify and delineate different NDVI-based ecological groups within different biogeographic regions, we assumed mean NDVI value (mNDVI) for each observation $i$ is represented by the following model:

$$\text{mNDVI}^{i} \sim \text{Normal}(\mu_i, \sigma^2),$$

$$\mu_i \approx f(\boldsymbol{x}_i)$$

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where mean $\mu_i$ is well approximated by a regression tree (Breiman, Friedman, Olshen, & Stone, 1984) function $f$ of covariates $\boldsymbol{x}_i$ and the error variance is $\sigma^2$.

We used Pearson coefficients to identify significant climate and edaphic predictors of NDVI at both pantropical and biogeographic region scales. Bonferroni corrections were used whenever multiple pairwise comparisons were made. The rpart package (Therneau & Atkinson, 2019) in R version 3.6 computer programming language (R Core Team, 2019) was used to compute a regression tree with a maximum depth of 30. We performed 10-fold cross validation to select the value of the complexity parameter that minimizes the cross-validation error. The complexity parameter penalizes the regression tree for adding further splits. See documentation of *rpart* for more details (Therneau & Atkinson, 2019). We repeated the 10-fold cross validation 99 more times to compute a total of 100 values for the optimal complexity parameter. We then used the average of the 100 values as the optimal complexity parameter to prune the regression tree. This led to a tree with 137 splits and an $r^2$ of 0.90. We also pruned the regression tree so that the $r^2$ was reduced to 0.80, which led to a regression tree with 13 splits. While this second tree is expected to have more biased predictions than the tree selected by cross-validation, it has the practical value of 13 splits being generally easier to interpret and discuss compared with 137 splits. Pruning the regression tree to an $r^2$ of 0.70 resulted in 5 splits, which we present and discuss below. Finally, using the NDVI differentiated ecological groups from the regression tree, multiple regressions were used to explore variation against principal components in analyses designed to capture edaphic or climatic driven variation in NDVI.

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## 3 RESULTS

### 3.1 Tropical dry landscapes and NDVI distributions across ecoregions

The five biogeographic regions examined here contain 80 TDL ecoregions that were distributed across four continents (Figure 2). The Afrotropic biogeographic region represented 68% of global TDL and contained 25 ecoregions, one of which accounted for 15% of all TDL (Sahelian Acacia Savanna). The Neotropic biogeographic region represented 24% of total TDL and contained 35 ecoregions. The Indo-Malayan, Australasian, and Oceanian biogeographic regions combined to represent 8.4% of all TDL with 20 ecoregions. We found considerable variation in average NDVI values across biogeographic regions, with mean values increasing as follows: Afrotropic < Indo-Malayan < Neotropic < Australasia < Oceania (Figure 2).

### 3.2 Variation of climatic and edaphic metrics

The classic TDF metrics of MAT, MAR, and mean annual number of dry months were important predictors of mean annual NDVI across the 5,831 TDL sample points and showed high variation across biogeographic regions (Table 1). MAT varied from 25.9 to 39.3 °C, MAR varied from 662 to 1505 mm, and number of dry months varied between 6 and 9. Similarly, our two drought intensity metrics were highly variable, with mean minimum precipitation in the driest month ranging from < 1 mm to 14 mm, and total precipitation in the driest quarter ranging from 6 mm to 71 mm (Table 1). We found that mean annual evapotranspiration ($ET_m$) varied from 554 to

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1214 mm $yr^{-1}$ while the coefficient of variation (CV) for the Lang and Martonne aridity indices was nearly 60% (Table 1). Global scale variation in physical soil properties was low for bulk density (CV = 9.6%) but high for potential water storage (CV = 62.3%). For soil chemical properties, pH varied from 5.7 to 6.9. For soil biological properties, organic carbon storage ranged from 26.1 to 57.9 Mg $ha^{-1}$ (0-1.0 m in depth) while total phosphorus concentrations ranged from 272 to 504 g $m^{-2}$ (0-0.5 m in depth) (Table 1).

### 3.3 Relationships of NDVI with climate and edaphic metrics

Pearson correlation analysis indicates that mean annual NDVI was strongly correlated with all 11 climatic metrics ($p < 0.001$), and these relationships were stronger than those with soil metrics (Supporting Information Table S4). The NDVI relationships with MAT, Lang Aridity Index, ET, and number of months under hydric stress were particularly strong, indicating a robust basis for using these three-climate metrics as primary TDL indicators (Figure 3). The strength of NDVI relationship with the 13-soil metrics was more variable, ranging from $r = -0.60$ in the case of pH ($p < 0.001$) to a non-significant relationship with total phosphorus content ($r = -0.02$, $p > 0.05$). We also observed differences in NDVI among biogeographic regions (Figure 2b), with the strength and number of significant metrics (Supporting Information Table S4).

We observed strong negative correlations between mean annual NDVI and the mean annual number of months under hydric stress ($r = -0.73$), mean temperatures in the warmest month ($r = -$

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0.70), and the mean number of the dry months ($r$ = -0.64). Conversely, we observed strong positive correlations between NDVI and MAR ($r$ = 0.71), mean rainfall in the wettest month ($r$ = 0.51), mean total rainfall during the rainy season ($r$ = 0.60), mean total rainfall in the driest quarter ($r$ = 0.42), and mean rainfall in the driest month ($r$ = 0.40) (Supporting Information Figure S1). The number of dry months also had a negative relationship with NDVI, with the highest NDVI values associated with 2 to 4 months of drought, while the lowest NDVI being associated with the highest number of dry months (Supporting Information Figure S1). The highest NDVI values were correlated with the highest $ET_m$ values, while the lowest NDVI values were associated with the lowest MAP values (Supporting Information Figure S1). Of the edaphic metrics, pH was the best predictor of NDVI ($r$ = -0.60), while water holding capacity and field capacity were the best physical predictors of NDVI ($r$ = 0.38 and 0.31, respectively; Supporting Information Figure S2). Soil organic carbon was the best but a somewhat weak biological predictor of NDVI ($r$ = 0.25; Supporting Information Figure S3).

### 3.4 Tropical dry landscape classification model

Our regression tree statistical modeling identified 14 climate and soil metrics as the most important predictors of NDVI variation across TDL (capture 90% of variation; Figure 4a). This regression tree was pruned to reduce the number of splits, with only three variables needed to capture 70% of the variation in NDVI. This most parsimonious regression tree model included three climatic metrics (ET, Lang Aridity Index, MAT), which we used to partition our global

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TDL dataset into five NDVI-based ecological groupings (Figure 4b). The TDL with the highest NDVI value (G*roup 5*; Figure 4b) included sites with an $ET_m$ above of 989 mm. The number of months under hydric stress and the maximum temperature of the hottest month also had high importance values within the statistical model (Figure 4a). The lowest NDVI groups were located mainly in the Afrotropic biogeographic region, while the highest were in the Neotropic and Indo-Malayan biogeographic regions (Figure 4c). These analyses provide a quantitative global characterization that refines our understanding of the variability of this biome across spatial scales (Supporting Information Table S1).

## 4 DISCUSSION

### 4.1 What are tropical dry landscapes really?

Mooney, Medina, & Bullock (1995) identified TDF as those forests occurring in tropical regions characterized by pronounced seasonality in precipitation distribution. Others have elaborated on the conditions required to sustain TDF including the role of MAP, MAT, and the number of dry months (Supporting Information Table S1). To assess these classic relationships, we systematically characterized the climatically and edaphically driven spatial variation in TDL NDVI. Specifically, by inventorying a global distribution of 5,831 TDL sites and analyzing how NDVI for these sites correlate with 34 climatic and edaphic variables in regression tree analyses, we have developed a comprehensive statistical model for describing variation in global TDL.

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This model includes three climatic metrics: ET, Lang Aridity Index, and MAT. This model represents a parsimonious and robust improvement over classic single index-based approaches to explaining ecoregional scale variation in NDVI across TDL.

We found that ET, Lang Aridity Index, and MAT were sufficient to delineate global TDL into five major NDVI categories, providing a novel climatic categorization of this forest into distinct biogeographic TDL types defined by NDVI – a remotely sensed attribute strongly linked to forest structure and function. The underlying climate relationships with NDVI indicate strong spatial variability in TDL structure and productivity across biogeographic regions and ecoregions. To this end, our five-tier categorization of TDL provides a structurally and functionally quantitative way to describe its global variation. Taken together, these findings highlight the value of a remote sensing based statistical modeling approach to quantifying extent and variation of the TDF biome. The climatic and edaphic variables used in the full model explained 90% of NDVI variation across TDL. Moreover, although the pruned fitted regression tree model identified MAT, $ET_m$, and Lang Aridity Index as important predictors of NDVI, explaining 70% of NDVI variation. Neither $ET_m$ not Lang Aridity Index have been used previously to characterize TDF biogeography.

### 4.2 NDVI of tropical dry landscapes

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Our statistical model relied on 34 climatic and edaphic characteristics to describe NDVI of the TDL inventoried here. We used NDVI as an index of ecosystem productivity which we used delineate five TDL types. NDVI is easily accessible through GIS and provides the longest temporal record of global vegetation condition, which allows for analyses of interannual variation, baseline climate change, or impact of specific events (Schloss, Kicklighter, Kaduk, Wittenberg, & Intercomparison, 1999). Generally, mean NDVI varied widely among TDL biogeographic regions, with more sensitivity to spatial variation in climate (positive relationship with $ET_m$ and MAP; negative relationship with MAT) than with soils. These analyses suggest that TDL productivity is significantly constrained by the energy demand as defined by ET, and water supply as defined by MAR– the Budyko effect (Zhou, Yu, Huang, & Wang, 2015). The effects of $ET_m$ and precipitation on NDVI observed in our study aligns with findings that global C fluxes in water-limited regions are primarily controlled by precipitation and ET (Poulter et al., 2014; Zhang et al., 2016). Our results show the strong coupling of NDVI to spatial variations in water availability in TDL, including water holding capacity of soils, at both global and regional scales, which aligns with the fast temporal response of vegetation to water deficit changes in intensely water-limited environments (Giraldo & Holbrook, 2011; Becknell et al., 2012; Vicente-Serrano et al., 2013; Portillo-Quintero, Sanchez-Azofeifa, Calvo-Alvarado, Quesada, & do Espirito Santo, 2015; Rojas-Robles et al., 2020), including seasonal moisture controls on ecosystem biogeochemistry (Castro et al., 2018; Liu, Zhang, Wu, Li, & Qin, 2018; Mendes et al., 2020). Our findings are consistent with the broadly appreciated control that air temperature and precipitation via soil moisture have on plant growth and TDF dynamics (Nemani, 2003; Seddon,

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Macias-Fauria, Long, Benz, & Willis, 2016; Humphrey et al., 2018; Liu et al., 2018; Green et al., 2019; Stan et al., 2021).

Conversely, because temperature is rarely limiting to canopy processes in the tropics (Huang et al., 2019), negative correlations with MAT are expected. As NDVI saturates over regions of dense vegetation (Jones & Vaughan, 2010), results in the tropics need to be interpreted with caution (Linscheid et al., 2020). Across tropical dry, moist, and wet forests, NDVI shows correlations with climate that vary within and across continents (Linscheid et al., 2020). Such spatial variation can be explained by the spatial variation in the strength of intra-annual seasonality of tropical environments, for example alterations in precipitation and temperature regimes associated with the Madden-Julian Oscillation (Zhang, 2005; 2013), which could drive temporal NDVI oscillations in the tropics (Hidayat, 2016; Mayta, Ambrizzi, Espinoza, & Dias, 2019; Wang, Chen, & Liu, 2019). Considering the long-term decrease in precipitation amount that is expected in seasonally dry tropical regions (Greve et al., 2014; Chadwick, Good, Martin, & Rowell, 2015; Huang, Yu, Guan, Wang, & Guo, 2016), further investigation is needed on additional climatic factors (e.g., radiation) that may also exert a strong influence on C cycling in tropical forests (Nemani, 2003; Seddon et al., 2016; Lyu, Giardina, & Litton, 2021).

Our study explores how productivity is regulated in TDL, with spatial variation being modestly dependent on soil properties. Soil pH consistently had a strong, negative relationship with NDVI across ecoregions, likely reflecting the influence of soil fertility on productivity (Castro et al.,

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2018; Corona-Núñez et al., 2018; Hofhansl et al., 2020). While there is evidence that productivity in TDF can be phosphorus-limited (Gei & Powers, 2014), our analyses of total soil phosphorus concentrations, a proxy for plant available phosphorus, show statistically non-significant relationships with mean annual NDVI across our 80 ecoregions. We cannot determine whether this pattern was driven by the negative relationship between NDVI and total soil phosphorus across Afrotropical and Indo-Malayan ecoregions, or whether a positive real effect of this nutrient on NDVI was obscured by the stronger influence of $ET_m$ and MAP on NDVI, with higher MAP, for example, driving lower phosphorus through enhanced weathering of soils.

### 4.3 NDVI, biogeographic patterns, and climate change

We found strong biogeographic patterns with respect to the NDVI groups at pantropical scale. The lowest NDVI group (*Group 1*) was located mainly in the Afrotropic biogeographic region, while the highest NDVI group (*Group 5*) was located mainly in the Neotropic and Indo-Malayan biogeographic regions. Despite this geographic segregation, all five groups occurred in all three biogeographic regions. This overlap between NDVI groups within continents could reflect comparable variability in climatic and edaphic factors within biogeographic regions. Conversely, the overlap could relate to the lack of floristic differences between Africa and Asia, with floristic differences for the TDL of the Neotropics (Dexter et al., 2015). Future research could focus whether TDL flora share a common biogeographic origin (Silk et al., 2018), where selection for

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drought and fire resistance has favored the dominance of similar plant lineages globally (Banda-R. et al., 2016; Ratnam, Tomlinson, Rasquinha, & Sankaran, 2016).

Our pruned climo-edaphic regression tree model relied MAT, $ET_m$, and Lang Aridity Index, which we used to identify five global NDVI categories of TDL and to highlight the structural and functional diversity of TDL (Figure 4b). We also suggest that these delineations may represent thresholds that can be used to identify which categories of TDL may be the most susceptible to climate change. For example, TDL in the *Group 5* category show the highest NDVI values, support the highest $ET_m$, and the lowest Lang Aridity Index values (Figure 5a, 5b), and so may represent areas that are less sensitive to warming and drying. Some *Group 5* category areas support TDF ecosystems that have resilience to both the high inter-annual droughts and the frequent within-rainy season droughts (Maass et al., 2017), and to high temperatures (González-M. et al., 2018). In contrast, *Group 1* areas with the lowest NDVI values and highest MAT (Figure 5c) may occur at the climatic margins of the TDF biome. For example, while $ET_m$ differentiated the group with the highest NDVI values (*Group 5*), the Lang Aridity Index differentiated the two groups with the lowest NDVI values (*Groups 1* and *2*). For *Group 1* areas found mainly in ecoregions of Africa and Neotropics of Brazil, MAR is very low and Lang Aridity Index is very high, which negatively affect plant growth (D'Onofrio et al., 2018). When tree species diversity is high, TDF areas exhibiting drought tolerance except under the most extreme circumstances (Stan & Sanchez-Azofeifa, 2019). When paired with climate change projections for an ecoregion or a biogeographic region, these delineations can be used to assess

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potential for rapid change including proximity to ecological tipping points (Scheffer et al., 2009). The existence of climate driven thresholds has been suggested for diverse terrestrial ecosystems including tropical rainforests (Lenton et al., 2008), but the nature of tipping points for TDF is poorly understood (Lenton et al., 2008; Seddon et al., 2016; but see also Campo, 2016).

## 5 CONCLUSIONS

We report here an improved approach to characterizing the TDF biome and address a long-standing question regarding climatic and edaphic controls on TDF distribution and function. This work advances a remote sensing based analysis to characterize previously under-appreciated controls the functioning of the TDF biome, with the 34 climatic and edaphic variables considered here explaining 90% of NDVI variation across TDL. Further, we report that the Lang Aridity Index, MAT, and $ET_m$ explain 70% of the variation in NDVI for this remarkably diverse biome. Our analysis point to a need however to explore how the quantitative insights into NDVI variability can be used to anticipate susceptibility of the TDF biome to climate change. Our delineation of TDL into five NDVI-based categories may prove useful in forecasting the ecosystem changes in response to climate change, especially declines in precipitation or increases in temperature.

**Data Availability Statement**. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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For Peer Review

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**Data Accessibility:** Data will be available upon request

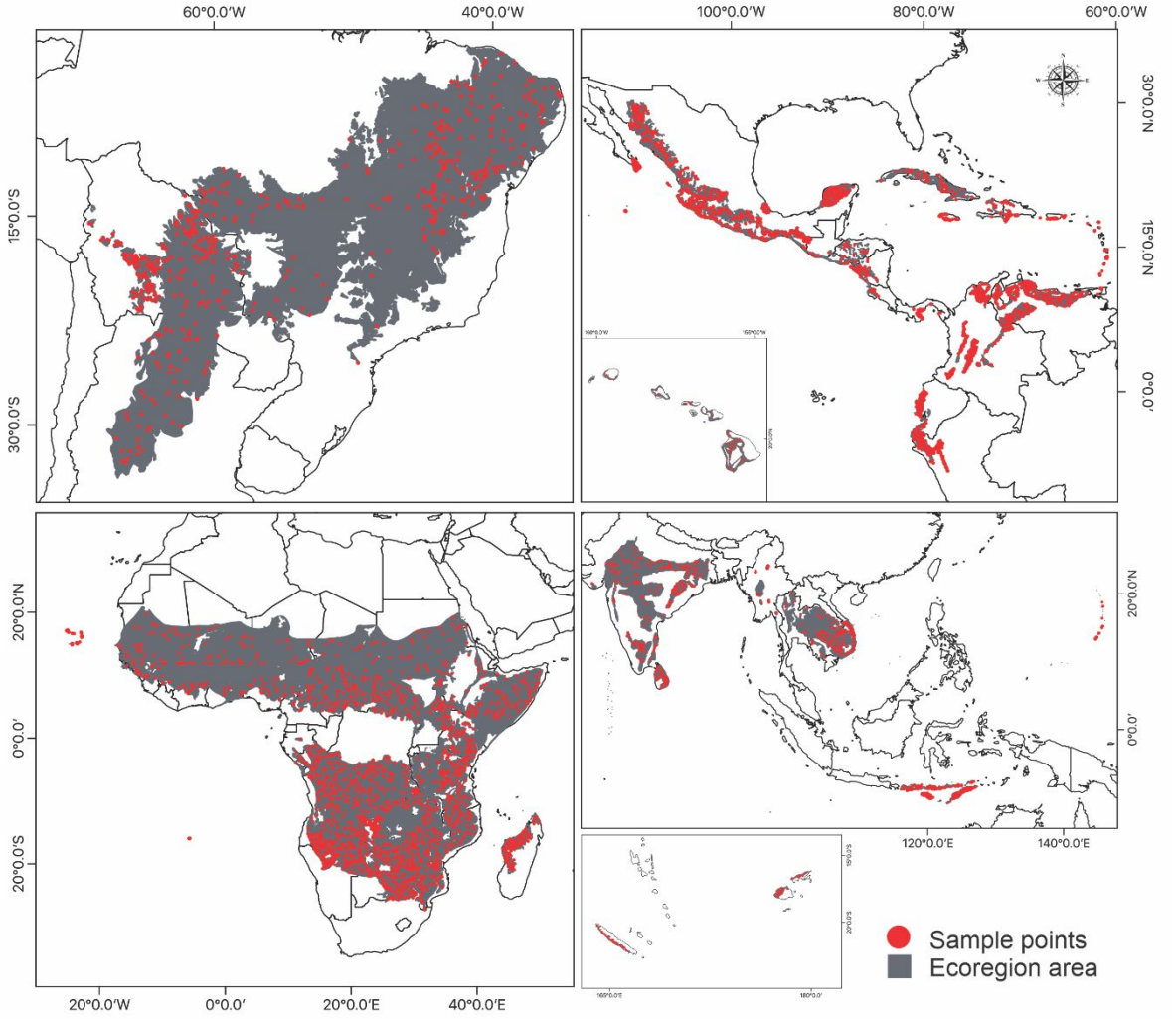

**FIGURE 1** The distribution of tropical dry forest ecoregions (in gray) examined in this global synthesis. Red circles indicate the distribution of the 100 sample points within each ecoregion.

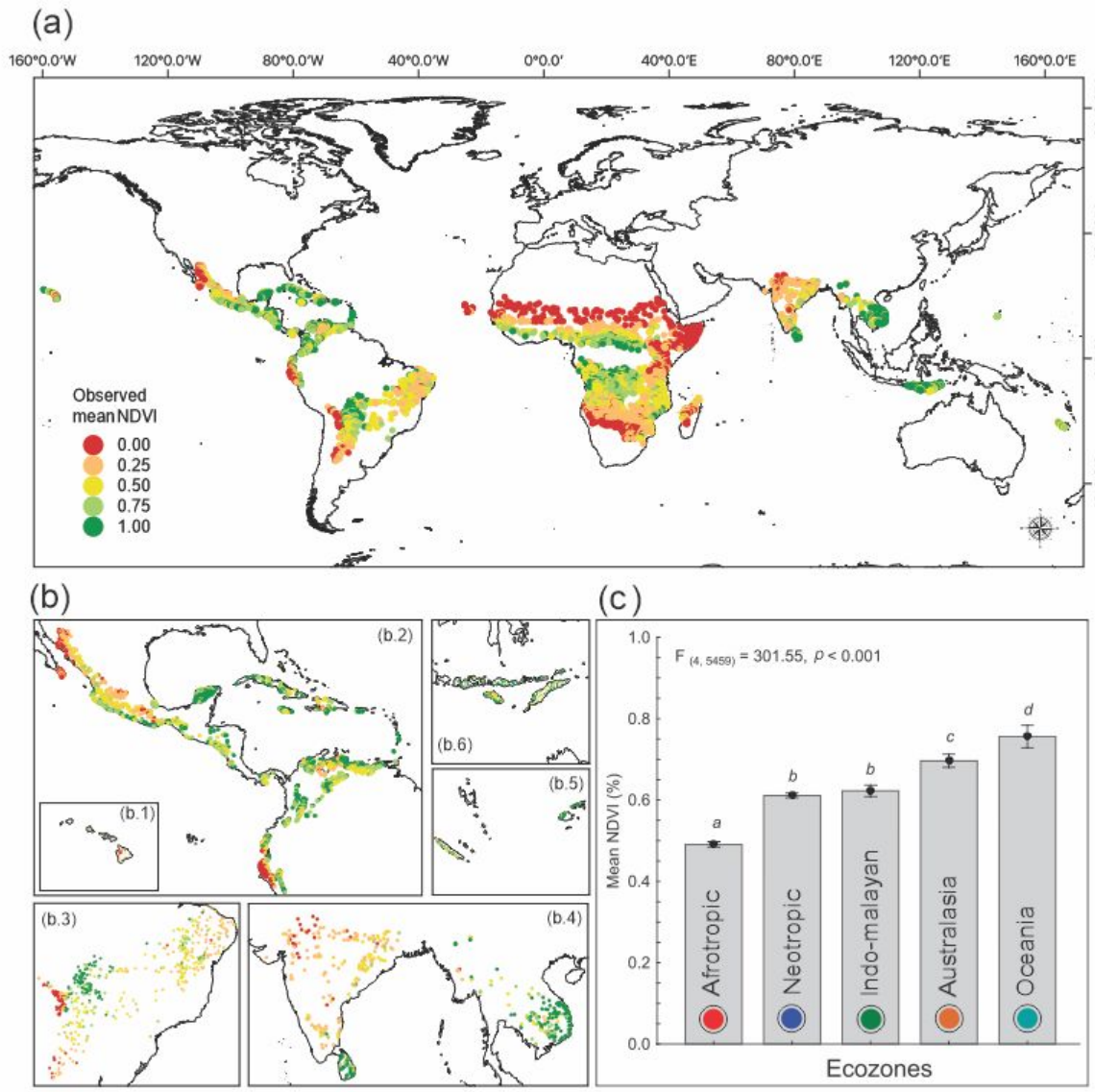


**FIGURE 2** (**a**) Distribution of normalized difference vegetation index across the biogeographic regions with (**b**) high resolution insets for (b.1) Hawaii islands, (b.2) Mexico and central America and Antilles islands, (b.3) South America, (b.4) Indian and Thailand region, (b.5) Micronesian islands and (b.6) Indonesian islands. (**c**) Mean and standard error of normalized difference vegetation index for each

biogeographic region. Circles indicate the means and the spreads denote 95% confidence intervals and different letters indicate significant differences ($p < 0.05$) among biogeographic regions.

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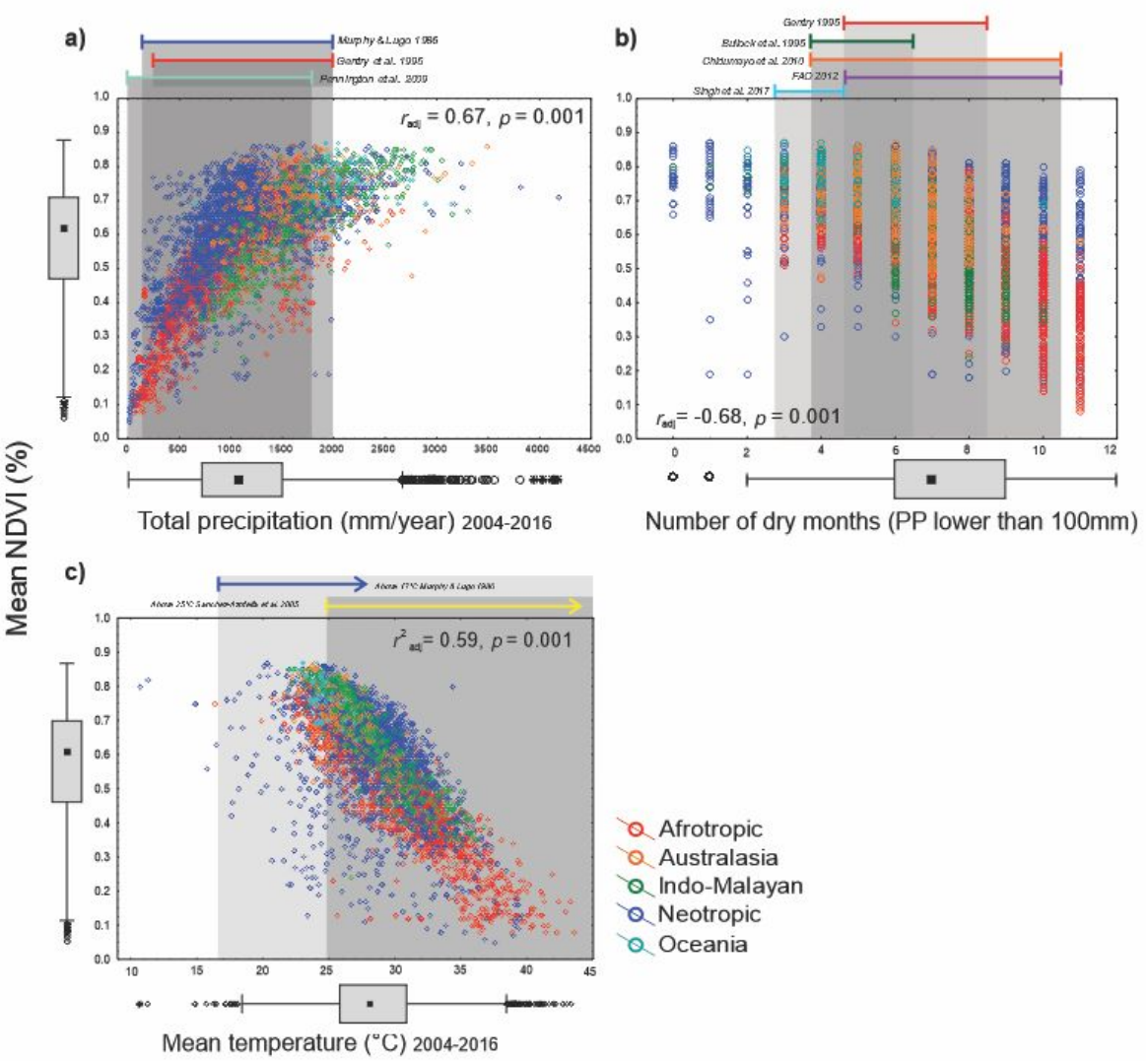


**FIGURE 3** Relationships between normalized difference vegetation index and (**a**) mean annual precipitation, (**b**) number of dry months (precipitation < 100 mm per month) and (**c**) mean annual temperature. Different colors represent the five different biogeographic regions. Grey shaded blocks identify regions of a figure defined as tropical dry forest by authors listed above each panel. Box plots show the median and standard deviation for each metric, while circles represent outliers and asterisk represent extreme values.

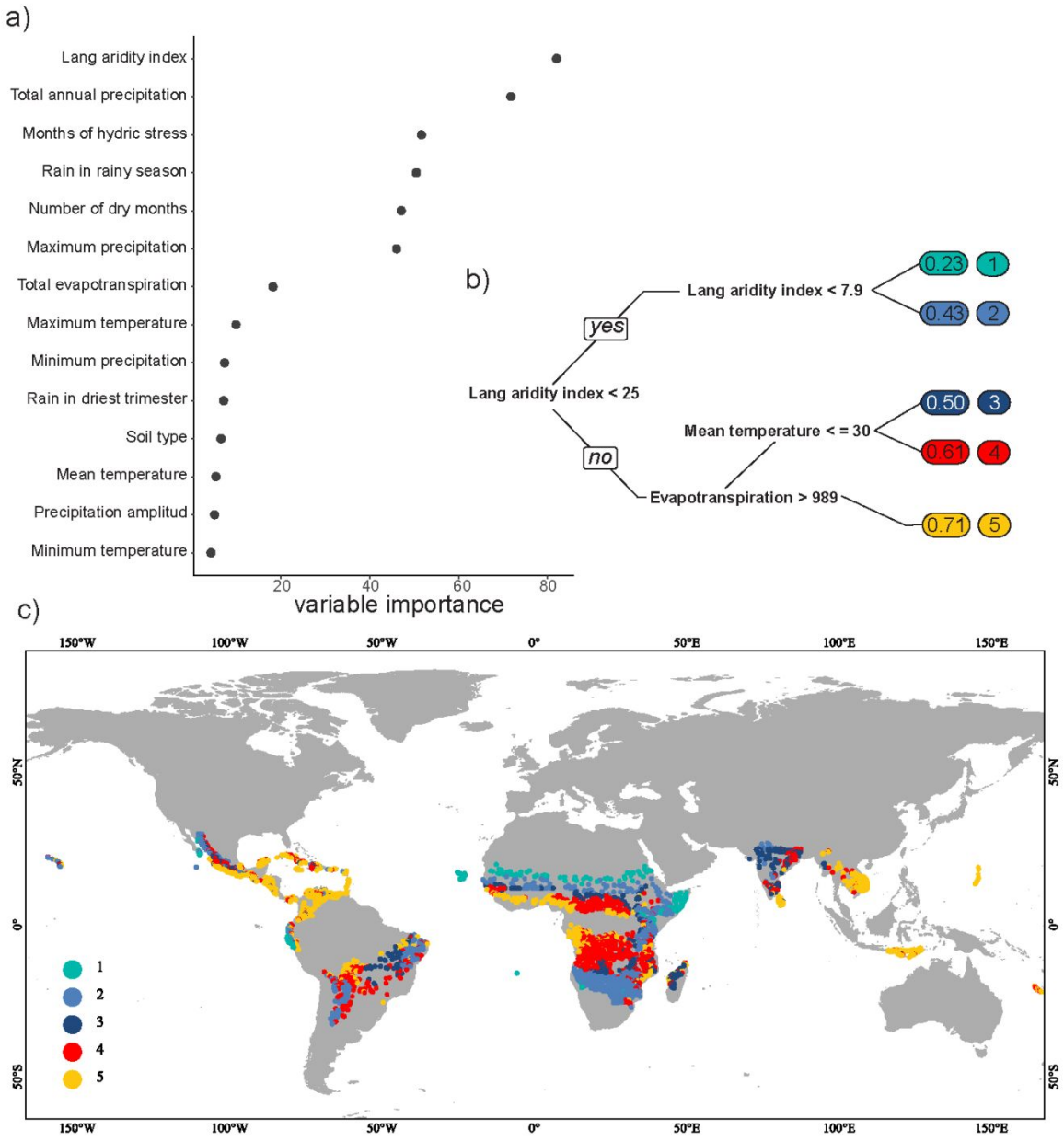


**FIGURE 4** (**a**) Classification of the tropical dry landscapes analyzed for the 80 tropical dry forest ecoregions, (**b**) importance of climate and soil metrics within the regression tree decision model and (**c**) map of the five identified NDVI-based regression tree delineated tropical dry landscape *Groups.*

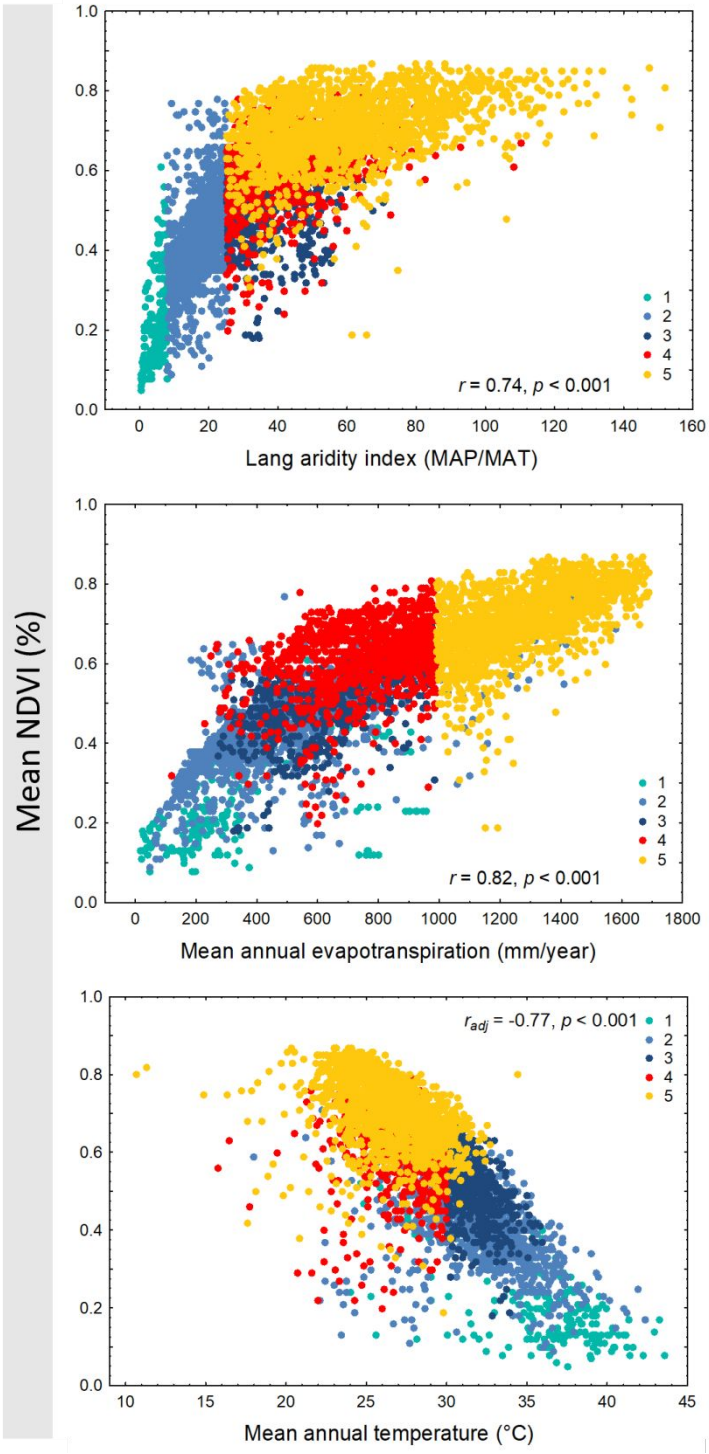


**FIGURE 5** Relationships between normalized difference vegetation index and (**a**) Lang Aridity Index (mean annual precipitation to mean annual temperature ratio), (**b**) mean annual evapotranspiration and (**c**)

mean annual temperature. Different colors represent the five NDVI-based regression tree delineated tropical dry landscape *Groups* (see Figure 4).

**TABLE 1** Normalized difference vegetation index (NDVI), climate and soil characteristics for the 80 tropical dry forest ecoregions studied. For each metric standardized units are presented.

| | Metrics | Mean | CV (%) | Qu. (0.25) | Median | Qu. (0.75) |
|---|---|---|---|---|---|---|
| | ***Vegetation*** | | | | | |
| 1 | *Normalized difference vegetation index* | 0.58 | 28.8 | 0.46 | 0.61 | 0.70 |
| | ***Climate*** | | | | | |
| 2 | *Mean annual temperature* (°C) | 28.6 | 13.2 | 25.9 | 28.2 | 39.3 |
| 3 | *Maximum temperature of the hottest month* (°C) | 34.4 | 16.9 | 29.7 | 34.3 | 39.3 |
| 4 | *Minimum temperature of the coldest month* (°C) | 24.1 | 12.4 | 22.5 | 24.1 | 25.6 |
| 5 | *Amplitude or range in temperature* (°C) | 10.3 | 48.2 | 6.3 | 9.9 | 14.5 |
| 6 | *Mean annual precipitation* (mm) | 1118.1 | 55.2 | 662.1 | 1060.6 | 1504.6 |
| 7 | *Maximum precipitation in the wettest month* (mm) | 229.9 | 53.0 | 146.2 | 216.2 | 290.7 |
| 8 | *Minimum precipitation in the driest month* (mm) | 11.5 | 154.8 | 0.79 | 4.2 | 14.0 |
| 9 | *Amplitude or range in precipitation* (mm) | 218.4 | 54.9 | 135.8 | 203.2 | 276.2 |
| 10 | *# Rainy months (> 100 mm of precipitation per month)* | 4.5 | 59.2 | 3 | 5 | 6 |
| 11 | *Total precipitation in the rainy season* (mm) | 891.1 | 72.9 | 348.8 | 872.7 | 1313.6 |
| 12 | *Concentration of precipitation in the rainy season* (%) | 67.5 | 45.1 | 54.8 | 81.6 | 89.2 |
| 13 | *# Dry months (< 100 mm of precipitation per month)* | 7.5 | 35.4 | 6 | 7 | 9 |
| 14 | *# Months under hydric stress* | 4.5 | 66.5 | 2 | 5 | 7 |
| 15 | *Precipitation in the driest quarter of the year* (mm) | 51.8 | 146.9 | 5.8 | 23.0 | 70.7 |
| 16 | *Lang Aridity Index* | 41.0 | 61.7 | 22.2 | 37.6 | 55.3 |
| 17 | *Martonne Aridity Index* | 29.9 | 59.8 | 16.7 | 27.7 | 40.4 |
| 18 | *Mean annual evapotranspiration* (mm) | 883.4 | 45.7 | 553.5 | 888.2 | 1214.2 |
| | ***Soil*** | | | | | |
| 19 | *Depth* (m) | 2.1 | 62.3 | 1.3 | 1.9 | 3.6 |
| 20 | *Bulk density*[1] (g $m^{-2}$) | 1.4 | 9.6 | 1.4 | 1.5 | 1.5 |
| 21 | *Coarse fragments*[1] (%) | 13.2 | 75.4 | 6.0 | 11.0 | 18.0 |
| 22 | *Clay content*[1] (%) | 33.9 | 29.8 | 30.0 | 36.0 | 41.0 |
| 23 | *Field capacity*[1] (mm) | 408.2 | 10.2 | 390.5 | 412.9 | 429.9 |
| 24 | *Water holding capacity** (mm) | 354.0 | 52.6 | 234.0 | 330.0 | 418.0 |
| 25 | *Wilting point*[1] (mm) | 171.5 | 23.9 | 153.0 | 176.2 | 197.9 |
| 26 | *Potential storage of water from soil texture** (mm) | 359.9 | 62.3 | 224.0 | 328.0 | 612.0 |
| 27 | *Potential storage of water in soil profile** (mm) | 1037.9 | 62.1 | 680.0 | 864.0 | 1529.0 |
| 28 | *pH*[1] *($H_2O$)* | 6.3 | 12.8 | 5.7 | 6.2 | 6.9 |

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|---|---|---|---|---|---|---|
| 29 | *Cation exchange capacity*[1#] ($cmol_c\ kg^{-1}$) | 17.6 | 40.8 | 12.3 | 17.5 | 21.7 |
| 30 | *Organic carbon*[2] ($Mg\ ha^{-1}$) | 59.2 | 115.1 | 26.1 | 37.8 | 57.9 |
| 31 | *Organic carbon*[1#] ($Mg\ ha^{-1}$) | 75.6 | 92.8 | 35.5 | 56.8 | 81.5 |
| 32 | *Total nitrogen*[1] ($g\ m^{-2}$) | 919.2 | 67.3 | 345.6 | 919.0 | 1364.7 |
| 33 | *Total phosphorus*[3‡] ($g\ m^{-2}$) | 430.9 | 71.1 | 272.4 | 321.9 | 503.8 |
| 34 | *Organic phosphorus*[3‡] ($g\ m^{-2}$) | 99.2 | 103.1 | 41.9 | 67.6 | 130.9 |
| 35 | *Labile inorganic phosphorus*[3‡] ($g\ m^{-2}$) | 40.1 | 87.9 | 19.7 | 34.7 | 42.5 |

*Notes.* 1, soil depth 0-1.0 m; 2, soil depth 0-0.3 m; 3, soil depth 0-0.5 m; *, soil depth non-indicated; #, this information was calculated using data of 0-0.05, 0.05-0.15, 0.15-0.30, 0.30-0.60 and 0.60-1.0 m soil layers in the case of cation exchange capacity and data of 0-0.30 and 0.30-1.0 m soil layers in the case of organic carbon; ‡, this information needs to be interpreted with caution, since the included values are very large considering the values of nitrogen.

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## Supplementary material

Table S1. Cited metrics used to describe tropical dry forests.

Table S2. Ecoregions included in this study.

Table S3. Analyzed metrics.

Table S4. Pearson correlation coefficients.

Figure S1. Relationships of normalized vegetation index with climate.

Figure S2. Relationships of normalized vegetation index with soil physical characteristics.

Figure S3. Relationships of normalized vegetation index with soil chemical characteristics.

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## SUPPLEMENTARY INFORMATION

**TABLE S1** Most cited metrics used to describe tropical dry forests. MAP, mean annual precipitation; MAT, mean annual temperature; ET, annual evapotranspiration.

| Name | MAP (mm) | MAT (˚C) | Number of dry months | Others | Reference |
|---|---|---|---|---|---|
| *Seasonally dry tropical forest* | 250 - 2000 | ≥ 17 | 4 - 6 | *ET/MAP*≥1 | Bullock et al. (1995) |
| | 100 - ~1800 | | 5 - 8 | Vegetation largely deciduous | Gentry (1995) |
| | < 1800 | | 5 - 6 | Frost-free | Pennington et al. (2009) |
| *Tropical dry deciduous forest* | 250 - 2000 | ≥ 13 | 3 - 4 | | Singh & Chaturvedi (2017) |
| | 300 - 1200 | | 5 - 10 | >30% tree cover | FAO (2012) |
| | 250 - 2000 | ≥ 17 | | Frost-free, *ET/MAP*≥1 | Murphy & Lugo (1986) |
| | 700 - 2000 | ≥ 25 | Bimodal or unimodal rainfall | | Sánchez-Azofeifa et al. (2005) |
| | | | Extended drought season | Latitude 20 to 10˚ North and South, 50 - 100% leaf loss in the dry season. 75% broad leaf cover. | Bezaury-Creel et al. (2010) |

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|---|---|---|---|
| *Semi-arid dry woodlands* | 250 - 450 | 7.5 - 10 | Chidumayo & Gumbo (2010) |
| *Warm mesic dry woodlands* | 600 - 1200 | 7.5 - 8 | |
| *Sub-humid dry forest* | 1200 - 2000 | 4 - 5 | |

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**TABLE S2** Ecoregions included in this study, their surface and the group number derived from the tree model.

| | Ecoregion | Surface ($km^2$) | NDVI-based ecological groups | Reference |
|---|---|---|---|---|
| 1 | Angolan Miombo Woodlands | 690,767 | *2,3,4* | (1) |
| 2 | Angolan Mopane Woodlands | 146,990 | *1,2* | (1) |
| 3 | Apure-Villavicencio Dry Forests | 69,342 | *5* | (2,3) |
| 4 | Atlantic Dry Forests | 120,431 | *2,3,4,5* | (2,3) |
| 5 | Bajío Dry Forests | 42,558 | *2,3,4* | (2,3) |
| 6 | Balsas Dry Forests | 69,149 | *2,3,4,5* | (2,3) |
| 7 | Bolivian Montane Dry Forests | 81,285 | *2,4,5* | (2,3) |
| 8 | Caatinga | 750,198 | *2,3,4,5* | (4) |
| 9 | Cape Verde Islands Dry Forests | 4,915 | *1* | (2,3) |
| 10 | Cauca Valley Dry Forests | 7,367 | *5* | (2,3) |
| 11 | Central American Dry Forests | 71,562 | *3,4,5* | (2,3) |
| 12 | Central Deccan Plateau Dry Deciduous Forests | 267,321 | *2,3,4* | (2,3) |
| 13 | Central Indochina Dry Forests | 343,625 | *4,5* | (2,3) |
| 14 | Central Zambezian Miombo Woodlands | 1,216,745 | *2,3,4,5* | (1) |
| 15 | Cerrado | 2,060,259 | *3,4,5* | (4) |
| 16 | Chhota-Nagpur Dry Deciduous Forests | 145,384 | *3,4* | (2,3) |
| 17 | Chiapas Depression Dry Forests | 15,155 | *3,4,5* | (2,3) |
| 18 | Chiquitano Dry Forests | 249,035 | *4,5* | (2,3) |
| 19 | Cuban Dry Forests | 76,074 | *3,4,5* | (2,3) |
| 20 | Dry Chaco | 965,297 | *2,4,5* | (4) |
| 21 | East Deccan Dry-Evergreen Forests | 26,570 | *3,4* | (5) |

| | | | | |
|---|---|---|---|---|
| 22 | East Sudanian Savanna | 935,406 | *2,3,4,5* | (1) |
| 23 | Eastern Miombo Woodlands | 505,945 | *3,4,5* | (1) |
| 24 | Ecuadorian Dry Forests | 21,204 | *1,2,4,5* | (2,3) |
| 25 | Fiji Tropical Dry Forests | 7,557 | *5* | (2,3) |
| 26 | Guinean Forest-Savanna Mosaic | 687,746 | *3,4,5* | (1) |
| 27 | Hawaiian High Islands: Hawaii Tropical Dry Forests | 5,751 | *2,3,4,5* | (2,3) |
| 28 | Hispaniolan Dry Forests | 17,244 | *2,3,4,5* | (2,3) |
| 29 | Irrawaddy Dry Forests | 39,996 | *3,4,5* | (2,3) |
| 30 | Islas Revillagigedo Dry Forests | 238 | *2* | (2,3) |
| 31 | Itigi-Sumbu Thicket | 7,937 | *2,3,4* | (1) |
| 32 | Jalisco Dry Forests | 29,331 | *3,4,5* | (2,3) |
| 33 | Jamaican Dry Forests | 2,553 | *4,5* | (2,3) |
| 34 | Kalahari Acacia-Baikiaea Woodlands | 384,289 | *2* | (1) |
| 35 | Khathiar-Gir Dry Deciduous Forests | 321,576 | *2,3* | (2,3) |
| 36 | La Costa Xeric Shrublands | 70,180 | *3,5* | (6) |
| 37 | Lara-Falcón Dry Forests | 17,494 | *2,5* | (2,3) |
| 38 | Lesser Antillean Dry Forests | 960 | *2,5* | (2,3) |
| 39 | Lesser Sundas Deciduous Forests | 40,171 | *4,5* | (2,3) |
| 40 | Madagascar Dry Deciduous Forests | 165,736 | *3,4,5* | (2,3) |
| 41 | Magdalena Valley Dry Forests | 19,643 | *3,4,5* | (2,3) |
| 42 | Mandara Plateau Mosaic | 7,735 | *2,3* | (7) |
| 43 | Marañón Dry Forests | 11,465 | *3,4,5* | (2,3) |
| 44 | Maracaibo Dry Forests | 31,031 | - | (2,3) |
| 45 | Marianas Tropical Dry Forests | 1,102 | *5* | (2,3) |
| 46 | Narmada Valley Dry Deciduous Forests | 199,313 | *2,3,4* | (2,3) |

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|---|---|---|---|---|
| 47 | New Caledonia Dry Forests | 5,078 | *4,5* | (2,3) |
| 48 | Northern Acacia-Commiphora Bushlands and Thickets | 325,257 | *1,2,3,4,5* | (1) |
| 49 | Northern Congolian Forest-Savanna Mosaic | 711,853 | *3,4,5* | (1) |
| 50 | Northern Dry Deciduous Forests | 66,246 | *3,4,5* | (2,3) |
| 51 | Panamanian Dry Forests | 5,192 | *3,4,5* | (2,3) |
| 52 | Patía Valley Dry Forests | 2,263 | *4,5* | (2,3) |
| 53 | Puerto Rican Dry Forests | 1,405 | *2,4,5* | (2,3) |
| 54 | Sahelian Acacia Savanna | 3,258,413 | *1,2,3* | (1) |
| 55 | Sierra De La Laguna Dry Forests | 4,726 | *1,2* | (2,3) |
| 56 | Sinaloan Dry Forests | 25,666 | *2,3,4,5* | (2,3) |
| 57 | Sinaí Valley Dry Forests | 93,173 | - | (2,3) |
| 58 | Somali Acacia-Commiphora Bushlands and Thickets | 1,063,581 | *1,2,4,5* | (1) |
| 59 | Sonoran-Sinaloan Transition Subtropical Dry Forest | 62,547 | *1,2,3,4* | (2,3) |
| 60 | South Deccan Plateau Dry Deciduous Forests | 85,460 | *2,3,4,5* | (2,3) |
| 61 | Southeastern Indochina Dry Evergreen Forests | 130,631 | *4,5* | (5) |
| 62 | Southern Acacia-Commiphora Bushlands and Thickets | 228,394 | *2,3,4,5* | (1) |
| 63 | Southern Africa Bushveld | 261,206 | *2,4* | (1) |
| 64 | Southern Congolian Forest-Savanna Mosaic | 573,357 | *4,5* | (1) |
| 65 | Southern Miombo Woodlands | 448,286 | *2,3,4,5* | (1) |
| 66 | Southern Pacific Dry Forests | 46,037 | *2,3,4,5* | (2,3) |
| 67 | Southern Vietnam Lowland Dry Forests | 36,953 | *5* | (2,3) |
| 68 | Sri Lanka Dry-Zone Dry Evergreen Forests | 49,122 | *3,5* | (5) |
| 69 | St. Helena Scrub and Woodlands | 141 | *1* | (1) |

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|---|---|---|---|---|
| **70** | Sumba Deciduous Forests | 11,037 | *3,4,5* | (2,3) |
| **71** | Timor and Wetar Deciduous Forests | 34,262 | *4,5* | (2,3) |
| **72** | Tumbes-Piura Dry Forests | 41,450 | *1,2,4,5* | (2,3) |
| **73** | Veracruz Dry Forests | 7,400 | *4,5* | (2,3) |
| **74** | West Sudanian Savanna | 1,705,016 | *2,3,4* | (1) |
| **75** | Western Congolian Forest-Savanna Mosaic | 416,006 | *4,5* | (1) |
| **76** | Yap Tropical Dry Forests | 104 | - | (2,3) |
| **77** | Yucatan Dry Forests | 56,488 | *4,5* | (2,3) |
| **78** | Zambezian and Mopane Woodlands | 530,736 | *1,2,3,4,5* | (1) |
| **79** | Zambezian Baikiaea Woodlands | 289,048 | *2,3,4* | (1) |
| **80** | Zambezian Cryptosepalum Dry Forests | 40,419 | *3,4,5* | (2,3) |
| | Total | 21,568,591 | | |

Reference: (1) Chidumayo & Gumbo *(*2010); (2) Blackie et al. *(*2014); (3) FAO (2012); (4) Pennington et al. (2009); (5) Everard (2018); (6) Fearnside (2013); (7) Kemeuze et al. (2015).

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**FIGURE S1** Relationships of normalized vegetation index with (**a**) maximum temperature in the hottest month, (**b**) minimum temperature in the coldest month, (**c**) mean annual precipitation, (**d**) maximum precipitation in the wettest month, (**e**) precipitation in the driest quarter of the year, (**f**) amplitude or range in precipitation, (**g**) number of dry months and (**h**) number of months under hydric stress. Different colors

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represent distinct tropical dry forest groups.

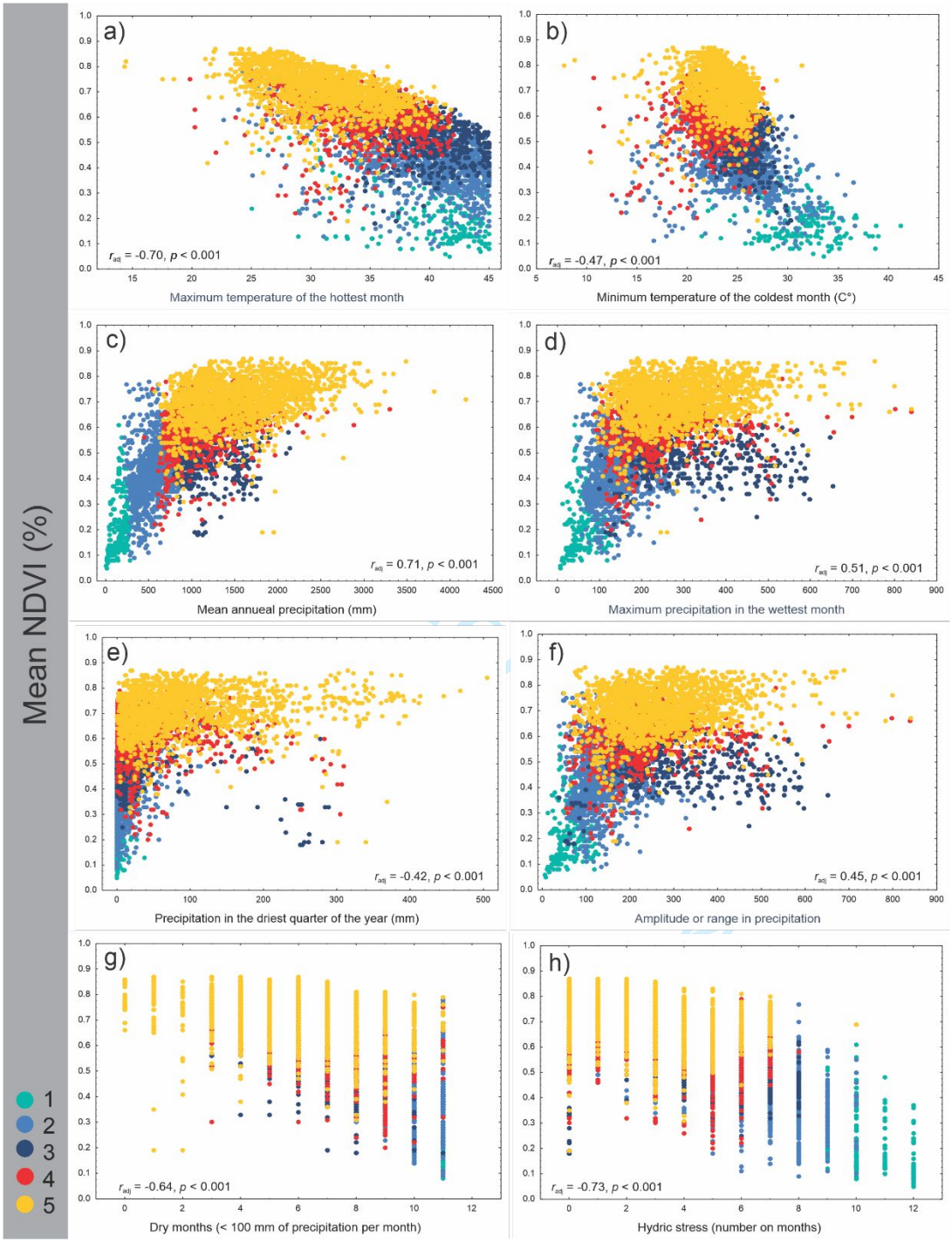

**FIGURE S2** Relationships of normalized vegetation index with soil (**a**) depth, (**b**) coarse fragment content, (**c**) bulk density, (**d**) clay content, (**e**) field capacity, (**f**) water holding capacity and (**g**) potential storage of water. Different colors represent distinct tropical dry forest groups.

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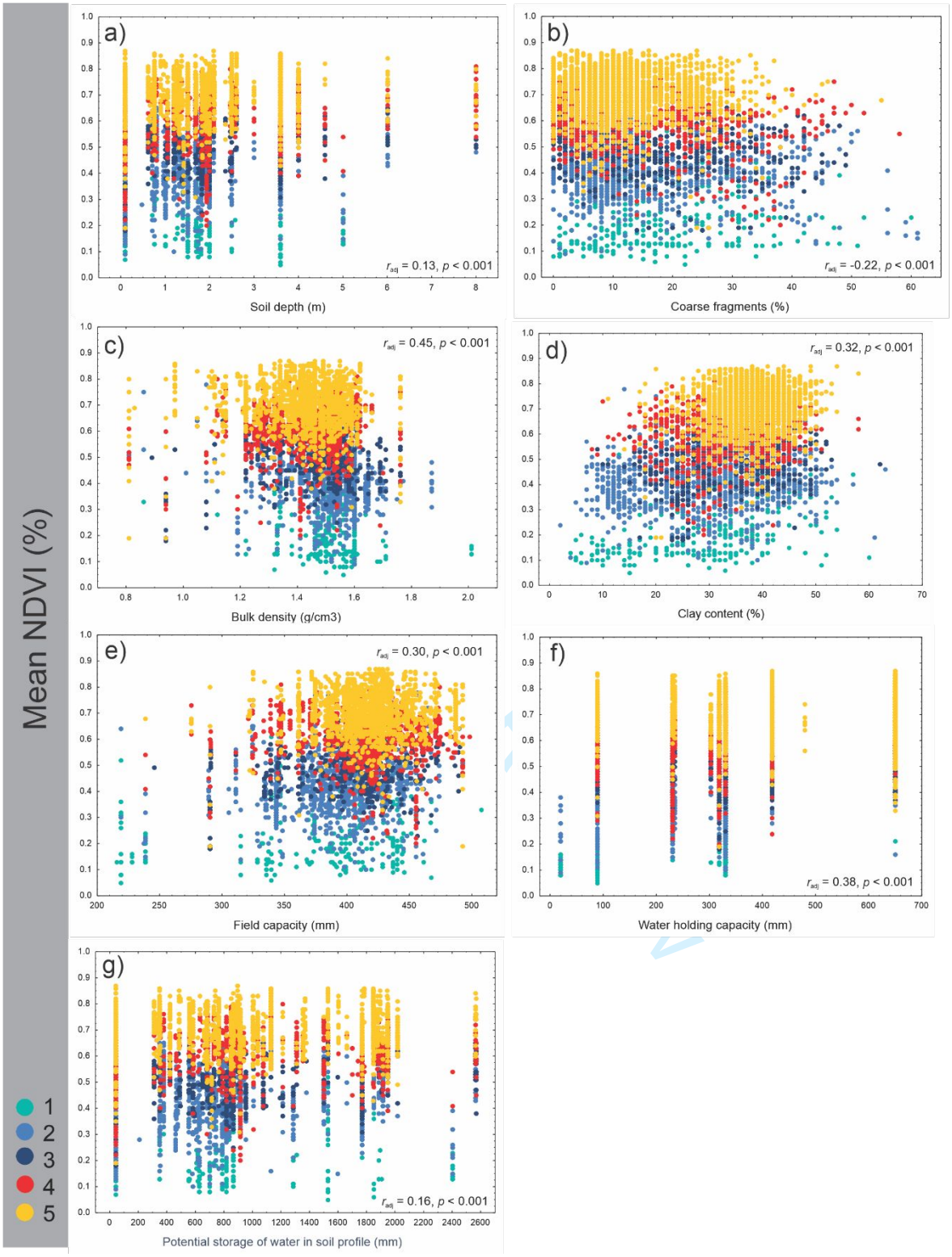


**FIGURE S3** Relationships of normalized vegetation index with soil (**a**) pH, (**b**) cation exchange capacity, (**c**) organic carbon content, (**d**) total nitrogen content, (**e**) total phosphorus content, (**f**) organic phosphorus

content and (**g**) labile inorganic phosphorus content. Different colors represent distinct tropical dry forest groups.

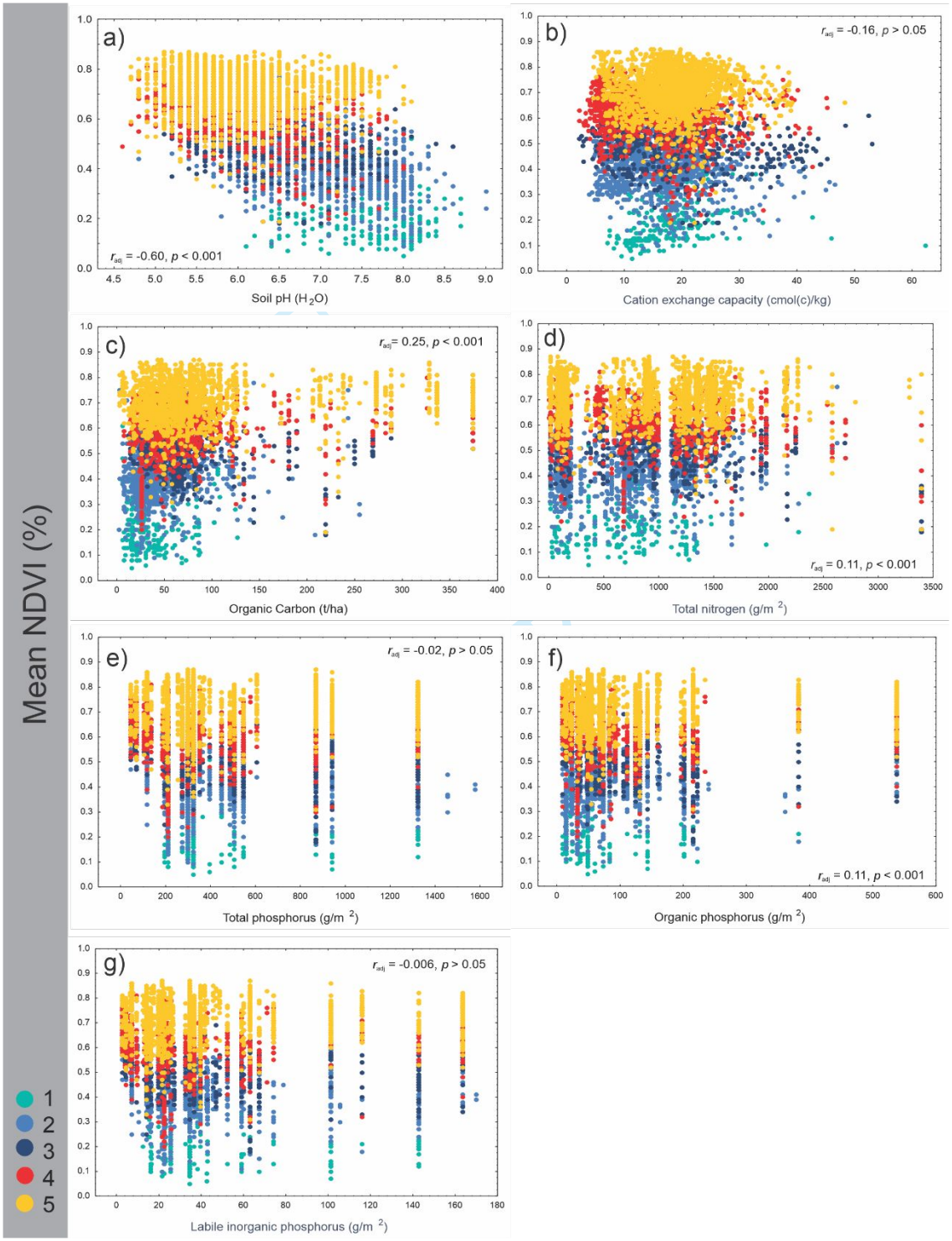

**TABLE S3** Analyzed metrics with time period (single period only included data from a single sampling), information on scale, units and reference sources.

| | Metric | Time period | Pixel size (km) | Pixel size (degrees) | Units | Reference link |
|---|---|---|---|---|---|---|
| Climate | Temperature (mean, maximum, minimum, amplitude) | 2004-2016 | 11.17 | 0.1 | ˚C | https://www.nasa.gov |
| | Precipitation (total annual, maximum, minimum, amplitude, concentration in the rainy season, amount of rain in rainy season months, number of dry months, months under hydric stress, rainfall in the driest quarter) | 2004-2016 | 5.6 | 0.05 | mm | https://www.ucsb.edu |
| | Evapotranspiration (total annual) | 2004-2014 | 5.6 | 0.05 | mm/year | https://modis.gsfc.nasa.gov |

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| | | | | | | |
|---|---|---|---|---|---|---|
| Soil | Total phosphorus, organic phosphorus and labile inorganic phosphorus (0-50 cm in depth) | Single period | 55.6 | 0.5 | g P/$m^2$ | https://daac.ornl.gov |
| | Soil organic carbon (0-0.3 m, 0.3-1 and 0-1 m in depth) | Single period | 55 | 0.5 | kgC/$m^2$ | https://daac.ornl.gov |
| | Soil total nitrogen (0-1 m in depth) | Single period | 111.7 | 1 | g/$cm^3$ | |
| | Soil depth | Single period | 111.7 | 1 | m | |
| | Clay content (0-1 m in depth) | Single period | 111.7 | 1 | % | |
| | Coarse fragments (0-1 m in depth) | | | | | |
| | Soil pH ($H_20$) | Single period | 55.8 | 0.5 | | |
| | Water holding capacity | Single period | 111.7 | 1 | mm | |
| | Potential storage of water in the soil profile | Single period | 111.7 | 1 | mm | |
| | Potential storage of water in the root zone | Single period | 111.7 | 1 | mm | |

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|---|---|---|---|---|---|---|
| | Potential storage of water derived from soil texture | Single period | 111.7 | 1 | mm | |
| | Soil wilting point | Single period | 111.7 | 1 | g/cm$^3$ | |
| | Soil field capacity | Single period | 111.7 | 1 | mm | https://neo.sci.gsfc.nasa.gov/ |
| | Soil bulk density | Single period | 111.7 | 1 | g/cm$^3$ | https://daac.ornl.gov |
| Vegetation | Normalized difference vegetation index (NDVI) | 2004-2014 | 5.6 | 0.05 | dimensionless | ftp://neoftp.sci.gsfc.nasa.gov/geotiff.float/MOD_NDVI_M/ |
| Descriptive | Surface area | | | | km$^2$ | |

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**TABLE S4** Pearson correlation coefficients (*r*) between normalized difference vegetation index (NDVI) and climate or soil metrics in tropical dry forest ecoregions. Bonferroni correction was applied to *p*-values. Not all sample points within a biogeographic region have information on all metrics.

| Metrics | Pantropical | Afrotropic | Australasia | Indo-Malayan | Neotropic | Oceania |
|---|---|---|---|---|---|---|
| *(n)* | 5,831 | 2,128 | 358 | 438 | 2,638 | 269 |
| *Climate* | | | | | | |
| Mean annual temperature (°C) | -0.77*** | -0.88*** | -0.62*** | -0.89*** | -0.57*** | 0.80*** |
| Minimum temperature of the coldest month (°C) | -0.47*** | -0.77*** | -0.39*** | -0.43*** | -0.13*** | 0.73*** |
| Mean annual precipitation (mm) | 0.71*** | 0.79*** | 0.39*** | 0.80*** | 0.64*** | 0.52*** |
| Precipitation in the wettest month (mm) | 0.51*** | 0.50*** | 0.36*** | 0.46*** | 0.54*** | 0.54*** |
| Precipitation in the driest month (mm) | 0.40*** | 0.35*** | 0.16NS | 0.41*** | 0.45*** | -0.49*** |
| Total precipitation in the rainy season (mm) | 0.67*** | 0.77*** | 0.39*** | 0.77*** | 0.59*** | 0.60*** |
| Dry months (number of months with < 100 mm of precipitation) | -0.71*** | -0.83*** | -0.38*** | -0.73*** | -0.64*** | 0.43*** |
| Months under hydric stress (number) | -0.73*** | -0.82*** | -0.29*** | -0.77*** | -0.68*** | 0.06NS |
| Precipitation in the driest quarter of the year (mm) | 0.38*** | 0.36*** | 0.21** | 0.49*** | 0.47*** | -0.20*** |

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|---|---|---|---|---|---|---|
| Lang aridity index | 0.74*** | 0.82*** | 0.48*** | 0.84*** | 0.67*** | 0.60*** |
| Mean annual evapotranspiration (mm) | 0.82*** | 0.74*** | 0.75*** | 0.91*** | 0.80*** | 0.84*** |
| *Soil* | | | | | | |
| Depth (m) | 0.12*** | 0.33*** | 0.27NS | 0.48*** | 0.09NS | 0.41NS |
| Coarse fragment content[1] (%) | -0.22*** | -0.24*** | 0.08NS | -0.39*** | -0.33*** | 0.38*** |
| Bulk density[1] (g $cm^{-3}$) | -0.17*** | -0.38*** | -0.24*** | -0.55*** | 0.01NS | 0.71*** |
| Clay content[1] (%) | 0.32*** | 0.27*** | 0.15NS | -0.16NS | 0.14*** | 0.52*** |
| Field capacity[1] (mm) | 0.31*** | 0.38*** | 0.19NS | 0.17NS | 0.17*** | 0.39*** |
| Water holding capacity[1] (mm) | 0.38*** | 0.30*** | 0.17NS | 0.23*** | 0.44*** | 0.41NS |
| Potential storage of water in soil profile[4] (mm) | 0.16*** | 0.33*** | 0.25NS | 0.48*** | 0.11*** | 0.40NS |
| pH[1] | -0.60*** | -0.80*** | -0.13NS | -0.75*** | -0.48*** | -0.65** |
| Cation exchange capacity[1] (cmol $kg^{-1}$) | -0.01NS | -0.42*** | 0.28*** | -0.63*** | 0.02NS | -0.53** |
| Organic carbon[2] (Mg $ha^{-1}$) | 0.25*** | 0.26*** | 0.24** | 0.37*** | 0.27*** | -0.72** |
| Organic carbon[1] (Mg $ha^{-1}$) | 0.25*** | 0.27*** | 0.24** | 0.28** | 0.28*** | -0.65*** |
| Total nitrogen[1] (g $m^{-2}$) | 0.11*** | 0.08NS | 0.21NS | -0.14NS | 0.11*** | -0.70*** |
| Total phosphorus[3] (g $m^{-2}$) | -0.02NS | -0.32*** | 0.39** | -0.33** | 0.12*** | nd |

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nd, non-available data. Soil depth: 1, 0-1.0 m; 2, 0.3 m; 3, 0-0.5 m; 4, non-indicated. Significance: NS, $p > 0.05$; *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$

For Peer Review

Dear Dr. Brian McGill, Dr. Maria Dornelas and Dr. Richard Field

Editors-in-Chief, Global Ecology and Biogeography

We write to submit a revised version of our manuscript entitled, “Climatic and edaphic-based predictors of Normalized Difference Vegetation Index in tropical dry landscapes: A pantropical analysis” (GEB-2021-0495R) co-authored by Marines de la Peña-Domene, Gerardo Rodríguez-Tapia, Natalia Mesa-Sierra, Anaitzi Rivero-Villar, Christian P. Giardina, Nels G. Johonson and Julio Campo, to Global Ecology and Biogeography. All changes are highlighted in color blue.

We confirm that neither the manuscript nor any parts of its content are currently under consideration or published in another journal. All authors have approved the manuscript and agree with its submission to Global Ecology and Biogeography.

Sincerely,

Julio Campo

Professor, Instituto de Ecología

Universidad Nacional Autónoma de México

For Peer Review

| EDITOR'S COMMENTS TO AUTHORS<br>Editor: Gillespie, Thomas<br>Comments to the Author: | Authors answers |
|---|---|
| Thank you so much for your revisions. The revised ms was significantly improved and I believe you can see this in the reviewer's comments and suggestion. I really would like to thank the authors for including a land cover mask in the revision and defining your extent as tropical dry forest landscapes instead or tropical dry forest which significantly improved the analyses. The manuscript also reads much clearer now which I | We greatly appreciate the suggestions made by the editor and we also agree that they served to greatly improve the manuscript |

| | |
|---|---|
| think is great. Please see comments and suggestions from Reviewer 2 which I agree with. | |
| Page 7, Line 9 to 17. Thank you for using a land cover mask. This is a great idea. Thank you. | We also found it to be a great idea and will continue to look further into this mask and the dynamics of land use in TDLs |
| Page 7, Line 6. This centroid idea is now a nice way to examine the TD landscapes. Very standard and repeatable. | Thank you for the observation |
| Page 6, Line 20. This section about Australia needs a citation at the end. | The sentence was rewritten (section 2.1, lines 21-23) |
| Page 6, Line 21. This is fine about Yap. | Great |
| NDVI. Did you use 250 m or 1 km MODIS data? Please state in Methods | Specified in the method section 2.3 (line 16) |
| Abstract<br>Location: Should the location be Pantropical instead of World? Pantropical is in the title. | Changed (Abstract, line 13) |
| Method: NDVI from MODIS? I think you should state that NDVI cames from MODIS imagery in the Abstract. I might even state the pixel size in the Abstract for clarity (e.g. 250 m or 1 km). | Added in the abstract (line 19) |
| Results: Note these thresholds are not mentioned in the Results or Discussion section of the MS. You have some really interesting main Results (see subheadings in Results) that I think should be highlighted here. E.g. “The # climatic and # edaphic variables used in the full model explained 90% of NDVI variation across TDL” Please make sure the Abstract results reflect the main Results section. | Three sentences in the abstracts result section were rewritten (lines 25-29) |
| Keywords: should MODIS be added to the keywords? | Following your suggestion “MODIS” was added to keywords |
| <u>Introduction</u> | |

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| | |
|---|---|
| Page 3, Line 10. Did Gentry really say 11 months of drought or dry season? That seems very long. Can you double check that he said this in that book chapter. | We reviewed Gentry's book chapter as (1995) well as other sources and confirmed that we made an error. The sentence was rewritten in Introduction chapter (page 3, lines 8-10), and reference to Gentry was corrected in figure 3 and in the supplementary material table S1. |
| Page 3 Ecotype. OK Ecotypes means has so many different things to different people. Using Google, Ecotypes is defined as "An ecotype is a population (or subspecies or race) that is adapted to local environmental conditions. The implication is that those individuals which were best adapted to the prevailing conditions left the most offspring." I think you need to either provide your clear definition of ecotypes in the Introduction but in your case you are identifying similar NDVI values correct? Later in the Results you say "NDVI-based ecological groupings" which I like much better than Ecotypes which has a number of meaning while your "NDVI-based ecological groupings" appears to more accurately reflect the results of the analyses. "NDVI-based ecological groupings" is also a novel and clearer way to define what you are doing. | We recognize that the word Ecotype can cause confusion and considering the reviewer's suggestion, we replace the word ecotype with "NDVI-based ecological groups" throughout the text. |
| <u>Methods</u> | |
| Page 8, Line 13. I really think you need to state the pixel size of each climate and soil metric so the reader understands the scale of the analyses. I believe they are all 1 km, is that correct? | We added: "Detailed information on the time frame, scale, units and reference sources of each of the 34 variables used are specified in Table S3" in the section Climatic and edaphic metrics (lines 7-8). Table S3 contains the detailed information on each data layer |
| Page 9, Line 2. I would say "for the purpose of the research" instead of paper. | For more clarity, the paragraph was rewritten (please see page 7 lines 2-8. |

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| | |
|---|---|
| Data Analyses | |
| "We used initial linear regressions (Pearson coefficients) to identify significant climate and 2 edaphic predictors of the NDVI at both pantropical scale and within each biogeographic region." Technical Pearson Coefficients are a correlation (R) not a regression analyses (R2) thus I would say "We used Pearson coefficients to …" | Following the reviewer's suggestion, we removed "linear regressions", and the sentence was rewritten. Page 7 lines 26-27 |
| Page 10, Line 3. I would remove "Also". And say "We used the r" | We removed the word "Also", and sentence was rewritten Page 7, lines 28-30 |
| The regression tree section reads much clear now. Thank you! | Fantastic |
| **Results** | |
| "The five biogeographic regions examined here contained 80 TDF ecoregions" I think to be clear your analyses included 80 WWF ecoregions, but not all were defined as WWF "tropical and subtropical dry broadleaf forest ecoregions". There are 53 World Wildlife Fund "tropical and subtropical dry broadleaf forest" ecoregions. It appears you have some savanna WWF ecoregions in there too which is fine. Indeed, my grad student found that the 53 WWF "tropical and subtropical dry broadleaf forest ecoregions" only contain 40% of plots defined as TDF while FAO definitions (which you include) was a better classification methods thus your analyses makes sense. Thus is it more accurate to say 80 WWF ecoregions? And these would be your TDL. Does that sounds correct? | The reviewer is correct and we addressed the issue so that there would be no misunderstanding based on the classification "tropical and subtropical dry broadleaf forest". As the reviewer stated, we examined 80 WWF ecoregions |
| 3.3 Relationships of NDVI with climate and edaphic metrics<br>Thank you this section is greatly improved! | We are so glad to hear that |
| Page 12, Line 8.<br>Table S4 | Following the reviewer's suggestion, we use the Bonferroni multiple-comparison correction. This |

For Peer Review

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| When doing correlations of multiple variables (34 metrics) and 5,831 points, given the large sample size and number of metric, one might expect high P values. In these case, it would be worthwhile to undertake a Bonferroni correction on the P Values. The Bonferroni correction is a multiple-comparison correction used when several dependent or independent statistical tests are being performed simultaneously. There is an easy calculator for this too. https://www.easycalculation.com/statistics/bonferroni-correction-calculator.php | was specified in the methods section (page 7, lines 27-28). Additionally, in Table S4 of the supporting information. |
| Page 13, Line 17. Again I really like this term you created "NDVI-based ecological groupings" this is much better than ecotypes. | We appreciate the reviewer's acknowledgment of our term and we used it to replace the word ecotype (see also above). |
| Discussion<br>Page 15, Line 3. "NDVI a remotely sensed canopy attribute strongly linked to forest structure and function". I think you should remove the word canopy because it appears some of the very dry areas may not have tree canopies. | Done (page 11, lines 11-12) |
| Conclusions<br>I might add something about this to the conclusions because it seems like a major finding of the study. "The # climatic and # edaphic variables used in the full model explained 90% of NDVI variation across TDL" | Thank you for the suggestion, we added it to the conclusions page (14, line 25-26) in the Conclusions chapter. |
| Please make sure you conform to GEB data availability standards. | The data will be available in the format requested by the journal once the article is accepted. We hope that this will not be an inconvenience for you. |

For Peer Review

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| Figure 1. I am not sure you need the global map in the middle of this figure. Your regions should be fine. | We took out the global map in figure 1 and kept the figure only with the regions |
| I like the other Figures. | Thank you! |
| Table 1 is very large. This might be ok but maybe include the variables in Figure 4 a in the Table and the full table as an appendix. That way the reader can focus on the most important metrics. | We do feel that the table is a key part of the paper, so we worked in making it as small as possible. However, if it's not possible to keep the table in the main text, then we would send it the supplementary materials |
| Table S2. Ecotype is misspelled but it could say "NDVI-based ecological groupings" here. | We changed the misspelled word with "NDVI-based ecological groups" in the Table S2. |
| TableS3. Change Pixcel to Pixel | Done |
| Table S4. Adding Bonferroni corrections seems reasonable. | Done |
| REVIEWER COMMENTS TO AUTHOR | |
| Referee: 2 | |
| Comments to the Author<br>The manuscript entitled "Climatic and edaphic-based predictors of Normalized Difference Vegetation Index in tropical dry landscapes: A pantropical analysis" brings a novel take on how to identify the main environmental drivers linked to the distribution and productivity (measured via NDVI) of Tropical Dry Landscapes. The analyses are sound, the results are pertinent and interesting and constitute an advancement in the field that is worth publishing. The figures are very well done and clearly communicate the message they were created to communicate. With that said, I do have some concerns on whether the authors are actually working with just TDFs. As the authors will see in my comments below, this is truly a manuscript on Tropical Dry Landscapes and not on Tropical Dry Forests. I have also added a few suggestions in | |

For Peer Review

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| places where I found improvement was needed. I hope the authors find these comments pertinent and helpful. | |
| Minor comments (first number is page number, subsequent numbers correspond to lines): | |
| 3 14-16: I think this difference between TDL and TDF must be more explicitly stated and discussed, especially considering that several vegetation categories / ecoregions in the analyses are actually savanas, non-forests and other fire-prone ecosystems. Perhaps all of the issues I reported below can be more easily solved if the authors state that they've worked with TDLs and not only TDFs? | We consider that the concept of TDL, as we have defined it, allows us to encompass the biome as comprising both forest and non-forest vegetation that together form tropical dry landscapes. Tropical dry forests are embedded in a very dynamic landscape matrix, and therefore, we feel in necessary to address the whole landscape and not just the forest patches. For some TDL, this means integrating large savanna portions as the matrix of tree patches or integrating fire-prone ecosystems that overlap with TDF portion, but that influence their ecosystem dynamics (addressed in page 3 lines 18-20). Also, in attention your concern two new references were included. Please, see page 3 lines 18-21.<br><br>Finally, as for the TDF sites, we refer to those sites that we selected based on the three criteria defined in the methods section, which have essentially been described as Tropical Dry Forest by some author at some point. |
| 4-14 What is atmospheric demand? | "Atmospheric demand" was clarified in page 4 lines 5-6)<br>. |
| 5-5 anthropogenic-induced climate change would be better here. Anthropogenic change alone can include many other aspects that are not relevant to this statement. | Changes were performed following reviewer's suggestion (page 4 line 18) |
| 5-16 "Ecologically ecotypes" sounds redundant, no? | We replace ecologically ecotypes by "NDVI-based ecological groups" throughout the text. |

For Peer Review

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| 5-18 Some of the points in South America and most of the points in Africa are in vegetation types that are known to be Savannas and that are actually prone to burning. By looking at maps produced by Archibald et al. (2013), Lehmann et al. (2011), Fayolle et al. (2019) and Aleman et al. (2020), It is possible to see that the areas the authors are indicating to be covered by TDFs are actual savannas / fire-prone ecosystems, which will function differently from TDFs and will have a different dynamics concerning productivity as well. I have never worked with Asian vegetation before, so I cannot say if the points in there are actual TDFs or not. | We address this concern in more detail, and we have included several remarks in this regard thorough the ms for example in Introduction (page 3, lines 18-21) and Methods (page 5, lines 16-19) chapters. |
| 6-10 Wouldn't Dinerstein et al. (2017) be a better reference for this? They conducted a series of fixes and updates on Olson et al. (2001)'s classification system. In fact, Olson is the second author in Dinerstein et al. (2017). | Done and thank you for your recommendation (see page 5, line 12) |
| 6 7-18: I appreciate that the authors established a series of objective criteria as the means to define which TDFs would be included in their study. Working at the global scale, this is the only way possible. However, by doing so, the authors ended up including vegetation types that are savannas / ecosystems prone to burning and are not usually classified as being TDFs in most of the specialized literature. For example, the following vegetation categories are also known as savannas and are known to be prone to burning: the Angolan Miombo and Mopane woodlands, the Central Zambezian Miombo Woodlands, the Cerrado, East Sudanian Savanna, Eastern Miombo Woodlands, Northern Congolian Forest-Savanna Mosaic, Southern Africa Bushveld, Southern | Taking into account the comment of the reviewer, we consider some aspects:<br>1. As the reviewer comments, there are authors who have included ecoregions such as woodland, shrubland, thicket, savanna and wooded grassland within their TDF classifications (Chidumayo & Gumbo 2010). Even when the classifications have undergone modifications over time, part of the interest we had with this study was to be able to compile all those classifications worldwide that are close and related to TDF in order to be able to recognize how they are related to each other, according to the variations of their NDVIs and the relationship with the climatic and edaphological variables. |

For Peer Review

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| Congolian Forest-Savanna Mosaic, Southern Miombo Woodlands, Western Congolian Forest-Savanna Mosaic, Zambezian and Mopane Woodlands, Zambezian Baikiaea Woodlands. I have no experience in working with Asian vegetation, so I cannot really say whether vegetation types other than TDFs have been included as well.<br>I checked the references on Supplementary Table S1 in order to understand how the inclusion of these ecoregions is being justified. I noticed that Chidumayo & Gumbo (2010) was among the citations for Africa. The terminology employed in order to build vegetation classification systems changed over the years and continues to change from one author to the other, leading to a lot of confusion in the field. Chidumayo & Gumbo (2010) admittedly included several vegetation types within their "Dry Forests and Woodlands" category and considered fire to be a natural feature of Dry Forests (which is how you start a fight with a lot of researchers out there). I got the passage below from Chidumayo & Gumbo (2010). It is on page 11.<br>"Here we define dry forest and woodland as vegetation dominated by woody plants, primarily trees, the canopy of which covers more than 10 percent of the ground surface, occurring in climates with a dry season of three months or more. Such a broad definition – wider than those used by many authors – incorporates vegetation types commonly termed woodland, shrubland, thicket, savanna and wooded grassland, as well as dry forest in its strict sense." | 2. The Cerrado is an ecosystem that in Brazil is adjacent to the TDF and according to Neotropical experts it is a transition ecosystem, so its differentiation and delimitation with TDF is not 100% clear (Gentry, 1995; Pennington et al. 2009). Due to these characteristics, we consider it pertinent to include it to see how much it could be differentiated from TDF ecosystems such as the Caatinga or how much its characteristics are related to other TDFs in the world. Thanks to this we were able to confirm that they are two ecoregions without strong differences that are related more to Afrotropic ecosystems than to Neotropic ones.<br>3. Additionally, different authors (Dexter, K. G., Pennington, R. T., Oliveira-Filho, A. T., Bueno, M. L., Silva de Miranda, P. L., & Neves, D. M. (2018). Inserting tropical dry forests into the discussion on biome transitions in the tropics. Frontiers in Ecology and Evolution, 6, 104.) have recognized that "underlying environmental drivers of transitions among tropical dry forests, moist forests and savannas, and demonstrate how incorporating tropical dry forests into our understanding of tropical biome transitions is critical to understanding the future of tropical vegetation under global environmental change." In this sense, we consider it pertinent to be able to analyze all the types of vegetation that we include in this study and to be able to contribute to their delimitation, as well as their relationships with different variables.<br>4. On the other hand, regarding fire, it is necessary to increase research efforts in this regard since different authors have recognized its relationship with TDF in different regions (Hamilton, R., Penny, D., & Hall, T. L. (2020). Forest, fire & |

For Peer Review

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| As for the South American Cerrado, I was unsure which references were used in order to justify its inclusion as a TDF. Though the Cerrado in Brazil does have patches of TDFs within it, most of it is actually composed of savannas, grasslands and woodlands (A.K.A Cerradão) and the red points on Figure 1 do not correspond to these patches of TDFs.<br>The best path forward here would be to admit that the classifications used by the authors include vegetation types that are not normally classified as TDFs and that their findings were analyzed in the light of that, since the occurrence of fire will likely have important effects on NDVI. Perhaps these fire-prone ecosystems can be found in one or two of the five NDVI categories the authors have delimited? I haven't seen the results section yet. Anyway, this needs to be carefully reviewed by the authors since savannas and TDFs will have meaningful differences in relation to carbon dynamics and productivity, which according to the authors, is what NDVI is summarizing. Alternatively, as I mentioned earlier, simply saying that the paper is on TDLs and not entirely focused on TDFs should put this issue to rest. | monsoon: Investigating the long-term threshold dynamics of south-east Asia's seasonally dry tropical forests. Quaternary Science Reviews, 238, 106334; Dexter K. G., Pennington R. T., Oliveira-Filho A. T., Bueno, M. L., Silva de Miranda, P. L., & Neves, D. M. (2018). Inserting tropical dry forests into the discussion on biome transitions in the tropics. Frontiers in Ecology and Evolution, 6, 104.), Corona Núñez, R. O., Li, F., & Campo, J. E. (2020) Fires represent an important source of carbon emissions in Mexico. Global Biogeochemical Cycles, 34, e2020GB006815, and not only for those African ecoregions that the reviewer mentioned. It has been recognized that TDF is a type of vegetation that, due to its seasonality, has a high susceptibility to fire and it has been observed that its species may be adapted to respond to this phenomenon, so the line that delimits these ecosystems mentioned by the reviewer It may be less clear than you think.<br>5. Taking into account the previous analysis and the reviewer's suggestion, on page 5, line 16-19 a comment was included to make it clear that we include vegetation types that are not commonly classified as TDF, but have been defined as such at some point. |
| 8-20: Table1 should have a column indicating which reference was used to obtain the values given in the other columns. I see now that this information is on table S3, but table S3 is not mentioned in the main text. | Apologies. Thank you for your observation. Table S3 was cited in page 7, lines 4 and 8: |
| 10-11: Why not give the exact R2? | Done (page 8, line 5) |
| 11-2 -> Figure 2: In panel (b), consider naming the sub-panels as (b.1), (b.2) and so on. At the | Addressed on figure 2 and in previous comments |

For Peer Review

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| moment, figure 2 is confusing due to having two panels a, b and c. I am not familiar with GEB's rules for labeling figures and their panels/sub-panels, so please make sure to check it first and adopt the appropriate format. Also in this line, the broadest TDF category is often classified as being a savanna and it is labeled as a savanna in Olson's classification system. I think this is a good example to show how important it is to discuss how vegetation types were classified as TDFs in this manuscript and how this classification procedure may have led to the appearance of meaningful differences from how these vegetation categories are more commonly classified. | |
| 11-18: Is ET (in the main text) the mean annual evapotranspiration (in table 1)? Also, in page 4, you mention PET. In order to avoid confusion, please define ET here and check whether it is worth keeping PET. | We addressed this comment in page 9, line 3) |
| 14-14: The results section was entirely written referring to TDFs, but in the discussion the TDLs gained prominence. As I said before, I think this change should be made throughout the manuscript as the authors are working with TDLs and not TDFs. | Agreed and attended |
| 18-6: I fully agree with the authors that the division of TDLs into 5 groups can provide information on likely climate tipping points, which is information that is not at all available for drier ecosystems. However, as it stands right now, this section is rather speculative and the authors should search the literature in order to find support for their narrative here. For example, you could implement an equally valid narrative that goes in the opposite direction: changes in aridity | We acknowledge the reviewer's argument and strengthen this section. Please see the new 4.3 section that was rewritten (page 13 line 14 to page 14 line 18). Likewise, we want to highlight that even when the future of TDFs worldwide is not entirely clear in terms of climate change, identifying the variables that most explain the productivity for each type of TDF enriches the debate on their vulnerability and conservation importance and restoration. |

For Review

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| could bring about changes to group 5, as it is covered by vegetation not entirely adapted to high aridity. On the other hand, vegetation in group 1 is highly resilient and is potentially capable of withstanding large stretches of time without any precipitation. Therefore, changes in aridity would not affect group 1 that much because its plants are already adapted to very dry conditions. In fact, this is known to happen in parts of the Brazilian Caatinga. The fate of drier ecosystems under climatic change is not yet clear, so it will be important to reference this paragraph throughout with information that is already published/available. | |
| 19-13: I don't really understand why it is surprising to find matching NDVI classes among the biogeographic regions analyzed. Can this be elaborated further in the text? Is there a correlation between NDVI and floristic composition? Can floristic dissimilar regions hold nearly similar NDVI values? On the other hand, interesting biogeographic aspects such as groups 5 and 4 are close to the borders of moist forests in Africa and South America, the prevalence of group 1 in Africa is due to the high aridity of this continent (the Sahel and the vegetation covering the horn of Africa are known to be amongst the most arid vegetation types) and how group 2 seems to be roughly linked to mountain ranges and other few aspects are not even mentioned by the authors. It would be interesting if the authors could extend this discussion a bit further. | These ideas were rewritten. Please see the content of the new section "**4.3 NDVI, biogeographic patterns, and climate change**" |

For Peer Review

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| 19-20: I think Dexter et al. (2015) only mentions the lack of meaningful floristic difference between savannas and dry forests. Moist Forests were not included in this statement. In fact, what is written in the abstract of Dexter et al. (2015) is that "Neotropical moist forest, savanna and seasonally dry tropical forest are floristically distinct, but elsewhere there is no clear floristic division of savanna and seasonally dry tropical forest, though moist and dry formations are separate". | We expect that changes performed in the new "4.3 NDVI, biogeographic patterns, and climate change" resolve your concern |

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