# Supporting Online Material for

## Plant Species Richness and Ecosystem Multifunctionality in Global Drylands

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Map S1

**Materials and Methods**

Characteristics of the study sites

We restricted our study to arid, semi-arid and dry-subhumid ecosystems ("drylands" hereafter), defined as sites with an aridity index (precipitation/potential evapotranspiration) between 0.05 and 0.65 (*35*). Original field data were gathered at 224 sites located in 16 countries from all continents except Antarctica (Argentina, Australia, Brazil, Chile, China, Ecuador, Iran, Israel, Kenya, Mexico, Morocco, Peru, Spain, Tunisia, United States of America and Venezuela, map S1). Site selection aimed to capture as much as possible the wide variety of abiotic (climatic, soil type, slope) and biotic (type of vegetation, total cover, species richness) features characterizing dryland ecosystems while keeping the total number of sites at a manageable size (map S1). To obtain data as representative as possible of "real world" ecosystems, we did not limit our survey to pristine or unmanaged ecosystems. The sites surveyed encompass a wide range of human uses, ranging from those with very low human impacts over recent time scales (e.g. National Parks and other protected areas) to those where human activities such as grazing, grass fiber/wood collection and game hunting are currently, or have been recently, carried out. However, we excluded areas devoted to horticulture, occupied by riparian/coastal ecosystems, recently engineered (e.g. planted or recently restored areas) or used for other human activities that have completely removed their vegetation and altered their geomorphologic characteristics (e.g. infrastructure/mining).

To ensure that all the sites surveyed had an index of aridity below 0.65, we used cartography available at the global scale from the United Nations Food and Agriculture Organization (FAO, http://www.fao.org/geonetwork/ srv/en/main.home). This information was complemented with more precise aridity maps (e.g. http://www.cazalac.org/mapa_za_gm_2011.html for Central and South America) and with available local climatic data. Standardized climatic data from all the sites were obtained from Worldclim (www.worldclim.org), a high resolution (30 arc seconds or ~ 1km at equator) database based on a high number of climate observations and topographical data (see *36* for details). Mean annual precipitation and annual mean temperature of the study sites span the entire range found in dryland areas (excluding hyper arid areas, which usually have little or no perennial vegetation, *37*), and varied from 66 mm to 1219 mm, and from -1.8°C to 27.8°C, respectively (map S1). All the sites included in this study experience high seasonal variability in rainfall and seasonal drought, which varies in intensity and duration depending on location. The range of soil types present at the studied sites is also large, including more than 25 categories from the FAO classification (*38*) and encompassing all main soil types present in drylands (map S1). Slope values ranged between 0.2° and 28° (Database S1). To minimize the potential effects of different microclimates promoted by slope aspect, which can be very important in drylands (*39-44*), all sites that had slope values > 2° were located on SE-SW and NE-NW facing slopes in the Northern and the Southern hemispheres, respectively. Elevation varies between 69 m and 4668 m a.s.l. (Database S1). The sites surveyed encompass a wide variety of the representative vegetation physiognomies found in drylands

(grasslands, shrublands, savannas and open woodlands with shrubs, fig. S1). Perennial plant cover also varied widely, and ranged between 3% and 83%.

Field sampling

Data collection took place between February 2006 and December 2010, and all researchers in our global study used a standardized sampling protocol. At each site, we established a 30 m × 30 m plot representative of the vegetation present in that area. In the upper left corner of each plot, we located one 30 m transect oriented downslope for the vegetation survey. Three parallel transects of the same length, spaced 8 m apart across the slope, were added. The cover of perennial vegetation was measured in each transect using the line-intercept method (45). Site estimates were obtained by averaging the values registered in the four transects sampled. We also placed 20 contiguous quadrats (1.5 m × 1.5 m) in each transect and visually estimated the cover of each perennial vascular plant present. We restricted our study to perennial plants because they are instrumental in maintaining ecosystem functioning and preventing desertification in drylands (37, 46). Moreover, annual plant composition in drylands shows a high degree of intra- and inter-annual variability (e.g. 37, 47). Thus, we did not include these annual species in our observational design to avoid confounding effects in the differences on multifunctionality among study sites derived from sampling "incomplete" communities depending on the time of the year and/or year sampled. The total number of perennial species found in the 80 quadrats was used as an effort-standardized estimator of species richness. Strictly speaking, our data give us a measure of "species density" rather than richness (see 48 for a detailed discussion), but we refer to "species richness" throughout the text because this is the term commonly used in the biodiversity-ecosystem functioning literature (e.g. 49). Our surrogate of richness was highly correlated with the total number of species found in the 30 m × 30 m plot, as indicated from detailed surveys carried out at a subset of the sites sampled (fig. S2). From our survey we also obtained other diversity metrics, such as the exponential of the Shannon index and the inverse of the Simpson index (50).

Soils were sampled during the dry season in most of the sites using a stratified random procedure. At each plot, five 50 cm × 50 cm quadrats were randomly placed under the canopy of the dominant perennial vegetation element and in open areas devoid of perennial vegetation. A composite sample consisting of five 145 cm$^3$ soil cores (0-7.5 cm depth) was collected from each quadrat, bulked and homogenized in the field. When more than one dominant plant species was found, samples were also collected under the canopies of five randomly selected individuals of the co-dominant species. Thus, the number of soil samples varied between 10 and 15 per site (over 2600 samples were collected). After field collection, the soil samples were taken to the laboratory, where they were sieved (2 mm mesh), air-dried for one month and stored for laboratory analyses.

Assessment of ecosystem functions: rationale, variables measured and laboratory methods

We obtained data on 14 soil variables related to carbon (C), nitrogen (N) and phosphorus (P) cycling: nitrate ($NO_3^-$-N) and ammonium ($NH_4^+$-N) availability, organic

C, total N, available inorganic P, aminoacids, proteins, pentoses, hexoses, aromatic compounds, phenols, potential N transformation rate and the activity of two extracellular enzymes, β-glucosidase and phosphatase. These variables measure either "true" ecosystem functions (*sensu 51*, e.g. potential N transformation rate) or are key properties/processes (*sensu 52*, e.g., organic C, total N and soil enzymes), which together constitute a good proxy of nutrient cycling, biological productivity, and buildup of nutrient pools. Variables such as these have been used in previous studies of ecosystem functioning and multifunctionality (e.g. *53-57*), and are considered to be critical determinants of ecosystem functioning in drylands (see *37* for a review). For simplicity, all of these variables are hereafter called ecosystem functions (*54*). Most of these functions are also considered to be supporting ecosystem services, as other types of ecosystem services depend on them (*58-60*).

All soil samples were analyzed for each of the 14 ecosystem function indicators listed above. These analyses were carried out with dry samples for logistical reasons, as the large number of soil samples gathered made the analysis of fresh soil samples impossible. Previous studies have found that in drylands such as those we studied, air drying and further storage of soils does not appreciably alter the functions of interest in this study (*61-62*). Indeed, this storage approach is commonly used when analyzing physical and chemical soil properties in dryland environments worldwide (e.g., *57, 63-65*). It is also important to note that our sampled soils would have remained dry for a large portion of the year (e.g. *66-69*), and that most samples were collected when the soil was in this dry state. Thus, the potential bias induced by our drying treatment is expected to be minimal.

To avoid problems associated with the use of multiple laboratories when analyzing the soils from different sites, and to facilitate the comparison of results between them, dried soil samples from all the countries were shipped to Spain for analyses. All the analyses for organic C, available P and enzymatic activities were carried out at the laboratory of the Biology and Geology Department, Rey Juan Carlos University (Móstoles, Spain). Analyses of total N were carried out at the University of Jaén (Jaén, Spain). The remaining soil analyses were carried out at the laboratory of the Department of Physical, Natural and Natural Systems, Pablo de Olavide University (Seville, Spain).

Organic C was determined by colorimetry after oxidation with a mixture of potassium dichromate and sulfuric acid (*70*). Total N was obtained using a CN analyzer (Leco CHN628 Series, Leco Corporation, St Joseph, MI, USA). Available P was measured following a 0.5M $NaHCO_3$ (pH: 8.5) extraction (*71*). Soil extracts in a ratio of 1:5 were shaken in a reciprocal shaker at 200 rpm for 2 h. An aliquot of the centrifuged extract was used to the colorimetric determination of P inorganic available ($PO_4^{-3}$), based on the reaction with ammonium molybdate and development of the "Molybdenum Blue" color (*72*); the pH of the extracts was adjusted with 0.1N HCl when necessary. Phosphatase activity was measured by determination of the amount of *p*-nitrophenol (PNF) released from 0.5 g soil after incubation at 37 ºC for 1 h with the substrate *p*-nitrophenyl phosphate in MUB buffer (pH 6.5; *73*). The activity of β-glucosidase was assayed following the procedure for phosphatase, but using *p*-nitrophenyl-β-D-glucopyranoside as substrate and Trishydroxymethyl aminomethane instead of NaOH when preparing the buffer (*74*). The remaining soil variables were measured from $K_2SO_4$ 0.5 M soil extracts in a ratio 1:5. Soil extracts were shaken in an orbital shaker at 200 rpm

for 1 h at 20ºC and filtered to pass a 0.45-μm Millipore filter (*75*). The filtered extract was kept at 2 ºC until colorimetric analyses, which were conducted within the 24 h following the extraction. Sub-samples of each extract were taken for measurements of aromatic compounds, phenols, pentoses, hexoses, proteins and aminoacids according to Chantigny *et al.* (*76*). Ammonium ($NH_4^+$-N) and nitrate ($NO_3^-$-N) concentrations were also measured for each $K_2SO_4$ extract subsample. Ammonium concentration was directly estimated by the indophenol blue method using a microplate reader (*77*). Nitrate was first reduced to $NH_4^+$-N with Devarda alloy, and its concentration was determined by the indophenol blue method. Nitrate concentration in the extracts was calculated as the difference between Devarda-incubated and unincubated samples. Potential N transformation rate was measured by determination of total $K_2SO_4$-extractable N before and after incubation in the laboratory at 80% of field water holding capacity and 30ºC for 14 days (*78*).

Abiotic variables measured: rationale and laboratory/field methods

The coordinates and elevation of each plot were recorded *in situ* with a portable Global Positioning System, and were standardized to the WGS84 ellipsoid for visualization and analyses. The use of elevation as an environmental variable has been criticized because it may confound ecosystem attributes physically linked to altitude in terms of distance (e.g., atmospheric pressure and temperature) and others that are not (e.g. moisture, hours of sunshine, wind, and human activities, *79*). However, we included it in our analyses because given the important range found in this variable within our dataset (from 69 m a.s.l. to almost 5000 m a.s.l.), it may encapsulate microclimatic features of the sites that are not properly captured by the global interpolations used. Slope angle was measured *in situ* with a clinometer. This variable is an important driver of the hydrological behavior of drylands, as it strongly influences infiltration, water availability and run-on/run-off processes in these ecosystems (e.g., *80-83*).

In addition to the ecosystem functions listed in the preceding section, other soil variables were measured at the laboratory of the Rey Juan Carlos University. Soil pH was measured in all the soil samples with a pH meter, in a 1: 2.5 mass: volume soil and water suspension. Soil texture was measured in two/three composite samples per site, as preliminary analysis revealed that within-site variability was very low. One composite sample each per microsite (open areas or soil under the canopy of the dominant perennial plants) and site were analyzed for sand, clay and silt content according to Kettler *et al.* (*84*). The three textural variables measured (sand, clay and silt) were highly intercorrelated (Spearman $\rho_{sand-silt}$ = -0.966, $P$ < 0.001; Spearman $\rho_{sand-clay}$ = -0.562, $P$ < 0.001; Spearman $\rho_{silt-clay}$ = 0.365, $P$ < 0.001). Thus, we selected for further analyses the content of sand, which has been found to play key roles in controlling water availability, community structure and biogeochemical processes in drylands (*85-88*). This variable was also correlated with pH in our database (Spearman $\rho$ = -0.229, $P$ = 0.001), and thus pH was not used in subsequent analyses.

A total of 21 climatic variables related to different temperature and rainfall characteristics of the study sites were extracted from the Worldclim global database (see www.worldclim.org for details). In addition, we obtained values of the aridity index from another database using the data interpolations provided by Worldclim (*89*;

http://www.cgiar-csi.org/data/climate/item/51-global-aridity-and-pet-database). We first explored the correlations among these climatic descriptors, and excluded 11 variables that were strongly correlated (Pearson's r > 0.85) with the remaining variables (table S1). We then conducted a principal component analysis (PCA) using a correlation matrix and a Varimax rotation with the remaining 10 variables (annual mean temperature, mean diurnal temperature range, temperature seasonality, maximum temperature of the warmest month, mean temperature of the wettest quarter, mean temperature of the driest quarter, mean annual precipitation, precipitation seasonality [coefficient of variation of monthly precipitation], precipitation of the driest quarter and precipitation of the coldest quarter). All the components that had eigenvalues > 1 were retained for further analyses (*90*). Four components of this PCA had eigenvalues greater than one (Component 1 = 3.46, Component 2 = 2.43, Component 3 = 1.34, and Component 4 = 1.14), explaining over 84% of the variance in the data (Component 1 = 34.64%, Component 2 = 24.33%, Component 3 = 13.40%, and Component 4 = 11.42%). Mean annual precipitation (*r* = 0.910), precipitation in the coldest quarter (*r* = 0.791) and temperature seasonality (*r* = -0.766) showed the highest correlations with the first component of this PCA. The second component of this PCA had the highest correlation with the mean temperature of the driest quarter (*r* = 0.901) and the mean diurnal temperature range (*r* = -0.726). The seasonality in precipitation (*r* = -0.924) and the precipitation in the driest quarter (*r* = 0.946) were the climatic features most correlated with the third components, while the fourth component of the PCA was strongly correlated to annual mean temperature (*r* = 0.682) and the mean temperature of the wettest quarter (*r* = 0.884). We consider it preferable to use PCA components over these climatic variables in our analyses (see below) because these components are orthogonal, while variables such as annual temperature and precipitation, and mean temperature and precipitation in the driest quarter show an important degree of correlation among them (see table S1). This approach enables us to distinguish the unique effects of different variables, and is also commonly employed in studies working at regional, continental and global spatial scales and dealing with multiple, highly intercorrelated climatic variables (e.g., *91-94*).

Assessment of ecosystem multifunctionality: rationale, approach followed and comparison with alternative approaches

We focused our analyses on ecosystem multifunctionality, i.e. the ability of the ecosystem to maintain multiple functions simultaneously (*49, 51, 55, 95*). Most of the ecosystem functions evaluated are involved in biochemical pathways leading to the production of proteins and carbon structures, and thus directly linked to the maintenance of primary production, biomass accumulation and nutrient cycling ("ecosystem functioning" *sensu 52*). Organic C, total N and available P are good surrogates of C, N and P availability for plants and microorganisms in dryland ecosystems worldwide, and ultimately control many biogeochemical processes in drylands, as well as plant and microbial performance (e.g., *37, 96-98*). Ammonium is considered the preferred source of N for bacteria and fungi (*99, 100*), and both $NH_4^+$-N and $NO_3^-$-N are the main source of N for vascular plants (*101-102*). Proteins are an important N input to the soil in terrestrial ecosystems (*103-104*), while aminoacids provide N sources for both plants and microorganisms (*105-109*). Phenolic compounds, hexoses, pentoses and aromatic

compounds are an important source of C for heterotrophic organisms in a wide variety of environments (*76, 110-112*). Similarly, soil enzyme activities catalyze limiting steps in organic matter degradation and are often commonly used as indicators of microbial nutrient demand (*113*). According to this rationale, and taking into account the size of the plots surveyed and the spatial extent of our study, we assume that the higher the values for the different ecosystem functions measured at a given ecosystem, the higher the overall ecosystem functioning at that site. It should be noted, however, that some studies have reported phenolic inhibition of nitrification (*114, 115*), albeit contrasting results are also commonly found in many environments (e.g. *108, 116-117*). Indeed, positive correlations between the content of phenols and both potential N transformation rate (Spearman $\rho = 0.634$, n = 224, $P < 0.001$) and $NO_3^-$-N content (Spearman $\rho = 0.396$, n = 224, $P < 0.001$) have been found at our study sites.

Different approaches have been proposed to quantify ecosystem multifunctionality in the ecological literature. Some authors have used the average of multiple functions (previously standardized) as an index of ecosystem multifunctionality (*55, 118*). Others have used information criteria to identify the species that affected one or many ecosystem functions (*53, 59, 119*), or have established minimal thresholds for every function and then evaluated how combinations of different species affected the proportion of replicates/sites capable of maintaining multiple functions above such thresholds (*54, 120*). The use of a multifunctionality index based on the scaled mean minus the standard deviation of all functions has also been proposed (*121*). Among these alternatives, we decided to use the average of multiple functions (previously standardized) as an index of ecosystem multifunctionality, as it provided a straightforward and easily interpretable measure of the ability of different communities to sustain multiple functions simultaneously. We acknowledge that the use of such an average may preclude a detailed analysis of how particular species differ in their importance for different functions (e.g., *53, 122*), and that by using this average, declines in one function can theoretically be compensated for by increases in one or another function (something that has been criticized in the past; e.g. *54*). However, the extent of our global survey and the important differences in composition between the sites makes the identification of particular species that are important for different functions inappropriate, because species composition differs widely among regions and continents. We did not find that particular sites with high values of a single or a few functions had consistently low values for other functions. In our data set, the correlations between most ecosystem function variables were positive or close to 0, and the strongest negative correlation coefficient (r) between any pair of functions among the 224 sites was only -0.168. Moreover, the coefficient of variation among the functions evaluated at each site varied between only 1.24 and 2.36. Finally, the relatively large number of functions employed to calculate our multifunctionality index makes it relatively robust to outliers or atypical values.

To obtain a quantitative multifunctionality index for each site (*M*), we first calculated the Z scores of the 14 functions evaluated, estimated at the scale of each 30 m × 30 m plot surveyed. These estimates were obtained by using a weighted average of the mean values observed in bare ground and vegetated areas, weighted by their respective cover at each plot. Raw data were normalized prior to these calculations; a sqrt-transformation normalized most of the variables evaluated. Following this, the Z scores of the 14 variables were averaged to obtain *M*. This multifunctionality index follows a

normal distribution (Kolmogorov-Smirnof test = 0.058, df = 224, $P$ = 0.068). We preferred the use of Z scores over other transformations used in the multifunctionality literature (e.g. division by the maximum, *118*) because of their good statistical properties: i) average Z scores follow a normal distribution, ii) the means and variances of such averages are poorly correlated (r = 0.167 in our dataset), and iii) the Z scores do not constrain the variability found in the raw data, as do other indices that are bounded between 0 and 1.

Variation in cover has been used as proxy for plant biomass and productivity in a wide variety of environments, including grasslands and shrublands (*123-126*), and as such could be considered as another ecosystem function. However, with the approach we followed, total plant cover is taken into account when estimating ecosystem functions at the plot scale, and thus cannot also be used as an independent variable in subsequent analyses. Nevertheless, we compared the multifunctionality index obtained with our plot-level estimates (*M*) with an alternative index using average values of the ecosystem functions from bare ground areas plus total plant cover as another function. Both indices were strongly correlated (fig. S3). We therefore preferred to use *M* obtained with plot-level estimates because these represent ecosystem functioning more realistically at the landscape scale (which includes both bare ground and vegetated areas), and by doing so we avoid overestimating the effect of plant cover.

Prior to further analyses, and to ensure that our results were robust with respect to the method used to calculate ecosystem multifunctionality, we calculated two alternative multifunctionality indices: i) the average of multiple functions, previously standardized by dividing by the maximum (SD index, *118*), and ii) this average minus the standard deviation (SDSE index, *121*). The comparison between *M* and these alternative approaches revealed that all the indices were strongly related (fig. S4). Results from *M* were almost identical to those of the SD index. While highly correlated, results with the SDSE index showed more scatter (fig. S4). Thus, we repeated the different analyses conducted (described below) with both *M* and the SDSE index to ensure that our results and conclusions are robust to the choice of metric used to estimate multifunctionality.

Statistical analyses

We first evaluated the relationships between the richness of vascular plants and *M* using ordinary least squares (OLS) regression. In addition, and to account for potential effects caused by the spatial structure of the data, we also fitted the relationship between species richness and *M* using a simultaneous autorregresive (SAR) method (*127*), the SAR error model (*sensu 128*). This approach has been highly effective in removing spatial autocorrelation from residuals, while at the time minimizing time coefficient shifts compared to OLS regression (*129*). Species richness data were sqrt-transformed prior to regression analyses to approximate normality. Regression analyses were conducted using both *M* and similar indices conducted only with variables from the C (organic C, β-glucosidase, pentoses, hexoses, aromatic compounds and phenols), N ($NO_3^-$-N, $NH_4^+$-N, total N, aminoacids, proteins, and potential N transformation rate) and P (available inorganic P and phosphatase) cycles.

We then explored the relative effects and importance of species richness and different abiotic factors (sand content, slope, elevation and four components derived from

a principal component analysis of climatic data) as drivers of multifunctionality. We focused on species richness for this study because to date it has been the component of biodiversity most widely studied (*49*), and because other diversity metrics taking into account species abundance, such as the exponential Shannon´s index or the Simpson index, were not independent from species richness (fig. S5). Slope, elevation and species richness were sqrt-transformed prior to analyses to approximate normality. Separate analyses were conducted using *M* and similar indices conducted only with variables from the C, N and P cycles as dependent variables. All the analyses were based on linear regressions.

To examine whether observed effects of species richness were important compared to those of abiotic factors as drivers of multifunctionality, we used a multi-model inference approach based on information theory (*130*). This approach does not rely on the classical approach to fitting models, based on traditional hypothesis testing, but instead uses information theory to assess the probability that a given model is the most appropriate description of the observed data. Multi-model inference approaches are increasingly being used and recommended when dealing with observational data collected over large spatial scales and environmental gradients, as in this study (e.g., *94, 131, 132*). We evaluated all possible linear regression models containing *M* as the dependent variable and the following independent variables: species richness (sqrt-transformed), elevation (sqrt-transformed), slope angle (sqrt-transformed), sand content and the four components derived from the PCA of climatic data described above. The characteristics of our survey make the presence of spatial autocorrelation likely, since sites within each country are not fully independent from each other. While spatial autocorrelation can be a problem for significance tests, parameter estimates using OLS regressions are not seriously or systematically biased by residual autocorrelation in macroecological analyses (*129, 133*). However, spatial autocorrelation may still be a problem in multi-model approaches based on information theory, as the metrics chosen to select models are related to unexplained variance of the models, which can be in turn affected by the presence of spatial autocorrelation (*134*). To control for potential effects of spatial autocorrelation in the data, we also included latitude and longitude as explanatory variables in all the models (*129*).

We ranked all the 255 models that could be generated with our independent variables according to the second-order Akaike information criterion ($AIC_c$), calculated as described in Fotheringham *et al.* (*135*). The $AIC_c$ of each model was then transformed to $\Delta AIC_c$, which is the difference between $AIC_c$ of each model and the minimum $AIC_c$ found for the set of models compared. Values of $\Delta AIC_c$ above 7 indicate that a model has a poor fit relative to the "best" model (i.e. that with the lowest $AIC_c$), whereas values below 2 indicate that models are indistinguishable (*130*). The $\Delta AIC_c$ values were also used to obtain the Akaike weights of each model ($w_i$), according to Burnham and Anderson (*130*). This parameter provides evidence that the model is actually the best explanatory model. Akaike's weights were also used to define the relative importance of each predictor across the full set of models evaluated by summing $w_i$ values of all models that include the predictor of interest, taking into account the number of models in which each predictor appears (*130*).

Exploratory analyses showed that the relationships between ecosystem multifunctionality and some independent variables were explained better with quadratic,

rather than with linear, terms (figs. S6-S9). To ensure that non-linearity was not affecting our conclusions, we conducted an additional model selection analysis that included quadratic terms for elevation, sand content and the four PCA components derived from climatic data. To do this, we selected the best 10 OLS models according to $AIC_c$, and ran them again, including the quadratic term of the relevant variables. The addition of latitude and longitude effectively removed most of the spatial autocorrelation found in the data, which was virtually nonexistent when quadratic terms were included (fig. S10A). However, the residuals of the best fitted model without these terms still had some evidence of spatial autocorrelation (fig. S10B). To further ensure that spatial autocorrelation was not affecting our conclusions, we conducted an additional model selection based on spatial regression. As with the quadratic terms, we selected the best 10 OLS models according to $AICc$, and ran them again using SAR. The results of the analyses of our multifunctionality index conducted with both OLS, OLS with quadratic terms and SAR analyses were virtually identical (Table 1 in the main text, tables S2 and S3), and thus only the former are presented in the main text.

We also checked for potential biases induced by the covariation between species richness and the different abiotic predictors included in the OLS models. For doing so, we calculated the variance inflation factor (VIF) between the different predictors included in the best and most parsimonious OLS models as an indicator for colinearity between these predictors. The VIF was in all cases below four (table S15), suggesting the absence of colinearity problems (*136*).

Correlation, PCA and OLS analyses were performed using SPSS 15.0 (SPSS Inc., Chicago, IL, USA). Spatial regression and multi-model analyses were carried out using SAM 4.0 (*137*).
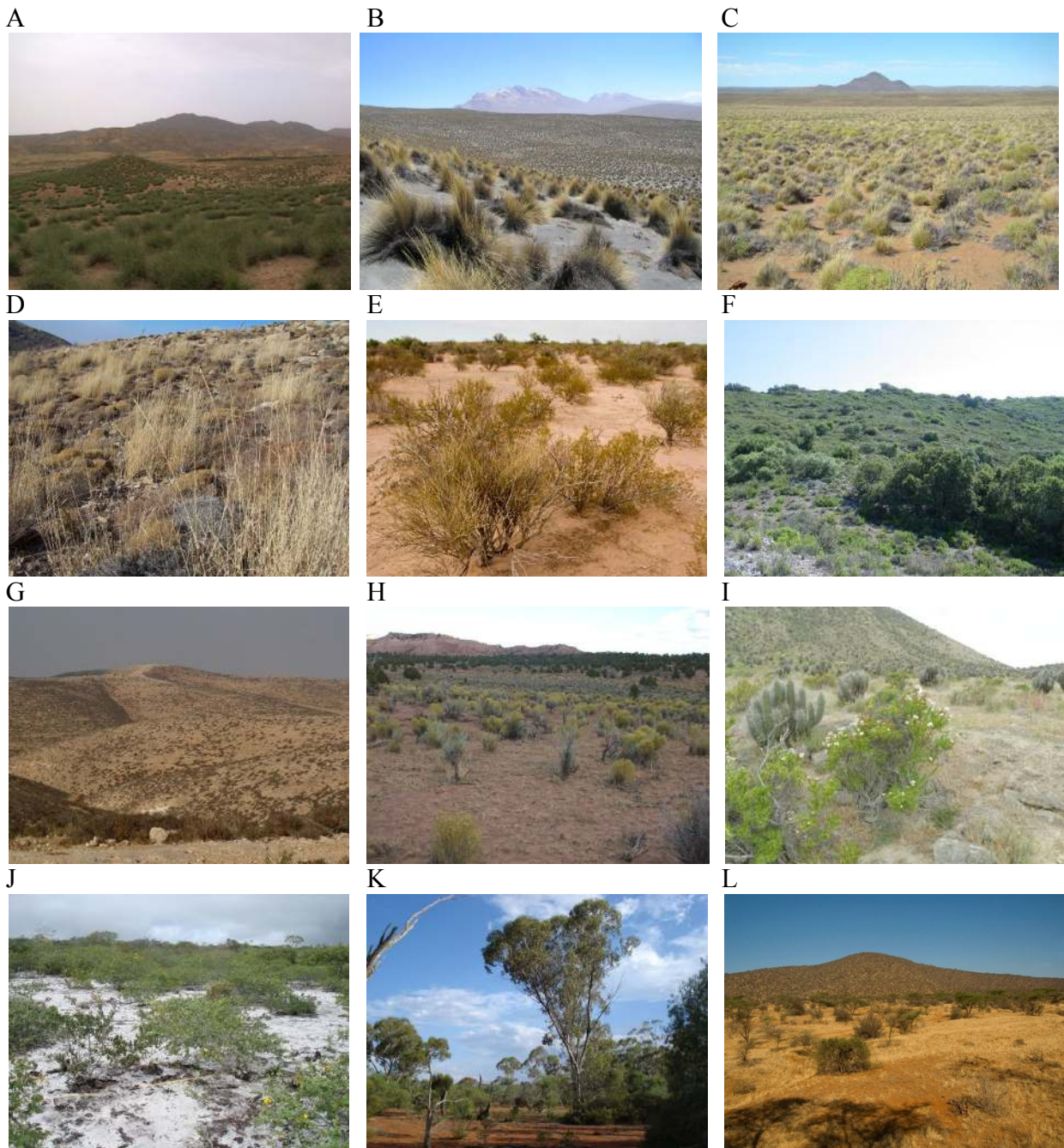
**Fig. S1.**

Examples of the vegetation types surveyed in this study. A = *Stipa tenacissima* grassland in Morocco (119), B = *Festuca orthophylla* grassland in Peru (128), C = grassland dominated by various *Stipa* and *Festuca* species in Argentina (2), D = Shrubland dominated by cushion shrubs (*Acantholimon evinaceum* and *Acanthophyllum glandulosum*) in Iran (83), E = *Larrea cuneifolia* shrubland in Argentina (18), F = Shrubland dominated by *Quercus coccifera*, *Q. ilex* and *Rosmarinus officinalis* in Spain (163), G = Shrubland dominated by *Coridothymus capitatus* in Israel (86), H = Mixed

shrubland dominated by *Ericameria nauseosum* in Utah, USA (203), I = Shrubland dominated by *Eulychnia acida* in Chile (49), J = Shrubland dominated by *Chamaecrista cytisoides* in Brasil (37), K = Open woodland dominated by *Eucalyptus populnea* and *Acacia aneura* in Australia (32), and L = Savanna of *Acacia totalis* in Kenya (99). The numbers in brackets indicate the number of the study site in Database S1 and map S1.
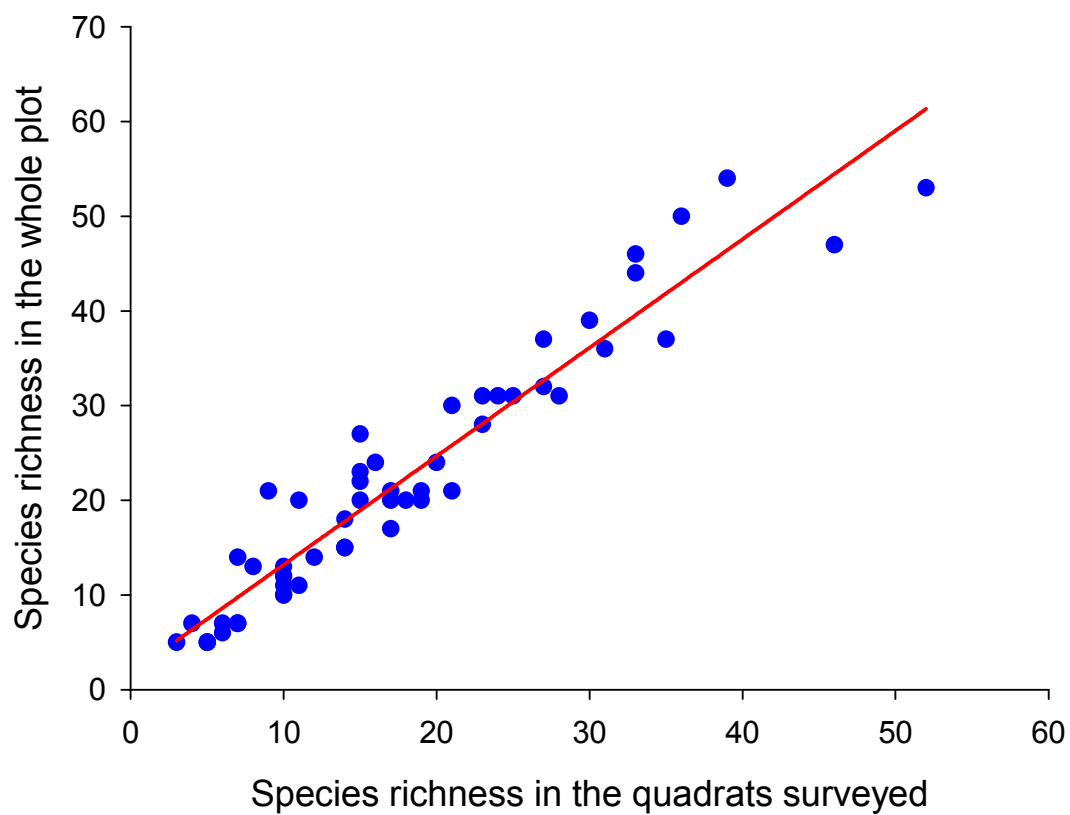
**Fig. S2**

Relationship between the number of species found within the 80 1.5 m × 1.5 m quadrats sampled and the total number of species present within the 30 m × 30 m plot in a subset of the study sites surveyed. The fitted line indicate results from a linear regression ($R^2$ = 0.914, *P* < 0.001).
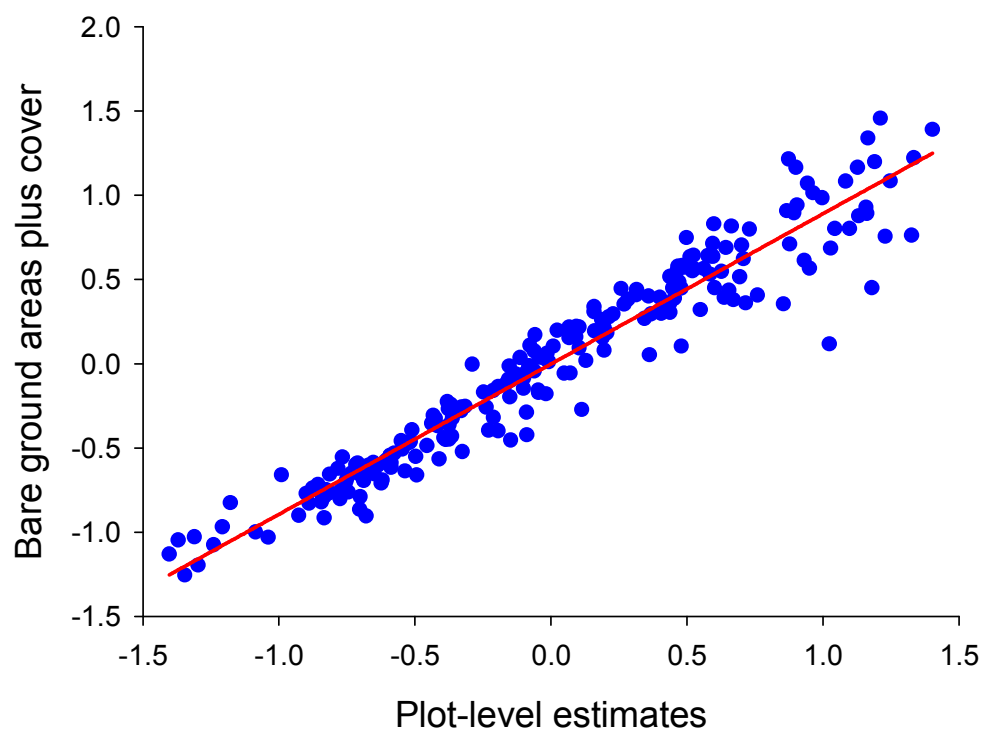
**Fig. S3**

Relationships between our multifunctionality index (*M*), based on plot-level estimates of soil functions, and an alternative index made using the values from areas of bare ground for the same functions plus total cover of perennial vascular plants as another function. The fitted line indicate results from a linear regression ($R^2 = 0.932$, $P < 0.001$).
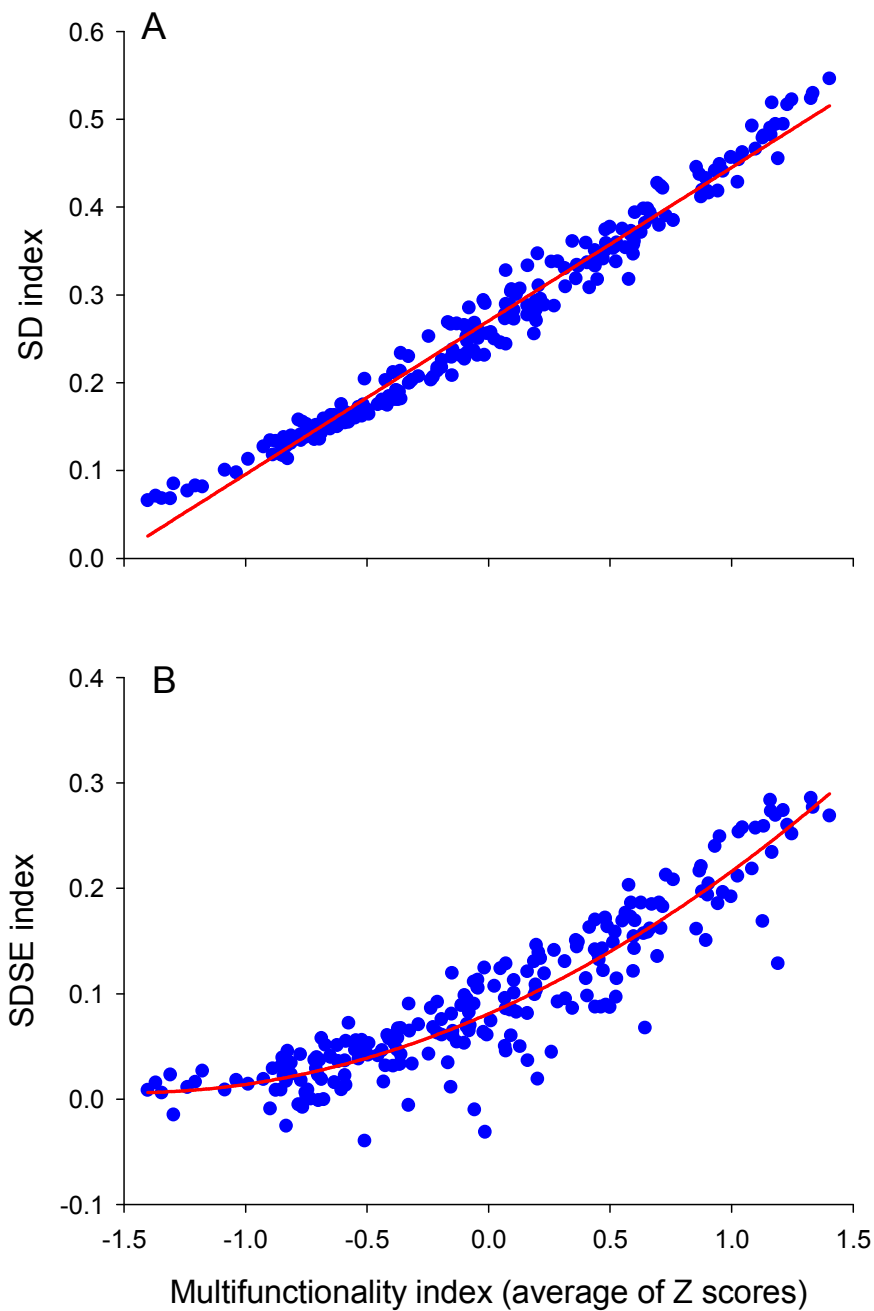
**Fig. S4**

Relationships between our multifunctionality index, based on the average of Z scores of plot-level estimates of ecosystem functions, and alternative indices based on: A) the average of the functions evaluated previously standardized by dividing by the maximum (SD index), and B) such average minus the standard deviation (SDSE index). The fitted lines indicate results from linear (A, $R^2 = 0.974$, $P < 0.001$) and quadratic (B, $R^2 = 0.854$, $P < 0.001$) regressions.
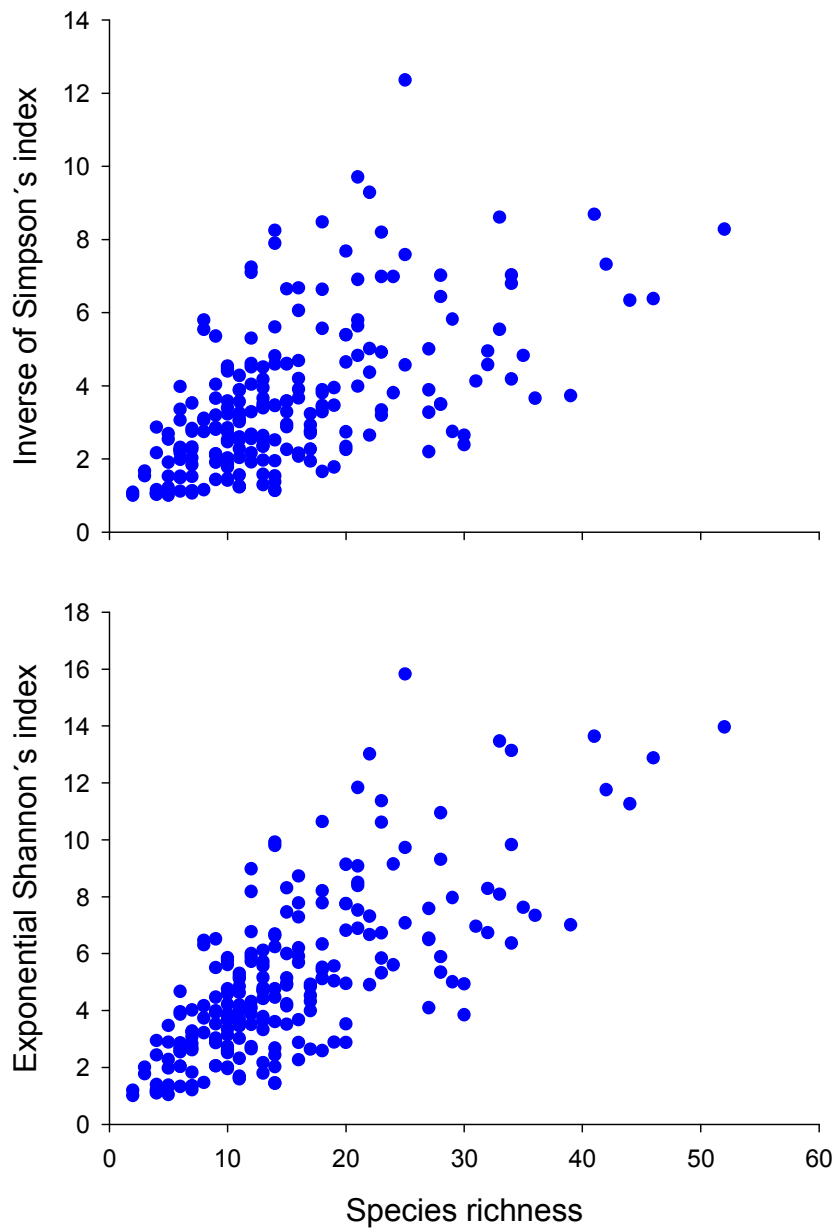
**Fig. S5**

Scatter plots illustrating the dependence between species richness and two metrics of species diversity: the inverse of the Simpson index (upper panel) and the exponential of Shannon´s index (lower panel).
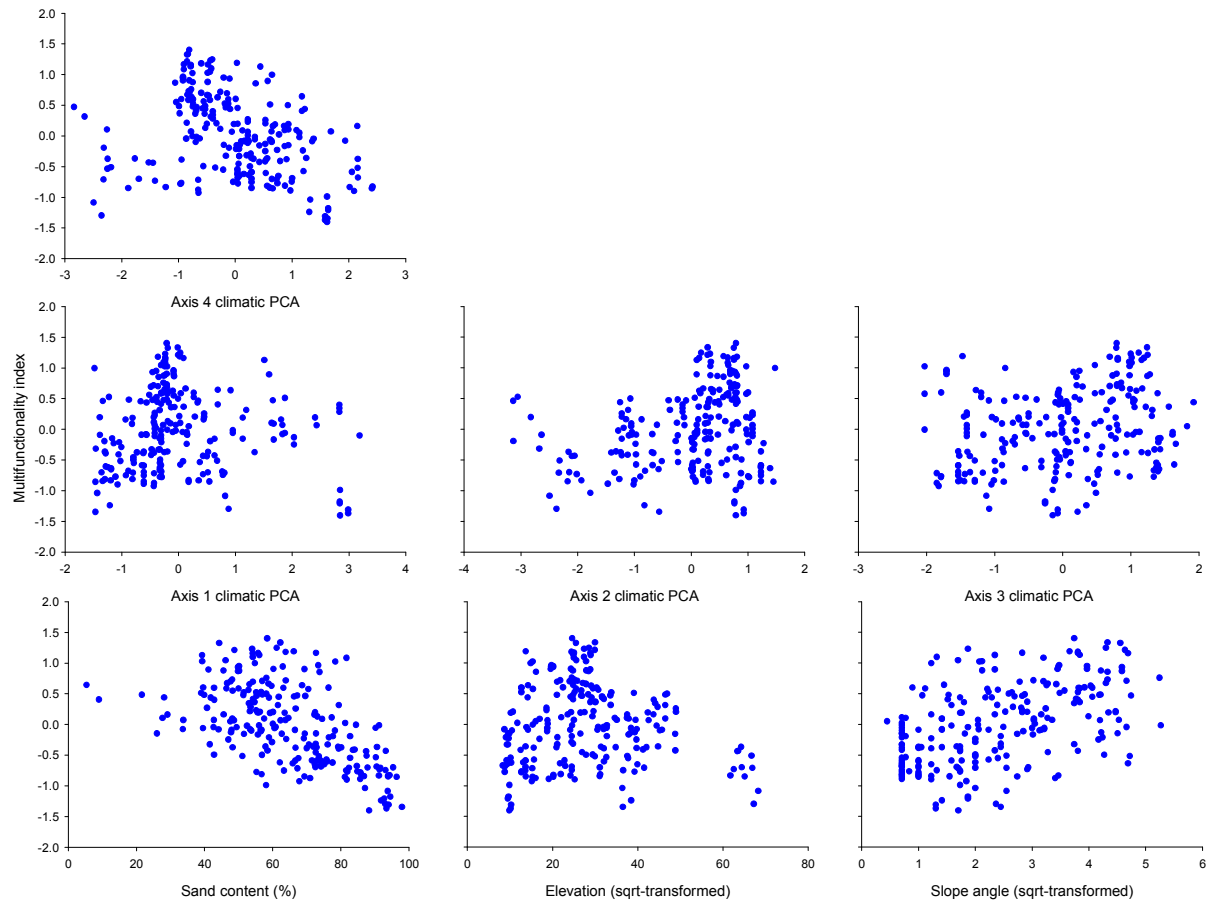
**Fig. S6**

Scatter plots illustrating the relationships between the abiotic variables included in the models and our multifunctionality index (*M*). For the same relationship between *M* and species richness, see fig. 1a in the main text.
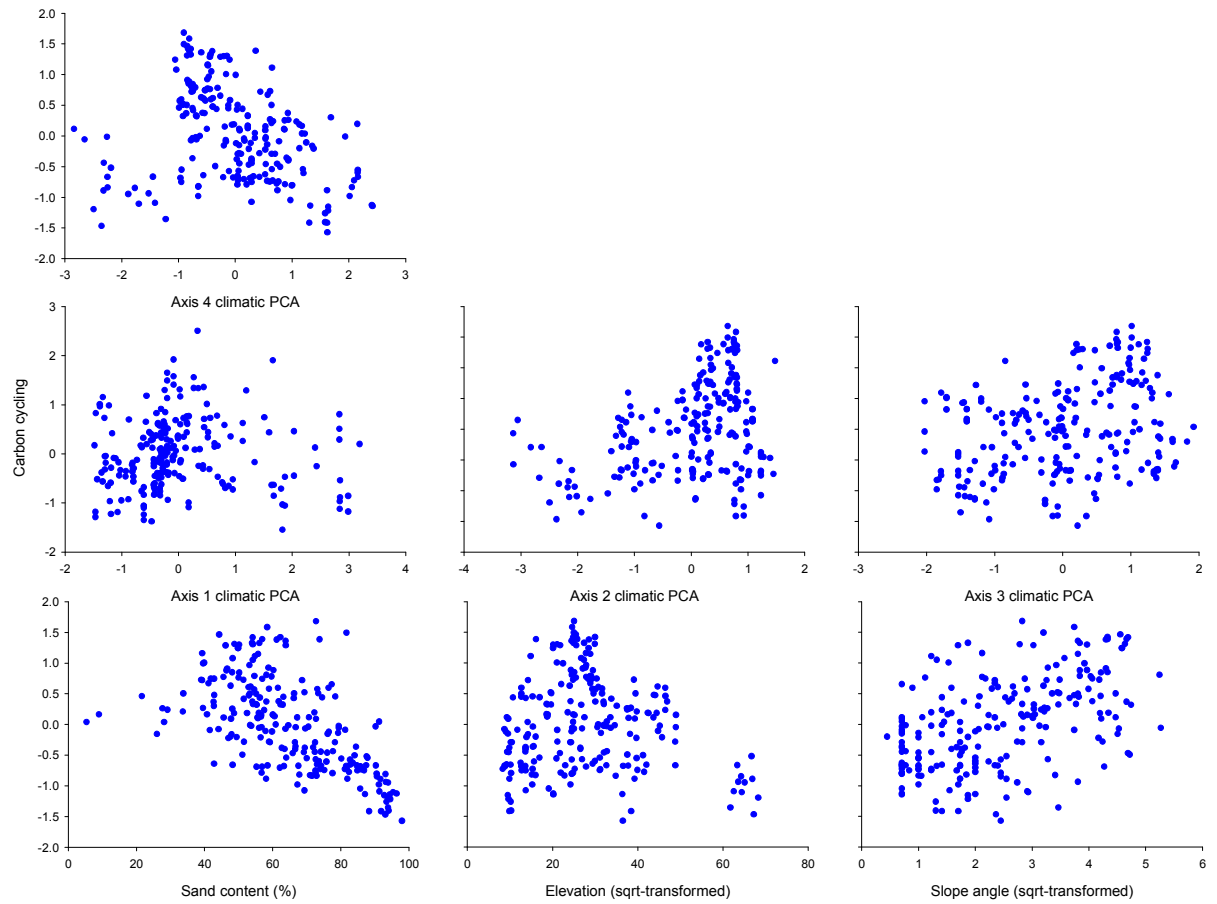
**Fig. S7**

Scatter plots illustrating the relationships between the abiotic variables included in the models and an index synthesizing multiple functions related to carbon cycling (average of Z scores of organic C, β-glucosidase, pentoses, hexoses, aromatic compounds and phenols). For the same relationship between this index and species richness, see fig. 1b in the main text.
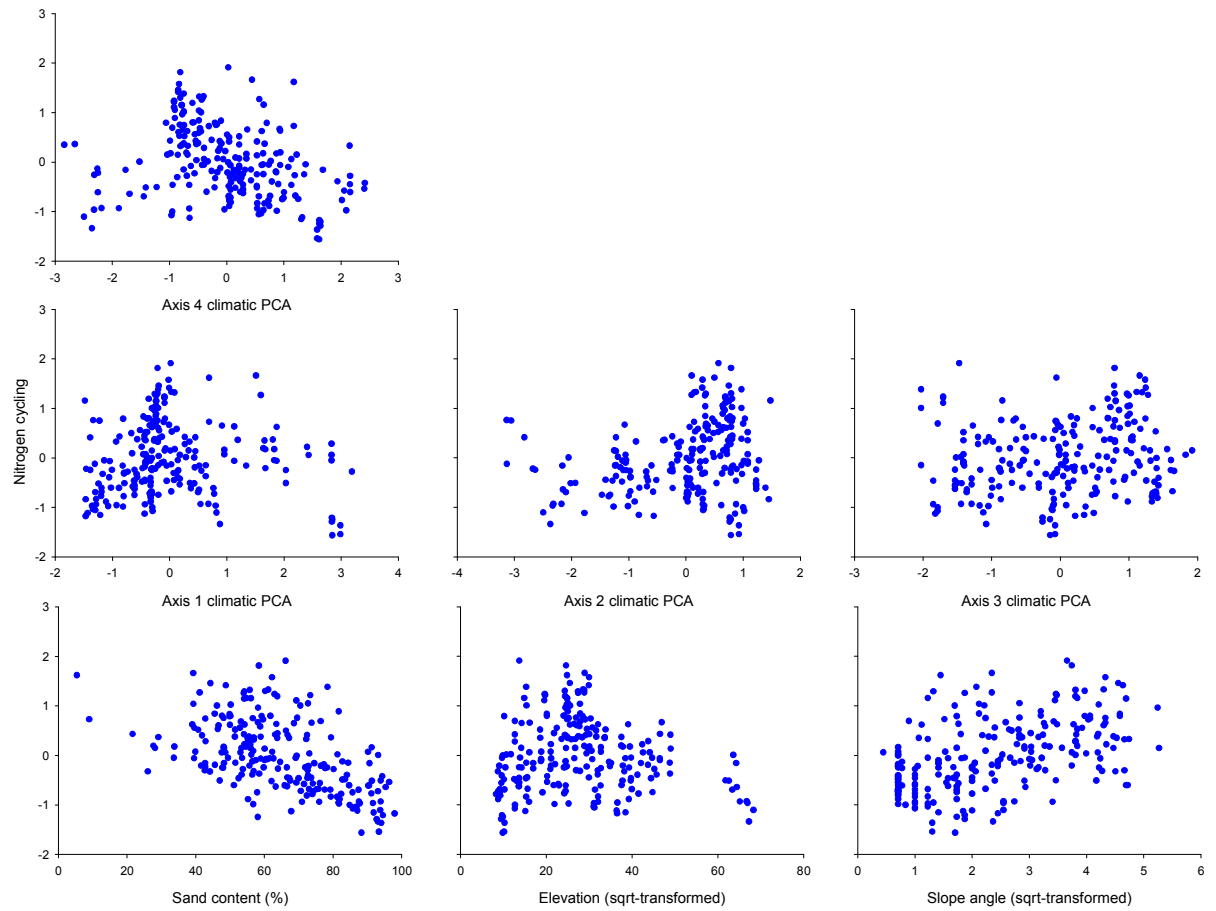
**Fig. S8**

Scatter plots illustrating the relationships between the abiotic variables included in the models and an index synthesizing multiple functions related to nitrogen cycling (average of Z scores of total nitrogen, $NO_3^-$-N, $NH_4^+$-N, aminoacids, proteins, and potential nitrogen transformation rate). For the same relationship between this index and species richness, see fig. 1c in the main text.
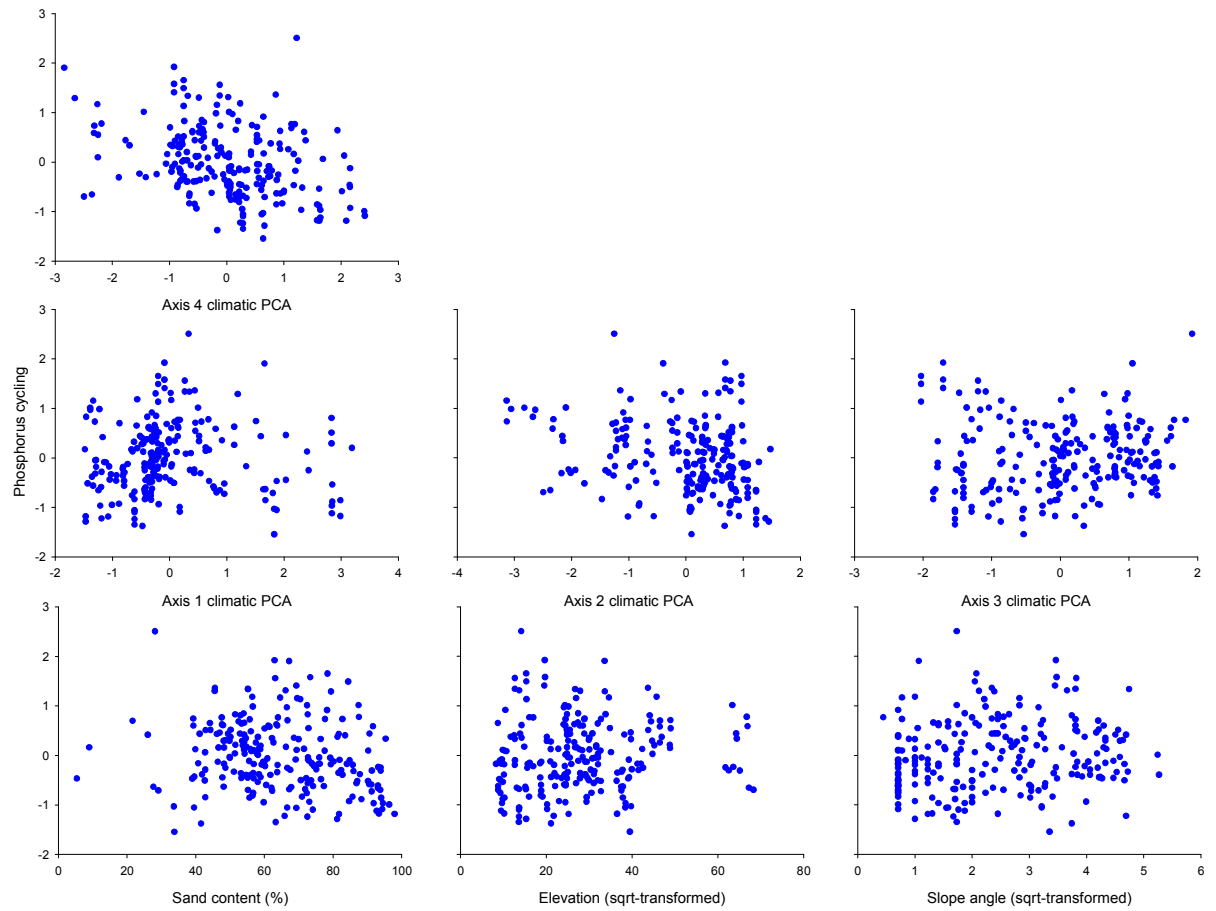
**Fig. S9**

Scatter plots illustrating the relationships between the abiotic variables included in the models and an index synthesizing multiple functions related to phosphorus cycling (average of Z scores of available inorganic phosphorus and phosphatase). For the same relationship between this index and species richness, see fig. 1d in the main text.
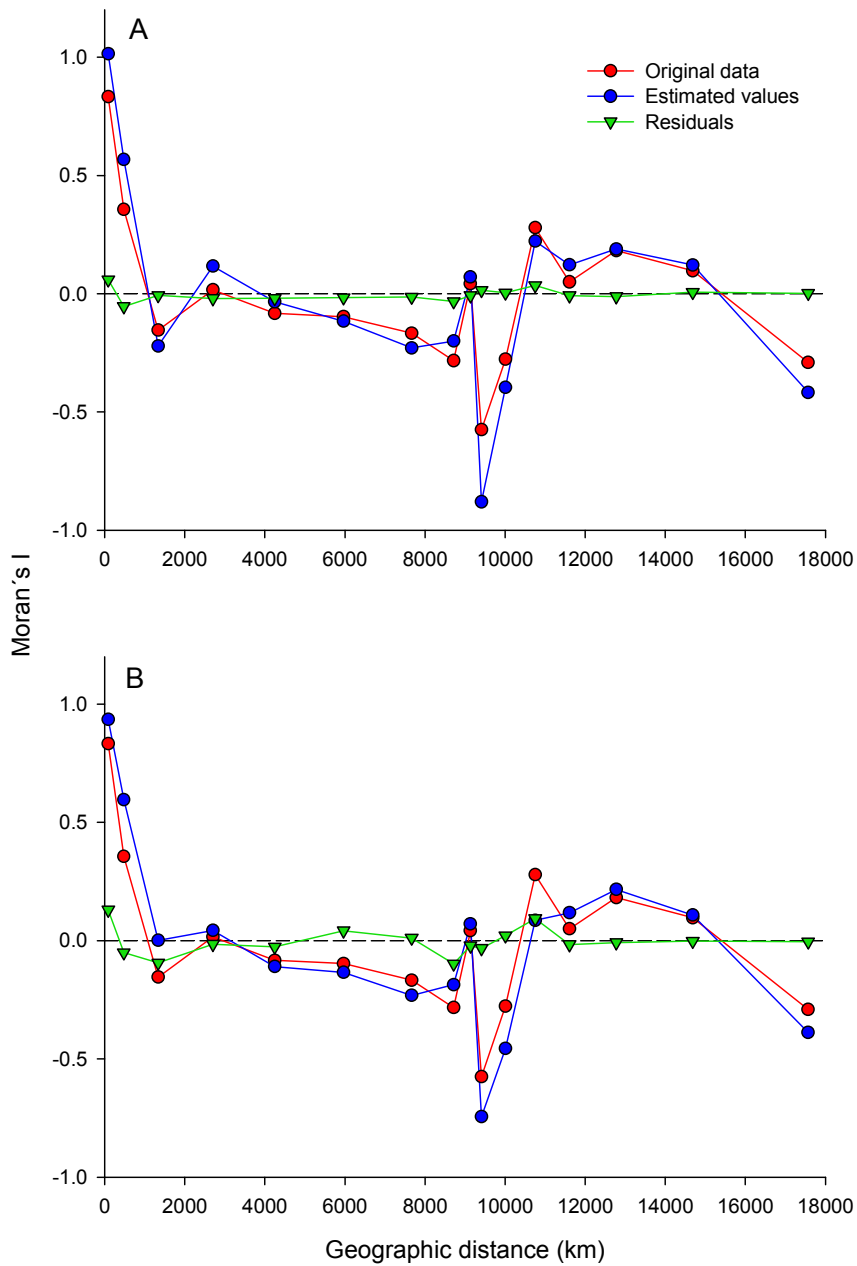
**Fig. S10**

Moran´s correlogram showing the spatial autocorrelation of the original data (red line),
the estimated values (blue line) and of the residuals (green line) of the best model fitted to
our multifunctionality index with (A) and without (B) quadratic terms in the independent
variables. See Table 1 and table S3 for the variables included in the models presented in
A and B, respectively.

**Table S1**.
Pearson correlations among the climatic variables obtained from the Worldclim database (*36*). Values > |0.85| are in bold.

| | AMT | MDR | ISO | TSE | MAWM | MICM | TAR | MTWEQ | MTDQ | MTWAQ | MTCQ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MDR | -0.359 | | | | | | | | | | |
| ISO | 0.423 | 0.082 | | | | | | | | | |
| TSE | -0.545 | 0.089 | **-0.898** | | | | | | | | |
| MAWM | 0.546 | -0.142 | -0.421 | 0.365 | | | | | | | |
| MICM | **0.927** | -0.435 | 0.606 | -0.776 | 0.245 | | | | | | |
| TAR | -0.610 | 0.349 | -0.825 | **0.962** | 0.308 | -0.847 | | | | | |
| MTWEQ | 0.576 | -0.044 | 0.371 | -0.212 | 0.345 | 0.410 | -0.213 | | | | |
| MTDQ | 0.713 | -0.481 | 0.055 | -0.351 | 0.495 | 0.731 | -0.445 | -0.032 | | | |
| MTWAQ | 0.697 | -0.360 | -0.290 | 0.218 | 0.954 | 0.424 | 0.108 | 0.461 | 0.562 | | |
| MTCQ | **0.919** | -0.290 | 0.691 | -0.830 | 0.198 | **0.984** | -0.857 | 0.463 | 0.658 | 0.363 | |
| RAI | 0.425 | -0.181 | 0.658 | -0.538 | -0.057 | 0.520 | -0.541 | 0.415 | 0.175 | 0.037 | 0.535 |
| RAWM | 0.289 | -0.083 | 0.745 | -0.565 | -0.279 | 0.404 | -0.550 | 0.381 | -0.041 | -0.161 | 0.446 |
| RADM | 0.148 | -0.021 | -0.023 | 0.007 | 0.228 | 0.127 | 0.001 | 0.221 | 0.081 | 0.189 | 0.101 |
| RASE | -0.157 | 0.005 | 0.377 | -0.286 | -0.592 | -0.043 | -0.283 | -0.030 | -0.356 | -0.464 | 0.008 |
| RAWEQ | 0.298 | -0.074 | 0.754 | -0.588 | -0.283 | 0.420 | -0.567 | 0.362 | -0.015 | -0.169 | 0.464 |
| RADQ | 0.100 | -0.053 | -0.142 | 0.091 | 0.286 | 0.078 | 0.080 | 0.141 | 0.152 | 0.218 | 0.038 |
| RAWAQ | -0.100 | 0.404 | 0.520 | -0.290 | -0.406 | -0.069 | -0.155 | 0.392 | -0.512 | -0.394 | 0.050 |
| RACQ | 0.449 | -0.364 | 0.509 | -0.460 | 0.020 | 0.553 | -0.531 | 0.214 | 0.338 | 0.140 | 0.518 |
| MTMAX | **0.979** | -0.160 | 0.465 | -0.558 | 0.545 | **0.885** | -0.569 | 0.599 | 0.649 | 0.657 | **0.908** |
| MTMIN | **0.984** | -0.519 | 0.372 | -0.517 | 0.526 | **0.932** | -0.626 | 0.536 | 0.745 | 0.706 | **0.897** |
| AI | 0.076 | -0.205 | 0.440 | -0.313 | -0.224 | 0.215 | -0.334 | 0.156 | -0.003 | -0.170 | 0.201 |

**Table S1.** Continuation.

| | RAI | RAWM | RADM | RASE | RAWEQ | RADQ | RAWAQ | RACQ | MTMAX | MTMIN |
|---|---|---|---|---|---|---|---|---|---|---|
| RAWM | **0.902** | | | | | | | | | |
| RADM | 0.284 | -0.025 | | | | | | | | |
| RASE | -0.004 | 0.386 | -0.724 | | | | | | | |
| RAWEQ | **0.915** | **0.991** | -0.023 | 0.366 | | | | | | |
| RADQ | 0.261 | -0.094 | **0.955** | -0.810 | -0.090 | | | | | |
| RAWAQ | 0.437 | 0.495 | 0.192 | 0.212 | 0.496 | 0.131 | | | | |
| RACQ | 0.798 | 0.773 | 0.019 | 0.112 | 0.789 | -0.021 | -0.065 | | | |
| MTMAX | 0.410 | 0.287 | 0.152 | -0.166 | 0.299 | 0.095 | -0.017 | 0.395 | | |
| MTMIN | 0.424 | 0.280 | 0.140 | -0.145 | 0.287 | 0.102 | -0.168 | 0.481 | **0.927** | |
| AI | **0.908** | 0.818 | 0.300 | -0.013 | 0.825 | 0.321 | 0.422 | 0.690 | 0.036 | 0.109 |

AMT = annual mean temperature, MDR = mean diurnal temperature range, ISO = Isothermality, calculated as 100*(annual mean temperature/[maximum temperature of the warmest month - minimum temperature of the coldest month]), TSE = temperature seasonality (standard deviation *100), MAWM = maximum temperature of the warmest month, MICM = minimum temperature of the coldest month, TAR = temperature annual range (maximum temperature of the warmest month - minimum temperature of the coldest month), MTWEQ = mean temperature of the wettest quarter, MTDQ = mean temperature of the driest quarter, MTWAQ = mean temperature of the warmest quarter, MTCQ = mean temperature of the coldest quarter, RAI = mean annual precipitation, RAWM = precipitation of the wettest month, RADM = precipitation of the driest month, RASE = precipitation seasonality (coefficient of variation of monthly precipitation), RAWEQ = precipitation of the wettest quarter, RADQ = precipitation of the driest quarter, RAWAQ = precipitation of the warmest quarter, RACQ = precipitation of the coldest quarter, MTMAX = mean of maximal temperatures, MTMIN = Mean of minimal temperatures, and AI = aridity index (annual rainfall/annual potential evapotranspiration).

**Table S2.**

Summary results of the modelling of ecosystem multifunctionality (*M* index) using ordinary least squares linear regression and quadratic terms in selected independent variables (sand content, elevation and the four components of a principal component conducted with climatic data), to account for potential effects of non-linear relationships between *M* and these variables (see fig. S6). The same models presented in Table 1 of the main text, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The second model of the table is the most parsimonious model; the same model without species richness had $R^2 = 0.611$, $AIC_c = 261.71$, and $\Delta AIC_c = 8.21$.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C1, $C1^2$, C2, $C2^2$, C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.637 | 253.00 | 0.00 |
| C1, $C1^2$, C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.629 | 253.50 | 0.50 |
| C1, $C1^2$, C2, $C2^2$, C3, $C3^2$, C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.638 | 257.33 | 4.33 |
| C1, $C1^2$, C3, $C3^2$, C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.630 | 257.60 | 4.60 |
| C1, $C1^2$, C2, $C2^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.589 | 276.54 | 23.54 |
| C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.579 | 277.47 | 24.47 |
| C2, $C2^2$, C3, $C3^2$, C4, $C4^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.594 | 278.34 | 25.34 |
| C1, $C1^2$, C3, $C3^2$, SA, $SA^2$, SR, SL, EL, $EL^2$, LA, LO | 0.584 | 279.21 | 26.21 |

$\Delta AIC_c$ = difference between the $AIC_c$ of each model and that of the best model, C1 = first component of a principal component analysis conducted with climatic data ($PCA_{clim}$, mainly related to mean annual precipitation, $r = 0.910$), C2 = second component of $PCA_{clim}$ (mainly related to mean temperature of the driest quarter, $r = 0.901$), C3 = third component of $PCA_{clim}$ (mainly related to precipitation in the driest quarter, $r = 0.946$), C4 = fourth component of $PCA_{clim}$ (mainly related to annual mean temperature [$r = 0.682$] and the mean temperature of the wettest quarter, $r = 0.884$), SA = sand content, SR = species richness (sqrt-transformed), SL = slope (sqrt-transformed), and EL = elevation (sqrt-transformed), LA =latitude, and LO = longitude. Superscripts indicate quadratic terms.

**Table S3.**

Summary results of the modelling of ecosystem multifunctionality (*M* index) using spatial simultaneous autorregression. The same models presented in Table 1 of the main text, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The first model of the table is the most parsimonious; the same model without species richness had $R^2 = 0.475$, $AIC_c = 316.88$, and $\Delta AIC_c = 7.75$. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C4, SA, SR, SL, EL | 0.498 | 309.13 | 0 |
| C2, C3, C4, SA, SR, SL, EL | 0.497 | 313.81 | 4.68 |
| C1, C4, SA, SR, SL, EL | 0.409 | 347.86 | 38.73 |
| C1, C2, C4, SA, SR, SL, EL | 0.406 | 350.98 | 41.85 |
| C1, C3, C4, SA, SR, SL, EL | 0.402 | 352.57 | 43.44 |
| C1, C2, C3, C4, SA, SR, SL, EL | 0.400 | 355.32 | 46.19 |
| C1, C2, SA, SR, SL, EL | 0.287 | 389.75 | 80.62 |
| C1, C3, SA, SR, SL, EL | 0.284 | 390.52 | 81.39 |

**Table S4.**

Best-fitting regression models of the C cycling index using ordinary least squares regression. Of all 255 possible models, the best ten models are presented, ranked according to the second-order Akaike information criterion ($AIC_c$). The first model of the table is the most parsimonious; the $\Delta AIC_c$ of the same model without species richness is indicated in bold. $w_i$ = Akaike weights. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ | $w_i$ |
|---|---|---|---|---|
| C3, C4, SA, SR, SL, EL, LA, LO | 0.600 | 320.156 | 0 | 0.298 |
| C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.603 | 320.644 | 0.488 | 0.234 |
| C1, C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.606 | 321.163 | 1.007 | 0.180 |
| C1, C3, C4, SA, SR, SL, EL, LA, LO | 0.601 | 321.607 | 1.450 | 0.145 |
| C1, C2, C3, C4, SA, SR, SL, LA, LO | 0.598 | 323.486 | 3.330 | 0.056 |
| C2, C3, C4, SA, SR, SL, LA, LO | 0.590 | 325.583 | 5.427 | 0.020 |
| C3, C4, SA, SL, EL, LA, LO | 0.585 | 326.134 | **5.978** | 0.015 |
| C2, C4, SA, SR, SL, EL, LA, LO | 0.588 | 326.782 | 6.626 | 0.011 |
| C4, SA, SR, SL, EL, LA, LO | 0.583 | 326.842 | 6.685 | 0.011 |
| C1, C3, C4, SA, SL, EL, LA, LO | 0.586 | 327.907 | 7.751 | 0.006 |

**Table S5.**

Best-fitting regression models of the N cycling index using ordinary least squares regression. Of all 255 possible models, the best ten models are presented, ranked according to the second-order Akaike information criterion ($AIC_c$). The first and second models of the table are the best and most parsimonious models, respectively; the same models without species richness had $R^2 = 0.420$, $AIC_c = 387.502$, $\Delta AIC_c = 20.344$, and $R^2 = 0.452$, $AIC_c = 374.698$, $\Delta AIC_c = 7.54$, respectively. $w_i$ = Akaike weights. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ | $w_i$ |
|---|---|---|---|---|
| C1, C4, SA, SR, SL, EL, LA, LO | 0.481 | 367.158 | 0 | 0.270 |
| C4, SA, SR, SL, EL, LA, LO | 0.475 | 367.544 | 0.386 | 0.222 |
| C2, C4, SA, SR, SL, EL, LA, LO | 0.477 | 368.965 | 1.807 | 0.109 |
| C1, C2, C4, SA, SR, SL, EL, LA, LO | 0.481 | 369.186 | 2.028 | 0.098 |
| C1, C3, C4, SA, SR, SL, EL, LA, LO | 0.481 | 369.267 | 2.110 | 0.094 |
| C3, C4, SA, SR, SL, EL, LA, LO | 0.475 | 369.728 | 2.570 | 0.075 |
| C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.477 | 371.153 | 3.995 | 0.037 |
| C1, C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.481 | 371.306 | 4.149 | 0.034 |
| C2, C4, SA, SL, EL, LA, LO | 0.461 | 373.464 | 6.306 | 0.012 |
| C2, C3, C4, SA, SL, EL, LA, LO | 0.464 | 374.224 | 7.067 | 0.008 |

**Table S6.**

Best-fitting regression models of the P cycling index using ordinary least squares regression. Of all 255 possible models, the best ten models are presented, ranked according to the second-order Akaike information criterion ($AIC_c$). $w_i$ = Akaike weights. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ | $w_i$ |
|---|---|---|---|---|
| C2, C4, SA, EL, LA, LO | 0.378 | 394.669 | 0 | 0.211 |
| C2, C4, SA, SR, EL, LA, LO | 0.382 | 395.297 | 0.629 | 0.154 |
| C2, C3, C4, SA, EL, LA, LO | 0.379 | 396.405 | 1.737 | 0.088 |
| C1, C2, C4, SA, EL, LA, LO | 0.379 | 396.451 | 1.782 | 0.087 |
| C1, C2, C4, SA, SR, EL, LA, LO | 0.385 | 396.588 | 1.919 | 0.081 |
| C2, C4, SA, SL, EL, LA, LO | 0.378 | 396.785 | 2.116 | 0.073 |
| C2, C4, SA, SL, SR, EL, LA, LO | 0.382 | 397.445 | 2.776 | 0.053 |
| C2, C3, C4, SA, SR, EL, LA, LO | 0.382 | 397.457 | 2.788 | 0.052 |
| C1, C2, C3, C4, SA, EL, LA, LO | 0.380 | 398.045 | 3.376 | 0.039 |
| C2, C3, C4, SA, SL, EL, LA, LO | 0.379 | 398.464 | 3.795 | 0.032 |

**Table S7.**

Summary results of the modelling of the C cycling index using spatial simultaneous autorregression (SAR). The same models presented in table S4, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The first model of the table is the most parsimonious; the same model without species richness had $R^2 = 0.529$, $AIC_c = 355.323$, and $\Delta AIC_c = 7.74$. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C2, C3, C4, SA, SR, SL | 0.545 | 347.583 | 0 |
| C2, C3, C4, SA, SR, SL, EL | 0.546 | 349.047 | 1.464 |
| C2, C4, SA, SR, SL, EL | 0.527 | 356.483 | 8.900 |
| C3, C4, SA, SR, SL, EL | 0.525 | 357.217 | 9.634 |
| C3, C4, SA, SL, EL | 0.517 | 358.910 | 11.327 |
| C4, SA, SR, SL, EL | 0.507 | 363.191 | 15.608 |
| C1, C3, C4, SA, SR, SL, EL | 0.464 | 386.489 | 38.906 |
| C1, C2, C3, C4, SA, SR, SL | 0.463 | 387.022 | 39.439 |
| C1, C2, C3, C4, SA, SR, SL, EL | 0.466 | 387.808 | 40.225 |
| C1, C3, C4, SA, SL, EL | 0.453 | 388.822 | 41.239 |

**Table S8.**

Summary results of the modelling of the N cycling index using spatial simultaneous autorregression (SAR). The same models presented in table S5, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The first model of the table is the most parsimonious; the same model without species richness had $R^2 = 0.414$, $AIC_c = 388.788$, and $\Delta AIC_c = 3.054$. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C4, SA, SR, SL, EL | 0.427 | 385.734 | 0 |
| C2, C4, SA, SR, SL, EL | 0.427 | 387.990 | 2.256 |
| C3, C4, SA, SR, SL, EL | 0.426 | 388.613 | 2.879 |
| C2, C4, SA, SL, EL | 0.416 | 390.262 | 4.528 |
| C2, C3, C4, SA, SR, SL, EL | 0.426 | 390.801 | 5.067 |
| C2, C3, C4, SA, SL, EL | 0.413 | 393.478 | 7.744 |
| C1, C4, SA, SR, SL, EL | 0.374 | 407.765 | 22.031 |
| C1, C2, C4, SA, SR, SL, EL | 0.370 | 411.621 | 25.887 |
| C1, C3, C4, SA, SR, SL, EL | 0.361 | 414.569 | 28.835 |
| C1, C2, C3, C4, SA, SR, SL, EL | 0.359 | 417.485 | 31.751 |

**Table S9.**

Summary results of the modelling of the P cycling index using spatial simultaneous autorregression (SAR). The same models presented in table S6, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C2, C4, SA, EL | 0.294 | 421.939 | 0 |
| C2, C4, SA, SL, EL | 0.290 | 425.294 | 3.355 |
| C2, C4, SA, SR, EL | 0.290 | 425.323 | 3.384 |
| C2, C3, C4, SA, EL | 0.284 | 427.120 | 5.181 |
| C2, C4, SA, SL, SR, EL | 0.286 | 428.632 | 6.693 |
| C2, C3, C4, SA, SL, EL | 0.284 | 429.258 | 7.319 |
| C2, C3, C4, SA, SR, EL | 0.283 | 429.532 | 7.593 |
| C1, C2, C4, SA, EL | 0.224 | 445.193 | 23.254 |
| C1, C2, C4, SA, SR, EL | 0.219 | 448.781 | 26.842 |
| C1, C2, C3, C4, SA, EL | 0.191 | 456.768 | 34.829 |

**Table S10.**

Summary results of the modelling of the C cycling index using ordinary least squares linear regression and quadratic terms in some independent variables (sand content, elevation and the four components of a principal component analysis conducted with climatic data), to account for potential effects of non-linear relationships between multifunctionality and these variables (see fig. S7). The same models presented in table S4, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The first model of the table is the most parsimonious; the $\Delta AIC_c$ of the same model without species richness is indicated in bold. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C1, C1$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.663 | 295.428 | 0 |
| C1, C1$^2$, C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.665 | 298.774 | 3.346 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.652 | 299.866 | 4.438 |
| C1, C1$^2$, C3, C3$^2$, C4, C4$^2$,SA, SA$^2$, SR, SL, LA, LO | 0.650 | 303.602 | 8.174 |
| C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.632 | 310.240 | 14.812 |
| C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.626 | 313.889 | 18.461 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.626 | 313.889 | 18.461 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.634 | 313.906 | 18.478 |
| C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.624 | 315.005 | 19.577 |
| C1, C1$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.614 | 316.442 | **21.014** |

**Table S11.**

Summary results of the modelling of the N cycling index using ordinary least squares linear regression and quadratic terms in some independent variables (sand content, elevation and the four components of a principal component analysis conducted with climatic data), to account for potential effects of non-linear relationships between multifunctionality and these variables (see fig. S8). The same models presented in table S5, ranked according to its second-order Akaike information criterion ($AIC_c$), are presented. The first model of the table is the most parsimonious; the same model without species richness had $R^2 = 0.573$, $AIC_c = 334.701$, and $\Delta AIC_c = 1.367$. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C1, C1$^2$, C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.575 | 336.068 | 0 |
| C1, C1$^2$, C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.577 | 339.596 | 3.528 |
| C1, C1$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.557 | 340.772 | 4.704 |
| C1, C1$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.561 | 343.054 | 6.986 |
| C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.509 | 363.626 | 27.558 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.514 | 366.047 | 29.979 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.508 | 366.205 | 30.137 |
| C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.491 | 367.089 | 31.021 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SR, SL, EL, EL$^2$, LA, LO | 0.495 | 369.782 | 33.714 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.496 | 369.880 | 33.812 |

**Table S12.**

Summary results of the modelling of the P cycling index using ordinary least squares linear regression and quadratic terms in some independent variables (sand content, elevation and the four components of a principal component analysis conducted with climatic data), to account for potential effects of non-linear relationships among multifunctionality and these variables (see fig. S9). The same models presented in table S6, ranked according to second-order Akaike information criterion ($AIC_c$), are presented. The second model of the table is the most parsimonious. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ |
|---|---|---|---|
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, EL, EL$^2$, LA, LO | 0.425 | 390.213 | 0 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, EL, EL$^2$, LA, LO | 0.411 | 391.098 | 0.885 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SR, EL, EL$^2$, LA, LO | 0.428 | 391.453 | 1.240 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SR, EL, EL$^2$, LA, LO | 0.412 | 392.898 | 2.685 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.411 | 393.352 | 3.139 |
| C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.428 | 393.689 | 3.476 |
| C1, C1$^2$, C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, EL, EL$^2$, LA, LO | 0.416 | 393.846 | 3.633 |
| C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SL, EL, EL$^2$, LA, LO | 0.412 | 395.167 | 4.954 |
| C1, C1$^2$, C2, C2$^2$, C4, C4$^2$, SA, SA$^2$, SR, EL, EL$^2$, LA, LO | 0.417 | 395.769 | 5.556 |
| C1, C1$^2$, C2, C2$^2$, C3, C3$^2$, C4, C4$^2$, SA, SA$^2$, EL, EL$^2$, LA, LO | 0.429 | 395.829 | 5.616 |

**Table S13.**

Best-fitting regression models of ecosystem multifunctionality using an alternative index that takes into account the variation in the individual functions (SDSE index, described in the Materials and Methods) and ordinary least squares regression. Of all 255 possible models, the best ten models are presented, ranked according to the second-order Akaike information criterion ($AIC_c$). The first model of the table is the most parsimonious; the $\Delta AIC_c$ of the same model without species richness is indicated in bold. $w_i$ = Akaike weights. Rest of legend as in table S2.

| Independent variables | $R^2$ | $AIC_c$ | $\Delta AIC_c$ | $w_i$ |
|---|---|---|---|---|
| C3, C4, SA, SR, SL, EL, LA, LO | 0.596 | -706.873 | 0 | 0.433 |
| C1, C3, C4, SA, SR, SL, EL, LA, LO | 0.599 | -706.177 | 0.696 | 0.306 |
| C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.596 | -704.661 | 2.212 | 0.143 |
| C1, C2, C3, C4, SA, SR, SL, EL, LA, LO | 0.599 | -704.079 | 2.794 | 0.107 |
| C4, SA, SR, SL, EL, LA, LO | 0.575 | -697.607 | 9.266 | 0.004 |
| C1, C4, SA, SR, SL, EL, LA, LO | 0.576 | -695.929 | 10.944 | 0.002 |
| C2, C4, SA, SR, SL, EL, LA, LO | 0.575 | -695.475 | 11.398 | 0.001 |
| C3, C4, SA, SL, EL, LA, LO | 0.568 | -694.051 | **12.822** | < 0.001 |
| C1, C2, C4, SA, SR, SL, EL, LA, LO | 0.576 | -693.942 | 12.931 | < 0.001 |
| C2, C3, C4, SA, SL, EL, LA, LO | 0.571 | -693.545 | 13.328 | < 0.001 |

**Table S14.**

Multimodel averaged parameter estimates of the analyses conducted with the multifunctionality index ($M$) as dependent variable and all possible combinations of the independent variables used. The results shown are the parameter estimates averaged across 255 models using Akaike weights (*130*) and ordinary least squares regression. STE = Standardized coefficient, SE = Standard error, and CI = confidence interval. Rest of legend as in table S2.

| Variable | Coefficient | STE | SE | t | 95% Lower CI | 95% Upper CI |
|---|---|---|---|---|---|---|
| C1 | -0.059 | -0.091 | 0.021 | -2.865 | -0.1 | -0.019 |
| C2 | -0.045 | -0.068 | 0.018 | -2.482 | -0.08 | -0.009 |
| C3 | 0.057 | 0.086 | 0.02 | 2.882 | 0.018 | 0.095 |
| C4 | -0.235 | -0.358 | 0.037 | -6.409 | -0.306 | -0.163 |
| SA | -0.017 | -0.461 | 0.002 | -8.319 | -0.021 | -0.013 |
| SR | 0.112 | 0.191 | 0.032 | 3.525 | 0.05 | 0.175 |
| SL | 0.116 | 0.224 | 0.032 | 3.593 | 0.053 | 0.18 |
| EL | -0.014 | -0.282 | 0.004 | -3.719 | -0.021 | -0.007 |

**Table S15.**

Variance inflation factors of the different predictors included in the best (B) and most parsimonious (MP) ordinary least squares regression models of the multifunctionality index ($M$), and carbon, nitrogen and phosphorus cycling indices. See Table 1 in the main text and tables S4, S5 and S6 for additional details on these models. Rest of legend as in table S2.

| Variable | $M$ | | Carbon cycling | Nitrogen cycling | | Phosphorus cycling |
|---|---|---|---|---|---|---|
| | B | MP | B* | B | MP | B* |
| C1 | 1.514 | - | - | 1.484 | - | - |
| C2 | - | - | - | - | - | 2.423 |
| C3 | 1.514 | - | 1.515 | - | - | - |
| C4 | 1.399 | 1.361 | 1.373 | 1.382 | 1.361 | 1.381 |
| SA | 1.446 | 1.325 | 1.400 | 1.388 | 1.325 | 1.241 |
| SR | 1.333 | 1.101 | 1.752 | 1.124 | 1.101 | - |
| SL | 1.865 | 1.677 | 1.752 | 1.765 | 1.677 | - |
| EL | 1.633 | 1.583 | 1.592 | 1.629 | 1.583 | 3.452 |
| LA | 1.757 | 1.291 | 1.362 | 1.634 | 1.291 | 1.327 |
| LO | 1.672 | 1.484 | 1.562 | 1.568 | 1.484 | 1.847 |

* The best model is also the most parsimonious in this case.

**Database S1**

1215442_DatabaseS1.xls: Data used in the primary analyses of this article. The data appear in the Data spreadsheet; the description and units of each variable appear in the Metadata spreadsheet.

**Map S1**

1215442_mapS1.kml: Interactive map showing the location of all the 224 study sites. Each site is represented by a red icon and a number, corresponding with the number given in Database S1. The following information of every study site appears after clicking on each icon: name, vegetation type, soil type (*38*), soil texture (USDA classification, obtained from http://soils.usda.gov/technical/aids/investigations/texture/), slope, annual mean precipitation, annual mean temperature, species richness, multifunctionality index, carbon cycling index, nitrogen cycling index, and phosphorus cycling index. The free software Google Earth (http://www.google.com/earth/index.html) is needed to view the file.

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