# EBONE

**European Biodiversity Observation Network:**

Design of a plan for an integrated biodiversity observing system in space and time

## WP3 Deliverable report D3.1

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# EXECUTIVE SUMMARY

Aim To develop a consistent quantitative stratification of the land surface of the world into relatively homogeneous bioclimate strata to provide a global spatial framework for the integration and analysis of ecological and environmental data. Methods A broad set of climate-related variables were considered for inclusion into a quantitative model which partitions geographic space into bioclimate regions. Statistical screening produced a subset of relevant bioclimate variables, which were further compacted into fewer independent dimensions using Principal Components Analysis (PCA). An ISODATA clustering routine was then used to classify the principal components into relatively homogenous environmental strata. The strata were aggregated into global environmental zones based on the attribute distances between strata to provide structure and support a consistent nomenclature. Results The Global Environmental Stratification (GEnS) consists of 125 strata, which have been aggregated into eighteen global environmental zones. The stratification has a 30 arcsec resolution (equivalent to 0.86 $km^2$ at the equator). Aggregations of the strata were compared to nine existing global, continental and national bioclimate and ecosystem classifications using the Kappa statistic. Values range between 0.54 and 0.72, indicating good agreement in ecosystem patterns between existing maps and the GEnS.  Main conclusions The Global Environmental Stratification has been constructed using rigorous statistical procedures. It provides a robust spatial analytical framework for the aggregation of local observations, identification of gaps in current monitoring efforts, and systematic design of complementary and new monitoring and research. The GEnS has potential to support global environmental assessments, and has been identified as a focal geospatial data resource for tasks of the recently launched Group on Earth Observation Biodiversity Observation Network (GEO BON).

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# INTRODUCTION

There is growing urgency for integration and coordination of global environmental and biodiversity data required to respond to the 'grand challenges' the planet is facing, including climate change and biodiversity decline (Parr *et al.*, 2003; MA 2005; Pereira & Cooper, 2006; Scholes *et al.*, 2008; Mooney *et al.*, 2009; Metzger *et al.*, 2010; Pereira *et al.*, 2010). On-going and new programmes are gathering valuable data through a profusion of projects at regional, national and international scales, e.g. the Long Term Ecological Research (LTER) programmes (Parr *et al.*, 2003), and activities related to the Global Earth Observation System of Systems (GEOSS; e.g. Muchoney, 2008). Nevertheless, major challenges remain, e.g. data aggregation across scales, consistent monitoring of global biodiversity change, and linking *in situ* and earth observations (Bunce *et al.*, 2008; Scholes *et al.*, 2008; GEOBON, 2010). Progress in these fields is essential to improve future assessments and policy targets relating to the stock and change of global ecosystem resources and biodiversity (Scholes *et al.*, 2008), including the recently launched Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES; Larigauderie & Mooney, 2010) and the United Nations Convention on Biological Diversity (CBD) Aichi targets (Nayar, 2010).

A consistent classification, or stratification[1], of land into relatively homogenous strata provides a valuable spatial framework for comparison and analysis of ecological and environmental data across large heterogeneous areas (Paruelo *et al.*, 1995; Lugo *et al.*, 1999; Mcmahon *et al.*, 2001; Leathwick *et al.*, 2003; Metzger *et al.*, 2005). A global stratification system would provide a flexible instrument in the coordination and analysis of global biodiversity observation efforts (Paruelo *et al.*, 1995; Lugo *et al.*, 1999; Leathwick *et al.*, 2003; Pereira & Cooper, 2006), e.g. for targeting research and monitoring efforts (cf Metzger *et al.*, 2010), aggregating observations (cf Firbank *et al.*, 2003), and for the comparison of trends within similar environments (cf Mooney, 1977) and between strata (cf the biome comparisons in the Millennium Ecosystem Assessment (MA, 2005)). Environmental stratifications can also form a framework for systematic global biodiversity conservation management (Margules & Pressey, 2000; Olson *et al.*, 2001; Leathwick *et al.*, 2003). A robust global stratification into ecologically representative areas will be crucial under the CBD Aichi targets to increase terrestrial nature reserves from 13% to 17% of the world's land area by 2020 (Nayar, 2010). Finally, it would provide a valuable tool for environmental assessments (e.g. IPBES), and global or continental scale agro-ecological and rural development studies.

In the global and continental context, climate is the main determinant of ecosystem and environmental patterns (Walter & Lieth, 1964; Odum, 1983; Klijn & De Haes, 1994; Godron, 1994), and climatically

[1] When classes are not meant as descriptive units, but specifically designed to divide gradients into relatively homogeneous subpopulations we prefer to use the statistical term *stratification*.

similar areas can be interpreted as having similar potentials to support ecosystems (Klijn & De Haes, 1994; Paruelo *et al.*, 1995; Metzger *et al.*, 2005). Broad climate classifications, as expressions of the environment, were first developed by the ancient Greeks (Sanderson, 1999), but saw a proliferation in the late 19th and first half of the 20th century when scientists sought to explain the diversity in vegetation they encountered on their travels (Von Humboldt, 1867; Köppen, 1900; Holdridge, 1947; Thornthwaite, 1948). More recently, bioclimate biome classifications have been used to underpin dynamic global vegetation models (Prentice *et al.*, 1992; Sitch *et al.*, 2003). However, these classifications provide limited regional detail by distinguishing only 10-30 classes globally, and with generally coarse spatial resolutions. More detailed approaches to distinguish global ecoregions (Bailey, 1998; Olson *et al.*, 2001) rely heavily on expert judgement for interpreting class divisions, making it difficult to ensure reliability across the world (Lugo *et al.*, 1999; Metzger *et al.*, 2005).

By contrast, statistical methods ensure consistency and the resulting stratifications are reproducible and, as far as possible, independent of personal bias (Leathwick *et al.*, 2003; Jongman *et al.*, 2006). This is of particular importance where large-scale continuous gradients are involved over thousands of kilometres. No clear boundaries between zones are present in such cases, but statistical methods provide robust divisions based on the balance between the input variables in the analysis. Multivariate clustering of climate data has proved successful in creating more detailed stratifications in many parts of the world (e.g. in Great Britain (Bunce *et al.*, 1996a; Bunce *et al.*, 1996b), Europe (Metzger *et al.*, 2005; Jongman *et al.*, 2006) New Zealand (Leathwick *et al.*, 2003) and Senegal (Tappan *et al.*, 2004)). These datasets have been used for stratified random sampling of ecological resources (Firbank *et al.*, 2003; Bunce *et al.*, 2008), the selection of representative study sites (Palma *et al.*, 2007), and summary reporting of trends and impacts (Thuiller *et al.*, 2005; Metzger *et al.*, 2008b). The stratifications are also flexible, and can be adapted for specific analyses or objectives (Hazeu *et al.*, 2010). Nevertheless, no high resolution global bioclimate classification derived from multivariate statistical clustering has been constructed until now.

This paper presents a novel Global Environmental Stratification (GEnS), distinguishing 125 strata and eighteen zones with 30 arcsec resolution (0.93 x 0.93 = 0.86 km$^2$ at the equator). The stratification is based on statistical clustering so that subjective choices are explicit, their implications are understood, and the strata can be seen in the global context. The dataset will form a global unifying framework within the Group on Earth Observations Biodiversity Observation Network[2] (GEO BON; Scholes *et al.*, 2008; GEOBON, 2010), and will be publicly available to support global ecosystem research.

[2] http://www.earthobservations.org/geobon.shtml

# DATA

## *Bioclimate indicators*

When constructing a global climate classification the use of monthly indicators (cf Bunce *et al.*, 1996a; Metzger *et al.*, 2005) is problematic due to the contrasting seasonality between hemispheres. Bioclimate indicators, which directly influence plant growth, overcome these problems. Furthermore, such indicators are directly related to plant physiological processes determining primary productivity and therefore also directly influence provisional ecosystem services (e.g. food, fibre, and bio-energy production). A suite of bioclimate indicators has been developed, whose origin can be traced to Köppen (1900).

Köppen used observed vegetation patterns to subdivide five global climate zones into thirty classes based on various temperature and precipitation related indicators, but various elements lack phytogeographic foundation (Thornthwaite, 1943; Sanderson, 1999). Thornthwaite stressed the importance of including better measures to represent seasonality and plant available moisture (Thornthwaite, 1943), developing a classification based on humidity and aridity indices (Thornthwaite, 1948). Meanwhile Holdridge (1947) devised a life zone system using a three dimensional bioclimate classification based on biotemperature, precipitation and an aridity index, and Emberger (1930) developed a tailored pluviothermic indicator for distinguishing climate zones in the Mediterranean. The latter is still used as a proxy for effective precipitation when data for evaporation is not available (Cabido *et al.*, 2008). Although there have been several more recent classifications using bioclimate indicators to model terrestrial ecosystem distributions (e.g. Bailey, 1998; Sayre *et al.*, 2009), they are now mainly used in modelling climate change impacts on vegetation (e.g. Cramer *et al.*, 2001; Sitch *et al.*, 2003; Thuiller *et al.*, 2005).

For this paper, several of the most important and contrasting methods have been reviewed to identify relevant bioclimate indicators. The resulting list (Table 1) is not exhaustive, but provides a wide range of relevant indicators that can be calculated using available climate datasets, which can then be analysed by statistical screening.

## *Datasets*

Global spatial climate data is available from several sources, but in this paper the WorldClim Global Climate Dataset was used (Hijmans *et al.*, 2005). WorldClim has the greatest spatial resolution (30 arcsec, approximately 1km2), enabling representation of regional environmental gradients, which dissolve at coarser resolutions, particularly in mountainous and other areas with steep climate gradients (Hijmans *et al.*, 2005; Hazeu *et al.*, 2010).

The WorldClim dataset (version 1.4) was created by spatial interpolation of climate observations from over 45,000 weather stations obtained from major climate databases. ANUSPLIN software was used to calculate thin plate smoothing splines using the latitude, longitude and elevation as independent variables (Hutchinson, 1998a; Hutchinson, 1998b). Variables included are monthly total precipitation, monthly mean, minimum and maximum temperature, and nineteen derived bioclimate variables (see Table 1). The data are available for download from http://www.worldclim.org as ERSI raster files with over 222.3 million 30 arcsec grid cells. Hijmans *et al.* (2005) provide a detailed description of the dataset construction.

Moisture availability is a crucial determinant for plant growth (Thornthwaite, 1943; Thornthwaite, 1948; Prentice *et al.*, 1992), but is not represented in WorldClim. However, several suitable indicators have been calculated from WorldClim data by the Consultative Group for International Agriculture Research Consortium for Spatial Information (CGIAR-CSI; Zomer *et al.*, 2008; Trabucco *et al.*, 2008) and were included in the analysis. These include: Potential EvapoTranspiration (PET), calculated using the Hargreaves method; an Aridity Index expressing the ratio between annual precipitation and PET; and Actual EvapoTranspiration (AET) calculated for a fixed soil water holding capacity and generalised vegetation coefficients (Trabucco *et al.*, 2008).

An additional eighteen bioclimate variables, identified by reviewing earlier studies, have been calculated using the available data, including those reflecting the growing season (cf Prentice *et al.*, 1992; Sitch *et al.*, 2003), a specific indicator developed for the Mediterranean (Emberger, 1930), and additional indicators used to distinguish isoclimate regions (Sayre *et al.*, 2009). Finally, altitude (Jarvis *et al.*, 2008) and clear-sky solar radiation (cf Allen *et al.*, 1998) were included following Leathwick *et al.* (2003). Table 1 provides an overview of the forty-two variables, and Appendix 1 explains the calculation of the eighteen new variables. To avoid negative numbers in subsequent calculations all temperature variables were converted to K.

Table 1. Overview of the forty-two bioclimate variables that were screened to derive a subset for the statistical clustering, and their use in other classifications (A-I). WorldClim data are described in Hijmans et al. (2005), CGIAR-CSI data in Trabucco et al. (2008) and Zomer et al. (2008), and the newly calculated indicators in Appendix 1. * denotes that the variable was calculated from the existing datasets. ~ denotes that a very similar variable was used.

| **Indicator** | | **Source** | **Unit** | **A** | **B** | **C** | **D** | **E** | **F** | **G** | **H** | **I** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ind_1 | Annual mean T | WorldClim | °C | X | | | | X | | | X | X |
| ind_2 | Mean diurnal range | WorldClim | °C | | | | | X | | | | |
| ind_3 | Isothermality | WorldClim | °C | | | | | | | X | | |
| ind_4 | T seasonality | WorldClim | - | | | | | | | | | |
| ind_5 | Maximum T of the warmest month | WorldClim | °C | | | | X | | | | | |
| ind_6 | Minimum T of the coldest month | WorldClim | °C | | | | | X | X | X | X | |
| ind_7 | Annual T range | WorldClim | °C | | | | | | | | | |
| ind_8 | Mean T of the wettest quarter | WorldClim | °C | | | | | | | | | |
| ind_9 | Mean T of the driest quarter | WorldClim | °C | | | | | X | | | | |
| ind_10 | Mean T of the warmest quarter | WorldClim | °C | | | | | ~ | | | | |
| ind_11 | Mean T of the coldest quarter | WorldClim | °C | | | | | | | | | |
| ind_12 | T sums when mean monthly T > 0°C | WorldClim* | °C | | | ~ | | X | ~ | ~ | | |
| ind_13 | T sums when mean monthly T > 5°C | WorldClim* | °C | | | | | | ~ | ~ | ~ | |
| ind_14 | Mean T of the coldest month | WorldClim* | °C | X | | | | X | | | | X |
| ind_15 | Mean T of the warmest month | WorldClim* | °C | X | | | | X | | | | |
| ind_16 | Maximum T of the coldest month | WorldClim* | °C | | | | | X | X | | | |
| ind_17 | Minimum T of the warmest month | WorldClim* | °C | | | | | | X | | | |
| ind_18 | Number of months with mean T > 10°C | WorldClim* | - | X | | | | | | | | |
| ind_19 | Thermicity index | WorldClim* | °C | | | | | X | | | | |
| ind_20 | Annual precipitation | WorldClim | mm | X | | X | | X | | | X | |
| ind_21 | Precipitation of the wettest month | WorldClim | mm | | | | | | | | | |
| ind_22 | Precipitation of the driest month | WorldClim | mm | X | | | | | | | | |
| ind_23 | Precipitation seasonality | WorldClim | - | | | | | | | | | |
| ind_24 | Precipitation of the wettest quarter | WorldClim | mm | | | | | X | | | | |
| ind_25 | Precipitation of the driest quarter | WorldClim | mm | | | | | X | | | | |
| ind_26 | Precipitation of the warmest quarter | WorldClim | mm | | | | | ~ | | | X | |
| ind_27 | Precipitation of the coldest quarter | WorldClim | mm | | | | | | | | X | |
| ind_28 | Minimum June July August precipitation | WorldClim* | mm | ~ | | | | | | | | |
| ind_29 | Maximum June July August precipitation | WorldClim* | mm | ~ | | | | | | | | |
| ind_30 | Minimum December January February precipitation | WorldClim* | mm | ~ | | | | | | | | |
| ind_31 | Maximum December January February precipitation | WorldClim* | mm | ~ | | | | | | | | |
| ind_32 | Total precipitation for months with mean T > 0°C | WorldClim* | mm | | | | | X | | | | |
| ind_33 | Annual actual evapotranspiration | CGIAR-CSI | mm/day | | | | | | | | | |
| ind_34 | Annual potential evapostranspiration | CGIAR-CSI | mm/day | | X | | | X | | | | |
| ind_35 | Coefficient of annual moisture availability | CGIAR-CSI* | - | | | | | | X | | ~ | |
| ind_36 | Aridity Index | CGIAR-CSI | - | | | X | | X | | | | ~ |
| ind_37 | PET seasonality | CGIAR-CSI* | - | | | | | | | | | |
| ind_38 | Thornthwaite humidity index | WorldClim-CGIAR-CSI* | - | | X | | | X | | | | |
| ind_39 | Thornthwaite aridity index | WorldClim-CGIAR-CSI* | - | | X | | | | | | | ~ |
| ind_40 | Emberger's pluviothermic quotient | WorldClim* | - | | | | X | | | | | |
| ind_41 | Annual solar radiation | CGIAR-CSI | evaporation equivalent in mm/day | | | | | | | | | ~ |
| ind_42 | Altitude | WorldClim | m | | | | | | | | | |

## CONSTRUCTING THE STRATIFICATION

The construction of the stratification consisted of three stages. Firstly, the initial pool of forty-two variables was screened to remove those variables with very high correlations and select a subset of variables that represent the dominant global gradients. The second stage entailed the actual statistical clustering. Finally, post-processing has made the dataset more accessible, including the development of a consistent nomenclature, an appropriate map legend and an aggregation scheme to distinguish global environmental zones. The detailed steps of the complete procedure are summarised in Fig. 1. Unless stated differently, all calculations were performed using ESRI ArcGIS 9.2 software.

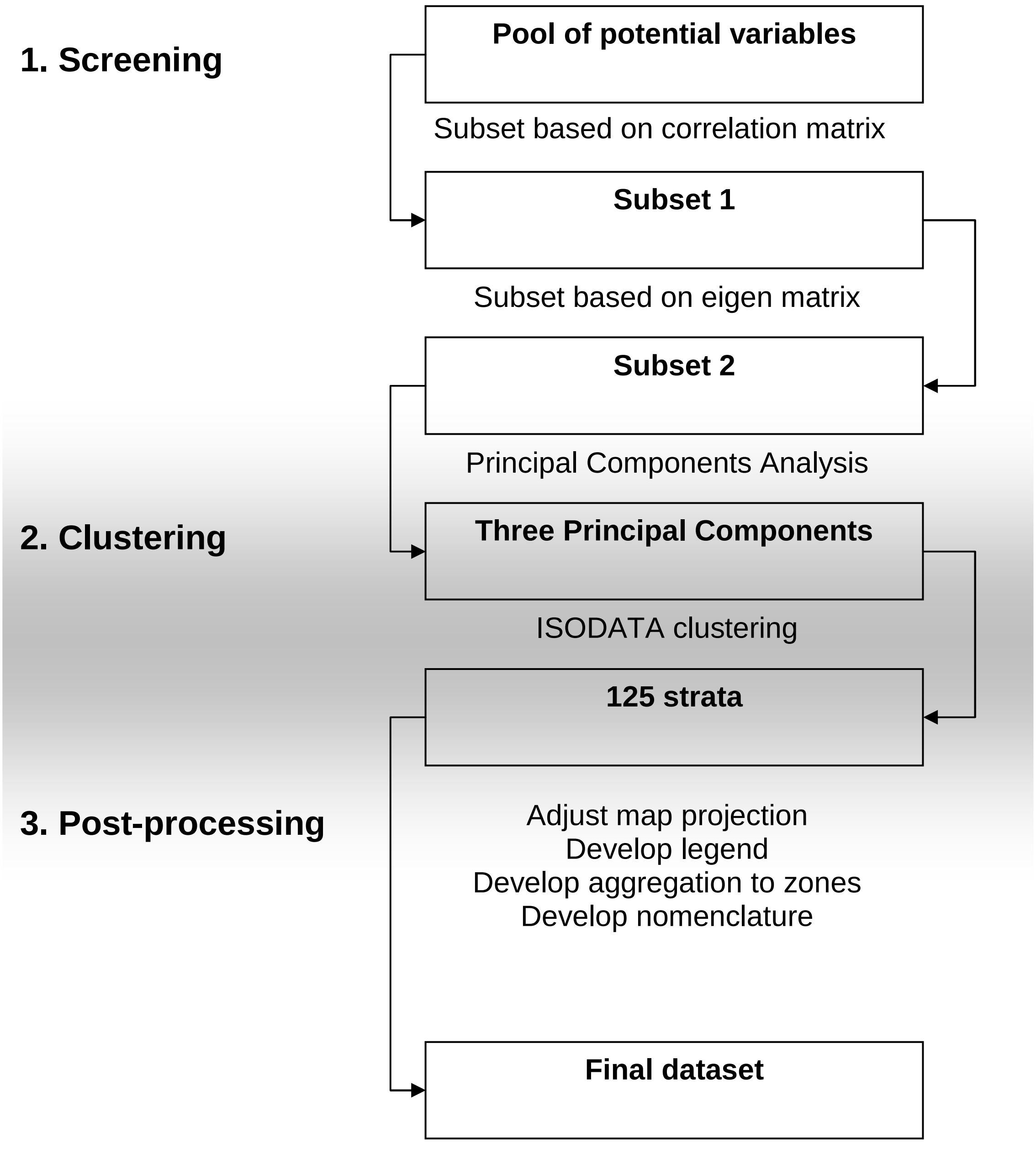


Figure 1. Flowchart illustrating the procedure for constructing the global environmental stratification.

### *Screening of the variables*

High correlation is likely between many of the variables listed in Table 1. To prevent the classification being weighted to the most common or correlated variables, a subset of the forty-two variables was used in the clustering procedure (cf Bunce *et al.*, 1996c). Firstly, a correlation matrix was calculated to identify highly correlated variables. For variables with a Pearson’s correlation coefficient of 1.00 the variable that was most easily interpreted ecologically was selected and any other variables omitted from further analysis. Principal Components Analysis (PCA) was performed on the remaining list to identify those variables that did not represent dominant trends in the data. All variables with eigenvector loadings <0.1 in the first three principal components were removed from the further analysis. The eigenmatrix was calculated using ERDAS IMAGINE 10.0.

### *Clustering*

The classification of the final list of screened variables followed the approach used by Metzger *et al.* (2005) in constructing the environmental stratification for Europe. PCA was used once more to reduce the subset of input variables into a set of fewer dimensions that are non-correlated and independent and are more readily interpretable than the source data (Faust, 1989; Jensen, 1996). The first three principal components were subsequently used in the statistical clustering algorithm to distinguish 125 classes in the data, an arbitrary choice that still permits characterisation and interpretation of the strata, whilst providing far greater detail than existing approaches.

The Iterative Self-Organizing Data Analysis Technique (ISODATA) (Tou & Conzalez, 1974) was used to cluster the principal components into environmental strata. This technique is used widely in image analysis fields, such as remote sensing and medical sciences (e.g. Banchmann *et al.*, 2002; Pan *et al.*, 2003). ISODATA is iterative in that it repeatedly performs an entire classification and recalculates statistics. Self-organizing refers to the way in which it locates clusters with minimum user input. The ISODATA method uses minimum Euclidean distance in the multi-dimensional feature space of the principal components to assign a class to each candidate grid cell.

### *Post-processing*

The source data have a geographic latitude-longitude coordinate system, which renders serious shape and area distortion. For analytical purposes, where equal area representation is important, the dataset was resampled to a 1km2 Mollweide equal area projection.  For presentation purposes, the stratification was projected to Winkel Tripel. This projection produces very small distance errors, small combinations of ellipticity and area errors, and exhibits the least skewness of any map projection

(Goldberg & Gott, 2007), and is also commonly used by the United States National Geographic Society.

To provide structure and support the development of a consistent nomenclature, as well as to facilitate summarising and reporting, it is useful to consistently aggregate the strata to a limited set of environmental zones (Bunce *et al.*, 1996a; Leathwick *et al.*, 2003; Metzger *et al.*, 2005). The dendrogram tool in ArcGIS was used to derive a hierarchical diagram showing the attribute distances between strata, thus illustrating the order in which the dataset progressively combines similar environments into larger groups. The dendrogram was then used to determine the aggregation of the 125 strata into fifteen to twenty Global Environmental Zones (GEnZs).

The GEnZs were ordered based on the mean values of their principal component scores using the dendrogram and assigned letters starting with 'A' for the zone with the lowest value. Likewise, within each GEnZ its strata were numbered by mean first principal component (PC1) score, assigning '1' to the lowest value. The strata were then assigned a unique code based on the combination of the letter (GEnZ) and number (e.g. A1 or D6). In addition, consistent descriptive names were attributed based on the dominant classification variables, as detailed in the results section. Finally, a legend was developed for the strata based on the mean scores of first three components in each stratum (cf Hargrove & Hoffman, 1999; Leathwick *et al.*, 2003).

### *Comparison with existing classifications*

The reliability of the patterns derived by the statistical clustering can be tested by comparing them to other datasets. This is not straightforward, because comparable datasets may not exist or have been created in a more subjective manner (Lugo *et al.*, 1999; Metzger *et al.*, 2005). Differences between datasets could therefore reflect differences in methodology and objectives, rather than illustrating the strength or weakness of any new classification (Hazeu *et al.*, 2010). Nevertheless, it is important to demonstrate that the GEnS distinguishes recognised environmental divisions as evidenced by high correlations with independent datasets. The strength of agreement between the GEnS and nine global, continental and national climate classifications was therefore determined by calculating Kappa statistics (Monserud & Leemans, 1992). This is identical to the approach used by Lugo *et al.* (1999) to 'verify and evaluate' their classification for the United States.

For the Kappa analysis, the datasets that are compared must have the same spatial resolution and distinguish the same classes. To meet these requirements, the classifications were resampled and projected to the Mollweide equal area projection, and the two classifications were clipped to the largest overlapping extent. A contingency matrix was calculated to determine the best way to aggregate the strata. Kappa could then be calculated using the Map Comparison Kit (Visser & De Nijs, 2006). The alternative classifications used in this comparison were: the biomes used to underpin the

World Wildlife Fund (WWF) ecoregions (Olson *et al.*, 2001); a recently updated Köppen map of the world (Peel *et al.*, 2007); the European Environmental Stratification (Metzger *et al.*, 2005); isoclimate maps for the United States (Sayre *et al.*, 2009), South America (Sayre *et al.*, 2008) and Africa (Sayre *et al.*, in prep.); the ecoregions map of the United States (CEC, 1997); the land classification of Great Britain (Bunce *et al.*, 1996a); and a geoclimate stratification of Spain (Regato *et al.*, 1999).

Finally, it was important to explore how the greater detail of the 125 GEnS strata compared spatially with two existing global classifications. The relation between the area of 202 countries and the number of strata in the 125 GEnS, the thirty Köppen climate classes (Peel *et al.*, 2007), and the fourteen WWF biomes (Olson *et al.*, 2001) was plotted, and the correlation between the classifications calculated. Similar graphs and high correlations would indicate that the GEnS provides greater detail within recognised climate zones, while deviations would identify possible biases towards specific regions.

## RESULTS

The correlation matrix of the forty-two variables listed in Table 1, which is presented in Appendix 2, confirmed that there were high correlations globally among many variables. There were ten variables with a correlation coefficient of 1.00 (Table 2). From these variables a subset of four readily interpretable variables was chosen for inclusion in the further analysis: minimum temperature of the coldest month; mean temperature of the warmest month; maximum temperature of the coldest month; and temperature sums when mean monthly temperature is above 0°C.

The subsequent PCA on the remaining thirty-five variables revealed that the first three components, explaining 99.9% of the total variation, were determined by only four variables (Table 3): annual temperature sums above 0°C, reflecting latitudinal and altitudinal temperature gradients; the Aridity Index, which forms an expression of plant available moisture; and temperature and PET seasonality, which express both seasonality and continentality. These four variables were used as the input to the actual clustering.

Table 2. Subset of the Pearson correlation matrix for the forty-two bioclimate variables (Appendix 2), for those with a correlation 1.00 (bold). The four underlined indicators were selected for inclusion in the further analysis

| **Indicator** | | ind_6 | ind_10 | ind_11 | ind_12 | ind_13 | ind_14 | ind_15 | ind_16 | ind_18 | ind_19 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ind_6 | Minimum T of the coldest month | $\boxed{\mathbf{1.00}}$ | | | | | | | | | |
| ind_10 | Mean T of the warmest quarter | 0.82 | **1.00** | | | | | | | | |
| ind_11 | Mean T of the coldest quarter | **1.00** | 0.85 | **1.00** | | | | | | | |
| ind_12 | T sums when mean monthly T > 0°C | 0.93 | 0.91 | 0.95 | $\boxed{\mathbf{1.00}}$ | | | | | | |
| ind_13 | T sums when mean monthly T > 5°C | 0.92 | 0.89 | 0.93 | **1.00** | **1.00** | | | | | |
| ind_14 | Mean T of the coldest month | **1.00** | 0.84 | **1.00** | 0.94 | 0.93 | **1.00** | | | | |
| ind_15 | Mean T of the warmest month | 0.79 | $\boxed{\mathbf{1.00}}$ | 0.82 | 0.89 | 0.87 | 0.81 | **1.00** | | | |
| ind_16 | Maximum T of the coldest month | 0.99 | 0.85 | $\boxed{\mathbf{1.00}}$ | 0.95 | 0.93 | **1.00** | 0.82 | **1.00** | | |
| ind_18 | Number of months with mean T > 10°C | 0.92 | 0.89 | 0.93 | **1.00** | **1.00** | 0.93 | 0.87 | 0.93 | **1.00** | |
| ind_19 | Thermicity index | 0.99 | 0.87 | **1.00** | 0.95 | 0.93 | **1.00** | 0.84 | **1.00** | 0.94 | **1.00** |

Table 3. Eigenvalues (A) and eigenvectors (B) for the first three components of the PCA for the subset of thirty-six bioclimate variables with a correlation < 1.00, explaining 99.9% of the total variation. Variable with eigenvector loadings > 0.1, which were selected as input to the clustering, are underlined.

**A)**

| | PC1 | PC2 | PC3 |
|---|---|---|---|
| **eigenvalues** | 1.0E+00 | 2.5E-01 | 1.9E-03 |
| **% explained** | 80.4% | 19.4% | 0.2% |
| **cumulative** | 80.4% | 99.8% | 99.9% |

**B)**

| **Indicator** | | PC1 | PC2 | PC3 |
|---|---|---|---|---|
| ind_1 | Annual mean T | 0.00 | 0.00 | 0.01 |
| ind_2 | Mean diurnal range | 0.00 | 0.00 | 0.00 |
| ind_3 | Isothermality | 0.00 | 0.00 | 0.00 |
| ind_4 | T seasonality | **-0.11** | 0.09 | **-0.94** |
| ind_5 | Maximum T of the warmest month | 0.00 | 0.00 | -0.01 |
| ind_6 | Minimum T of the coldest month | 0.01 | 0.00 | 0.02 |
| ind_7 | Annual T range | 0.00 | 0.00 | -0.03 |
| ind_8 | Mean T of the wettest quarter | 0.00 | 0.00 | 0.00 |
| ind_9 | Mean T of the driest quarter | 0.01 | 0.00 | 0.01 |
| ind_12 | T sums when mean monthly T > 0°C | **0.98** | **-0.18** | **-0.13** |
| ind_15 | Mean T of the warmest month | 0.00 | 0.00 | -0.01 |
| ind_16 | Maximum T of the coldest month | 0.01 | 0.00 | 0.02 |
| ind_17 | Minimum T of the warmest month | 0.00 | 0.00 | -0.01 |
| ind_20 | Annual precipitation | 0.01 | -0.02 | 0.07 |
| ind_21 | Precipitation of the wettest month | 0.00 | 0.00 | 0.01 |
| ind_22 | Precipitation of the driest month | 0.00 | 0.00 | 0.00 |
| ind_23 | Precipitation seasonality | 0.00 | 0.00 | 0.00 |
| ind_24 | Precipitation of the wettest quarter | 0.00 | -0.01 | 0.03 |
| ind_25 | Precipitation of the driest quarter | 0.00 | 0.00 | 0.01 |
| ind_26 | Precipitation of the warmest quarter | 0.00 | 0.00 | 0.01 |
| ind_27 | Precipitation of the coldest quarter | 0.00 | 0.00 | 0.02 |
| ind_28 | Minimum June July August precipitation | 0.00 | 0.00 | 0.00 |
| ind_29 | Maximum June July August precipitation | 0.00 | 0.00 | 0.00 |
| ind_30 | Minimum December January February precipitation | 0.00 | 0.00 | 0.01 |
| ind_31 | Maximum December January February precipitation | 0.00 | 0.00 | 0.01 |
| ind_32 | Total precipitation for months with mean T > 0°C | 0.01 | -0.01 | 0.08 |
| ind_33 | Annual actual evapotranspiration | 0.01 | 0.00 | 0.05 |
| ind_34 | Annual potential evapostranspiration | 0.02 | 0.00 | 0.00 |
| ind_35 | Coefficient of annual moisture availability | 0.00 | 0.00 | 0.00 |
| ind_36 | Aridity Index | **-0.19** | **-0.98** | -0.08 |
| ind_37 | PET seasonality | -0.01 | 0.05 | **-0.27** |
| ind_38 | Thornthwaite humidity index | 0.00 | -0.01 | 0.00 |
| ind_39 | Thornthwaite aridity index | 0.00 | 0.00 | 0.00 |
| ind_40 | Emberger's pluviothermic quotient | 0.00 | 0.00 | 0.00 |
| ind_41 | Annual solar radiation | 0.00 | 0.00 | 0.00 |
| ind_42 | Altitude | -0.01 | -0.01 | 0.09 |

Table 4. Eigenvalues (A) and Eigenvectors (B) for four principal components of the final clustering variables

**A)**

| | PC1 | PC2 | PC3 | PC4 |
|---|---|---|---|---|
| **eigenvalues** | 3.6E+08 | 8.7E+07 | 2.6E+06 | 4.8E+05 |
| **% explained** | 80.1% | 19.2% | 0.6% | 0.1% |
| **cumulative** | 80.1% | 99.3% | 99.9% | 100.0% |

**B)**

| **Indicator** | | PC1 | PC2 | PC3 | PC4 |
|---|---|---|---|---|---|
| ind_4 | T seasonality | -0.11 | -0.09 | 0.95 | -0.28 |
| ind_12 | T sums when mean monthly T > 0°C | 0.98 | 0.18 | 0.13 | -0.02 |
| ind_36 | Aridity Index | -0.19 | 0.98 | 0.07 | 0.02 |
| ind_37 | PET seasonality | -0.01 | -0.05 | 0.27 | 0.96 |

The PCA of the four clustering variables shows that each component mainly relates to one variable, although the other variables also display some influence (Table 4). The first two components explain the majority of the variation. PC1, which explains 80.1% of the variation, is mainly determined by the annual temperature sum, while PC2 (19.2 % of the variation) expresses the Aridity Index. PC3 and PC4 are determined by temperature and PET seasonality respectively.

The ISODATA clustering distinguished 125 Global Environmental Strata, which were aggregated to eighteen GEnZs (labelled A to R) based on the dendrogram (Fig. 2). The GEnZs and the strata were assigned consistent codes, as described above. In practice this means that cooler strata in a GEnZ will have a lower number. In addition, the zones were given a descriptive label based primarily on mean statistics for the annual temperature sums and the Aridity Index based on the classification in Table 5.

A map legend was constructed using the mean values of the first three Principal Components to define the red-green-blue colour scheme. PC1 was used to define the amount of red, PC2 the blue coloration and PC3 the green coloration. The resulting legend produces a map that clearly distinguishes well known climate zones, as well as more detailed divisions within these zones (Fig. 3). The GEnS recognises known environmental similarities, e.g. K5 identifies similar Mediterranean climates in Europe, Australia, Chile, South Africa and California; R9 links tropical parts of Northern Australia to Papua New Guinea, Indochina and beyond; and J4 connects the cool temperate and moist climates of Brittany (France) and Cornwall (UK) with the foothills of the Himalayas, including Darjeeling. This last association of frost free climates with mild temperatures and regular rainfall inspired recent tea production in Cornwall (Morris, 2005). An initial inspection also indicated that the GEnS strata corresponded well to global crop distribution patterns.

Table 6 shows that the Kappa values for the comparison of the GEnS with existing climate classifications range between 0.54 and 0.72 indicating ‘good’ and ‘very good’ comparisons, according to (Monserud & Leemans, 1992). These Kappa values are similar to those reported in earlier comparisons of European classifications (Bunce *et al.*, 2002; Metzger *et al.*, 2005) and although the details of the classifications differed there were broad similarities reflecting important divisions along major environmental gradients.

Finally, the comparisons between the area of countries and the number of strata occurring within countries for the GEnS, the Köppen map and the WWF biomes reveals a very similar pattern among the datasets (Fig. 4) and correlations with the GEnS are strong (0.86 for the Köppen climate classes; 0.84 for the biomes). Countries above the line, e.g. Chile, tend to have large topographic heterogeneity, whereas those below the line, e.g. Brazil generally do not. These results indicate that the GEnS provides a balanced subdivision of recognised climate zones

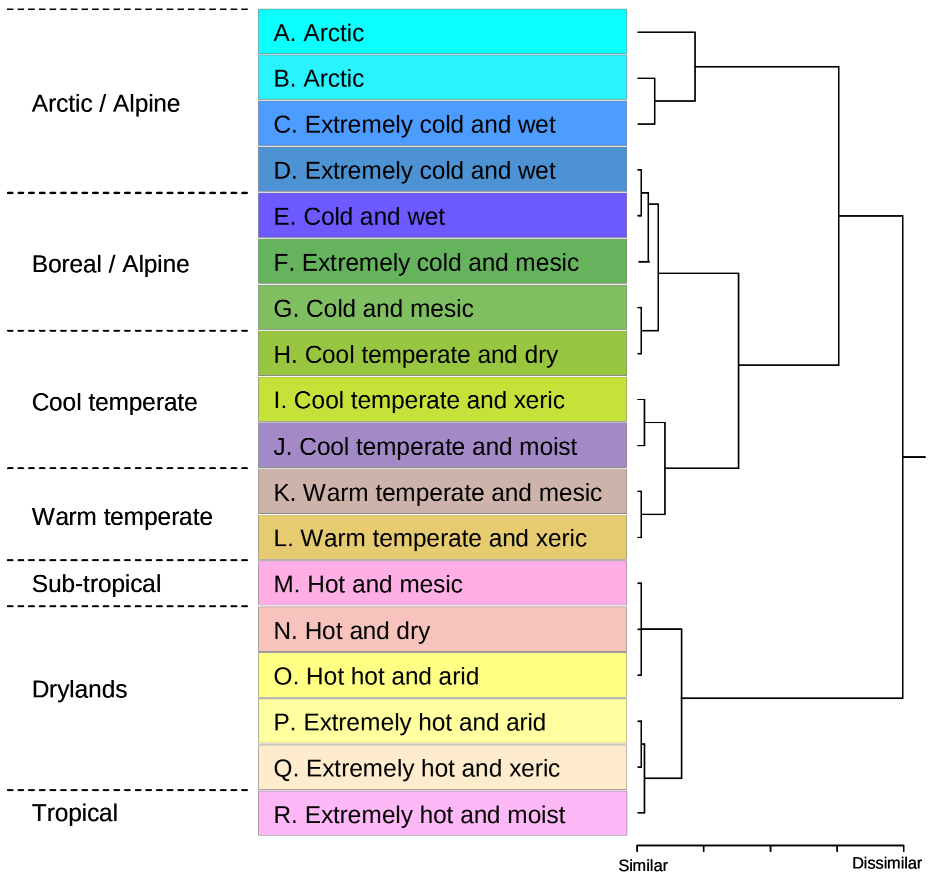


Figure 2. Dendrogram of the clustering illustrating the relation between the eighteen aggregated Global Environmental Zones and the number of strata per zone.

Table 5. The Global Environmental Zones (GEnZs) were given a descriptive names based on the mean values of the annual temperature sums (A) and the Aridity Index (B) for the strata. An exception was made for Arctic temperatures in which case only the label 'Arctic' was used.

**A)**

| **Annual temperature sums > 0°C** | **Label** |
|---|---|
| [ 0, 1000 ) | extremely cold |
| [ 1000, 2500 ) | cold |
| [ 2500, 4500 ) | cold temperate |
| [ 4500, 6500 ) | warm temperate |
| [ 6500, 8000 ) | hot |
| [ 8000, ? ) | extremely hot |

**B)**

| **Aridity Index** | **Label** |
|---|---|
| [ 0, 0.1 ) | arid |
| [ 0.1, 0.3 ) | xeric |
| [ 0.3, 0.6 ) | dry |
| [ 0.6, 1.0 ) | mesic |
| [ 1.0, 1.5 ) | moist |
| [ 1.5, ? ) | wet |

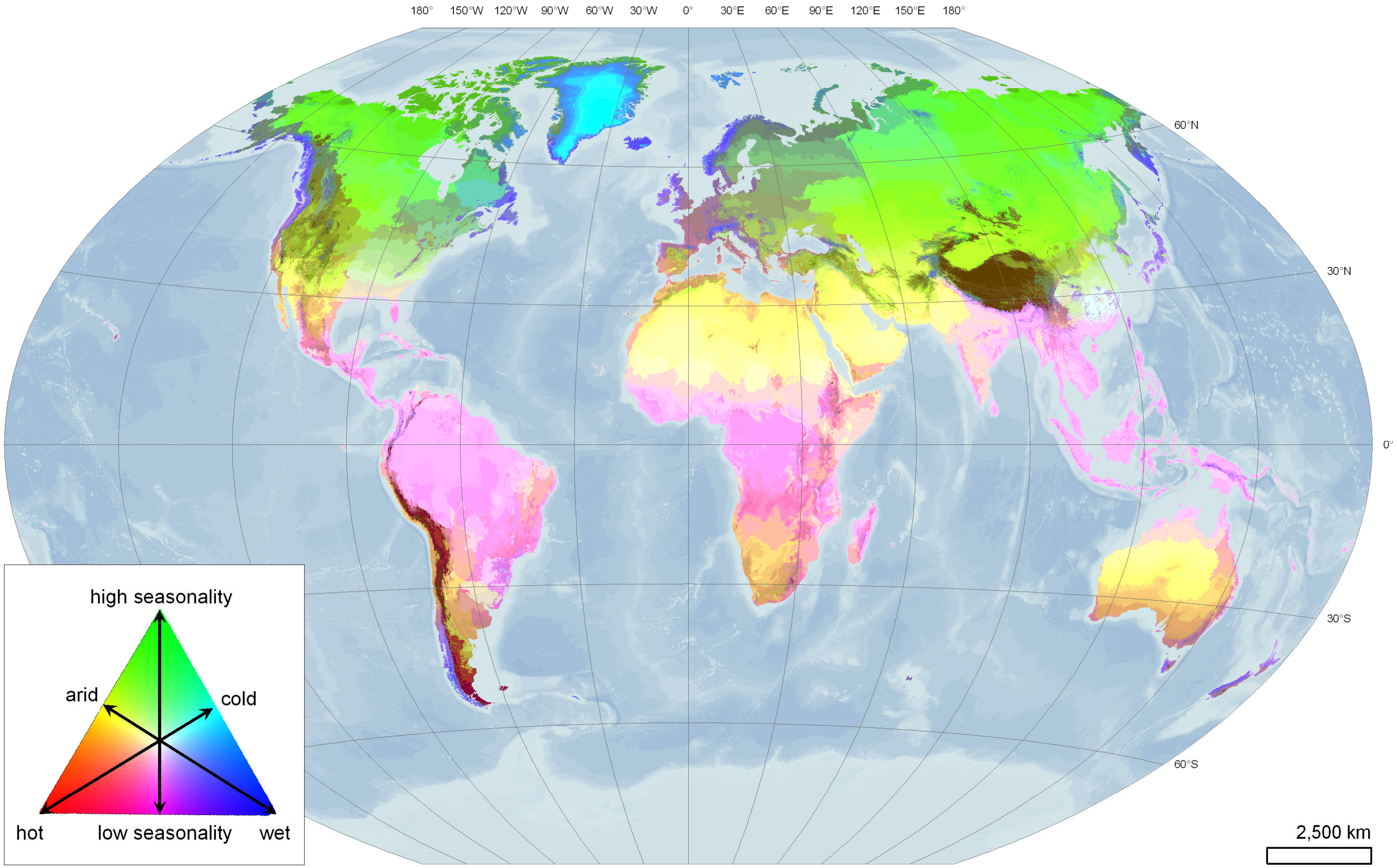


Figure 3. Map of the global environmental stratification, depicting 125 strata at a 30 arcsec (approximately 1km2) spatial resolution in the Winkel Tripple projection. The legend provides a visual combination of the three main climate gradients incorporated in the clustering.

Table 6 Strength of agreement, expressed by the Kappa statistic, between the GEnS and nine other climate ecosystem classifications. Monserud & Leemans (1992) give an indication of the strength of agreement for different ranges of Kappa, which are noted here.

| **Climate classification** | **Reference** | **Extent** | **# classes** | **#GEnS strat** | **Kappa** | **Strength of a** |
|---|---|---|---|---|---|---|
| Köppen | Peel et al. 2007 | global | 30 | 125 | 0.57 | Good |
| WWF biomes | Olson et al. 2001 | global | 14 | 125 | 0.65 | Good |
| EnS | Metzger et al., 2005 | Europe | 84 | 67 | 0.64 | Good |
| Ecoregions North America1 | 1) | North America | 183 | 121 | 0.65 | Good |
| USGS isoclimates | Sayre et al., 2009 | US | 125 | 86 | 0.68 | Good |
| USGS isoclimates | Sayre et al., 2008 | South America | 10 | 78 | 0.62 | Good |
| USGS isoclimates | Sayre et al. in prep | Africa | 156 | 87 | 0.72 | Very good |
| ITE land classes | Bunce et al. 1996ab | Great Britain | 41 | 13 | 0.54 | Good |
| CLARATES | Regato et al. 1999 | Spain | 218 | 40 | 0.62 | Good |

1) http://www.epa.gov/wed/pages/ecoregions/na_eco.htm

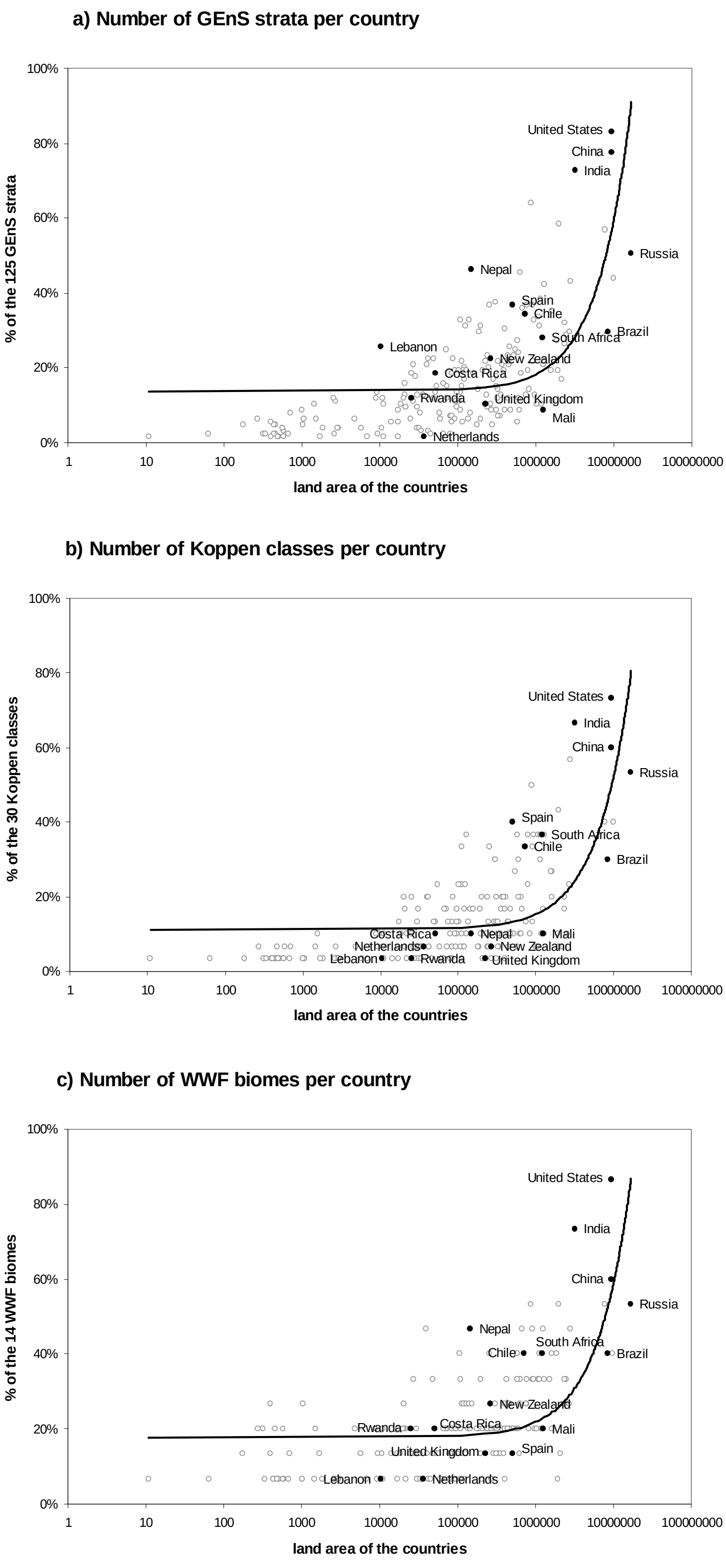


Figure 4. Relationship between the area of 202 countries and the number of strata in (a) the GEnS, (b) the Köppen climate classification (Peel *et al.*, 2007), and (c) the biome classes used to underpin the World Wildlife Fund ecoregions (Olson *et al.*, 2001). Linear regressions are shown to distinguish between relatively diverse countries (above the line) and more homogeneous countries (under the line). To facilitate comparison between the graphs labels have been added for sixteen countries.

# DISCUSSION

## *Subjective choices in the quantitative method*

The GEnS represents the first global high resolution quantitative stratification distinguishing more than the basic biome divisions in the twenty to thirty classes identified previously. Major advantages of quantitative approaches, argued for by Lugo *et al*. (1999) and summarised by Leathwick *et al.* (2003), include: the much greater objectivity, consistency, and spatial accuracy of the classification process; their ability to define hierarchical classifications that can be used at varying degrees of detail; and their open nature, which allows the ready incorporation of new or improved data. Nevertheless, despite the objective nature of the classification techniques used to construct the GEnS, judgemental decisions were required in each stage of the process (Fig. 1).

Firstly, choices were made in the variable selection. The wide range of bioclimate indicators required rigorous statistical screening, but the thresholds used in the final selection are inevitably arbitrary (i.e. eigenvector loadings > 0.1 in the first three principal components). The results nevertheless show that there is a distinct division between the dominant variables above the threshold (eigenvector loadings 0.98, .0.98, 0.94 and 0.27; Table 3), and the remaining variables (eigenvector loadings 0.09 and lower). Furthermore, the final four variables do represent bioclimate characteristics that are included in most existing classifications (cf Table 1), although seasonality is generally reflected through monthly extremes (e.g. the minimum temperature in the coldest month) instead of measures of annual variation (Table 1). Nevertheless, the correlation analysis shows that the monthly temperature extremes have high correlations with annual temperature seasonality (Pearson correlation coefficient between 0.69 and 0.89; Appendix 2). Thus the screening provides statistical rules for the selection of the condensed subset of variables.

The major decision was to classify 125 strata, an arbitrary number, but providing significantly more detail than earlier global numerical classifications. Although more strata could be distinguished, it was necessary to obtain a balance between increased detail and complexity. A greater number of divisions would complicate the interpretation and description of the strata. Furthermore, initial tests indicated that additional class divisions mainly lead to an increase in altitudinal and latitudinal bands, which in our opinion did not justify the added complexity. Bunce *et al.* (1996b) discuss statistical stopping rules and concluded that accepting an arbitrary number was appropriate. The chosen number of classes is comparable to the Environmental Stratification of Europe (Metzger *et al.*, 2005) and the isoclimates of the United States (Sayre *et al.*, 2009) (Table 6).

The decisions in the post-processing have no influence on delineation, but are designed to improve utility. One important choice, however, was the decision *not* to remove small patches or scattered individual pixels, as carried out by Metzger *et al.* (2005) and Bunce *et al.* (1996a) to eliminate potential errors in the input data or outliers in the clustering. Leathwick *et al.* (2003) argue strongly against such a ‘geographic’ approach, where spatially discrete units are created at the expense of environmental heterogeneity. In the GEnS small patches are in many cases interpretable ecologically, e.g. the East African mountain tops, which are linked to the Mediterranean in the GEnS, and as observed in the flora distribution of *Erica arborea* (Rikli 1933).

### *Utility of the Global Environmental Stratification*

At a global scale, climate is the main determinant of environmental patterns (Walter & Lieth, 1964; Odum, 1983; Klijn & De Haes, 1994; Godron, 1994), justifying the naming of the dataset. However, geomorphology, hydrology, geology, and soils follow climate in the conceptual hierarchy (Klijn & De Haes, 1994; Sayre *et al.*, 2009), but are not included mainly because of the difficulties in obtaining reliable data. Incorporating greater thematic detail would increase both the number of data layers, each with inherent uncertainties, and the choices that would need to be made for weighting or classifying the different dimensions (Hazeu *et al.*, 2010). Furthermore, it is difficult to get consistent global data and there are challenges in incorporating such different data sources in the clustering (Bunce *et al.*, 1996a; Metzger *et al.*, 2005).

There are also limitations to the climate data used to construct the GEnS, which will affect its quality. The high resolution of the climate surface does not imply that the quality of the data is always the same. Hijmans *et al.* (2005) discuss how the quality of the surfaces is spatially variable and depends on the local climate variability in an area, the quality and density of the observations, and the degree to which a spline can be fitted through it. Locally important climate drivers, e.g. those caused by aspect in mountain areas or the formation of sea fog along coastal ranges are also poorly represented. Finally, there remain errors in the Shuttle Radar Topography Mission (STRM) elevation data (Jarvis *et al.*, 2008) used in the spatial interpolation of the climate data. Despite these limitations, WorldClim provides sufficient spatial detail to distinguish and partition steep environmental gradients.

If required, climate stratifications can be integrated with other spatial datasets to provide additional thematic detail. The European Environmental Stratification (Metzger *et al.*, 2005) has been intersected with soils data to produce an agro-ecological typology (Hazeu *et al.*, 2010), and with an economic density indicator to produce a socio-ecological stratification (Metzger *et al.*, 2010). Similarly, Sayre *et al.* (2009; 2008) have intersected a climate classification with further data layers to define ecosystem classifications for the US, South America and Africa. Other useful intersects with the GEnS could include data such as global biogeographic realms (Udvardy, 1975), for the analysis of species data, or geomorphologic terrain forms, e.g. to separate alpine ranges from the arctic regions.

Even climatically, some heterogeneity remains when the global variation in bioclimate is partitioned in 125 strata. For example, regionally important gradients in precipitation, which can mark significant regional differences in dry ecosystems, are not always reflected sufficiently. In Israel the Northern Negev Desert and the city of Tel Aviv both fall in the hot and dry stratum N6, while the latter is considered Mediterranean with greater precipitation, concentrated in the winter. Additional strata would have provided more regional detail, but also incur the risk of losing global connections, a prime reason for developing the GEnS. Despite this limitation, the results showed good comparisons with existing classifications (Table 6) and confirm recognised climate patterns. While limitations remain, the GEnS has significant advantages over existing global climate classifications, making it suitable for a wide range of applications.

The primary reason for developing the GEnS was to provide a unifying framework for GEO BON activities (GEOBON, 2010). It should facilitate the integration and analysis of disparate sources of global biodiversity data, and help to compare trends in similar environments, as has been asked for by the 2010 Conference of Parties of the CBD in Nagoya. Furthermore, it can be used to target future monitoring and research to achieve a more balanced set of biodiversity observations. Other applications, discussed by Jongman *et al.* (2006) and Hazeu *et al.* (2010), include stratifying earth observations (cf Duro *et al.*, 2007) and scenario modelling (Metzger *et al.*, 2008a). The utility is not limited to biodiversity, as other global environmental and agricultural research could also benefit from the dataset, especially where there is a need for a consistent stratification across political boundaries.

## CONCLUSION

The GEnS provides a high resolution stratification of the global environment, constructed using rigorous quantitative methods. Compared with existing classifications, the rigorous statistical methods used to delineate strata and the high spatial resolution allows for improved identification of regional gradients. Comparisons with existing global, continental and national stratifications confirmed that the modelled strata successfully identify recognisable environmental gradients. The dataset therefore provides a valuable unifying framework for global biodiversity research, and should prove useful as a spatial analytical framework for aggregation and comparison of field observations, biodiversity conservation gap analyses, and systematic planning of environmental research and monitoring programs.

# REFERENCES


Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. (1998) Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56. Food and Agriculture Organization of the United Nations, Rome.

Bailey, R. G. (1998) Ecoregions: The Ecosystem Geography of Oceans and Continents, edn. Springer-Verlag, New York.

Banchmann, C. M., Donato, T. F., Lamela, G. M., Rhea, W. J., Bettenhausen, M. H., Fusina, R. A., Du-Bois, K. R., Porter, J. H. & Truitt, B. R. (2002) Automatic classification of land cover on Smith Island, VA, using HyMAP imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **40**, 2313-2330.

Bunce, R. G. H., Barr, C. J., Clarke, R. T., Howard, D. C. & Lane, A. M. J. (1996a) ITE Merlewood Land Classification of Great Britain. *Journal of Biogeography*, **23**, 625-634.

Bunce, R. G. H., Barr, C. J., Clarke, R. T., Howard, D. C. & Lane, A. M. J. (1996b) Land classification for strategic ecological survey. *Journal of Environmental Management*, **47**, 37-60.

Bunce, R. G. H., Carey, P. D., Elena-Roselló, R., Orr, J., Watkins, J. W. & Fuller, R. (2002) A comparison of different biogeographical classifications of Europe, Great Britain and Spain. *Journal of Environmental Management*, **65**, 121-134.

Bunce, R. G. H., Metzger, M. J., Jongman, R. H. G., Brandt, J., De Blust, G., Elena-Rossello, R., Groom, G. B., Halada, L., Hofer, G., Howard, D., Kovář, P., Mücher, C., Padoa-Schioppa, E., Paelinx, D., Palo, A., Perez-Soba, M., Ramos, I., Roche, P., Skånes, H. & Wrbka, T. (2008) A standardized procedure for surveillance and monitoring European habitats and provision of spatial data. *Landscape Ecol.*, **23**, 11-25.

Bunce, R. G. H., Watkins, J. W., Brignall, P. & Orr, J. (1996c) A Comparison of the Environmental Variability within the European Union States. *Ecological and landscape consequences of land use change in Europe : proceedings of the ECNC seminar on land use change and its ecological consequences, 16 - 18 February 1995, Tilburg, The Netherlands* (ed. by R.H.G. Jongman), pp 82-102. ECNC.

Cabido, M., Pons, E., Cantero, J. J., Lewis, J. P. & Anton, A. (2008) Photosynthetic pathway variation among C4 grasses along a precipitation gradient in Argentina. *Journal of Biogeography*, **35**, 131-140.

CEC (1997) Ecological Regions of North America, toward a Common Perspective. pp 71. Commission for Environmental Cooperation, Montréal, Canada.

Cramer, W., Bondeau, A., Woodward, F. I., Prentice, I. C., Betts, R. A., Brovkin, V., Cox, P. M., Fisher, V., Foley, J. A., Friend, A. D., Kucharik, C., Lomas, M. R., Ramankutty, N., Sitch, S., Smith, B., White, A. & Young-Molling, C. (2001) Global response of terrestrial ecosystem structure and function to CO2 and climate change: results from six dynamic global vegetation models. *Global Change Biology*, **7**, 357-373.

Duro, D., Coops, N. C., Wulder, M. A. & Han, T. (2007) Development of a large area biodiversity monitoring system driven by remote sensing. *Progress in Physical Geography*, **31**, 235-260.

Emberger, L. (1930) Sur une formule climatique applicable en géographie botanique. *Comptes Rendus Hebdomadaires des Séances de l´Academie des Sciences*, **181**, 389-391.

Faust, N. L. (1989) *Image Enhancement*, edn. Marcel Dekker Inc., New York.

Firbank, L. G., Barr, C. J., Bunce, R. G. H., Furse, M. T., Haines-Young, R. H., Hornung, M., Howard, D. C., Sheail, J., Sier, A. R. J. & Smart, S. M. (2003) Assessing stock and change in land cover and biodiversity in GB: an introduction to the Countryside Survey 2000. *Journal of Environmental Management*, **67**, 207-218.

GEO BON. (2010) Group on Earth Observations Biodiversity Observation Network (GEO BON) Detailed Implementation Plan.

Godron, M. (1994) The natural hierarchy of ecological systems. *Ecosystem classification for environmental management* (ed. by F. Klijn), pp 69-83. Kluwer Academic Publisher, Dortdrecht.

Goldberg, D. M. & Gott, J. R. (2007) Flexion and Skewness in Map Projections of the Earth. *Cartographica: The International Journal for Geographic Information and Geovisualization*, **42**, 297-318.

Hargrove, W. W. & Hoffman, F. M. (1999) Using multivariate clustering to characterize ecoregion borders. *Computing in Science & Engineering*, **1**, 18-25.

Hazeu, G. W., Metzger, M. J., Mucher, C. A., Perez-Soba, M., Renetzeder, C. & Andersen, E. (2010) European environmental stratifications and typologies: an overview. *Agriculture, Ecosystems & Environment*, **in press**.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, **25**, 1965-1978.

Holdridge, L. R. (1947) Determination of world planr formations from simple climatic data. *Science*, **105**, 367-368.

Hutchinson, M. F. (1998a) Interpolation of rainfall data with thin plate smoothing splines: I two dimensional smoothing of data with short range correlation. *Journal of Geographic Information and Decision Analysis*, **2**, 152-167.

Hutchinson, M. F. (1998b) Interpolation of rainfall data with thin plate smoothing splines: II analysis of topographic dependence. *Journal of Geographic Information and Decision Analysis*, **2**, 168-185.

Jarvis, A., Reuter, H. I., Nelson, A. & Guevara, E. (2008) Hole-filled seamless SRTM data V4.1. International Centre for Tropical Agriculture (CIAT).

Jensen, J. R. (1996) *Introductory Digital Image Processing: A Remote Sensing Perspective*, edn. Prentice-Hall, Englewood Cliffs, New Jersey.

Jongman, R. H. G., Bunce, R. G. H., Metzger, M. J., Mücher, C. A., Howard, D. C. & Mateus, V. L. (2006) Objectives and applications of a statistical environmental stratification of Europe. *Landscape Ecol.*, **21**, 409-419.

Klijn, F. & De Haes, H. A. U. (1994) A hierarchical approach to ecosystems and its implications for ecological land classification. *Landscape Ecol.*, **9**, 89-104.

Köppen, W. (1900) Versuch einer Klassification der Klimat, Vorsuchsweize nach ihren Beziehungen zur Pflanzenwelt. *Geographische Zeitschrift*, **6**, 593-611 ; 657-679.

Larigauderie, A. & Mooney, H. A. (2010) The Intergovernmental science-policy Platform on Biodiversity and Ecosystem Services: moving a step closer to an IPCC-like mechanism for biodiversity. *Current Opinion in Environmental Sustainability*, **2**, 9-14.

Leathwick, J. R., Overton, J. M. & Mcleod, M. (2003) An environmental domain classification of New Zealand and its use as a tool for biodiversity management. *Conservation Biology*, **16**, 1612-1623.

Lugo, A. E., Brown, S. L., Dodson, R., Smith, T. S. & Shugart, H. H. (1999) The Holdridge life zones of the conterminous United States in relation to ecosystem mapping. *Journal of Biogeography*, **26**, 1025-1038.

MA. (2005) Millennium Ecosystems Assessment Synthesis report. Washington DC.

Margules, C. R. & Pressey, R. L. (2000) Systematic conservation planning. *Nature*, **405**, 243-253.

Mcmahon, G., Gregonis, S. M., Waltman, S. W., Omernik, J. M., Thorson, T. D., Freeouf, J. A., Rorick, A. H. & Keys, J. E. (2001) Developing a Spatial Framework of Common Ecological Regions for the Conterminous United States. *Environ. Manage.*, **28**, 293-316.

Metzger, M. J., Bunce, R. G. H., Jongman, R. H. G., Mücher, C. A. & Watkins, J. W. (2005) A climatic stratification of the environment of Europe. *Global Ecology & Biogeography*, **14**, 549-563.

Metzger, M. J., Bunce, R. G. H., Leemans, R. & Viner, D. (2008a) Projected environmental shifts under climate change: European trends and regional impacts. *Environmental Conservation*, **35**, 64-75.

Metzger, M. J., Bunce, R. G. H., Van Eupen, M. & Mirtl, M. (2010) An assessment of long term ecosystem research activities across European socio-ecological gradients. *Journal of Environmental Management*, **91**, 1357-1365.

Metzger, M. J., Schröter, D., Leemans, R. & Cramer, W. (2008b) A spatially explicit and quantitative vulnerability assessment of ecosystem service change in Europe. *Regional Environmental Change*, **8**, 91-107.

Monserud, R. A. & Leemans, R. (1992) Comparing global vegetation maps with the Kappa statistic. *Ecological Modelling*, **62**, 275-293.

Mooney, H., Larigauderie, A., Cesario, M., Elmquist, T., Hoegh-Guldberg, O., Lavorel, S., Mace, G. M., Palmer, M., Scholes, R. & Yahara, T. (2009) Biodiversity, climate change, and ecosystem services. *Current Opinion in Environmental Sustainability*, **1**, 46-54.

Mooney, H. A. (1977) Convergent evolution in Chile and California: Mediterranean climate ecosystems Dowden, Hutchinson and Ross Stroudsburg, PA.

Morris, S. (2005) English breakfast tea? Make sure it's grown in Cornwall. *The Guardian 20 June 2005*, Manchester.

Muchoney, D. M. (2008) Earth observations for terrestrial biodiversity and ecosystems. *Remote Sensing of Environment*, **112**, 1909-1911.

Nayar, A. (2010) World gets 2020 vision for conservation *Nature*, **468**, 14.

Odum, H. T. (1983) *Systems ecology, an introduction*, edn. John Wiley and Sons, New York.

Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'amico, J. A., Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W. W., Hedao, P. & Kassem, K. R. (2001) Terrestrial Ecoregions of the World: A New Map of Life on Earth. *BioScience*, **51**, 933-938.

Palma, J. H. N., Graves, A. R., Bunce, R. G. H., Burgess, P. J., De Filippi, R., Keesman, K. J., Van Keulen, H., Liagre, F., Mayus, M., Moreno, G., Reisner, Y. & Herzog, F. (2007) Modeling environmental benefits of silvoarable agroforestry in Europe. *Agriculture, Ecosystems & Environment*, **119**, 320-334.

Pan, Y., Li, X., Gong, P., He, C., Shi, P. & Pu, R. (2003) An integrative classification of vegetation in China based on NOAA AVHRR and vegetation - climate indices of the Holdridge life zone. *International Journal of Remote Sensing*, **24**, 1009-1027.

Parr, T. W., Sier, A. R. J., Battarbee, R. W., Mackay, A. & Burgess, J. (2003) Detecting environmental change: science and society-perspectives on long-term research and monitoring in the 21st century. *The Science of the Total Environment*, **310**, 1-8.

Paruelo, J. M., Lauenroth, W. K., Epstein, H. E., Burke, I. C., Aguiar, M. R. & Sala, O. E. (1995) Regional Climatic Similarities in the Temperate Zones of North and South America. *Journal of Biogeography*, **22**, 915-925.

Peel, M. C., Finlayson, B. L. & Mcmahon, T. A. (2007) Updated world map of the Koppen-Geiger climate classification. *Hydrology and Earth System Sciences*, **11**, 1633-1644.

Pereira, H. M., Belnap, J., Brummitt, N., Collen, B., Ding, H., Gonzalez-Espinosa, M., Gregory, R. D., Honrado, J. O., Jongman, R. H., Julliard, R., Mcrae, L., Proenã§a, V. N., Rodrigues, P. C., Opige, M., Rodriguez, J. P., Schmeller, D. S., Van Swaay, C. & Vieira, C. (2010) Global biodiversity monitoring. *Frontiers in Ecology and the Environment*, **8**, 459-460.

Pereira, H. M. & Cooper, D. H. (2006) Towards the global monitoring of biodiversity change. *Trends in Ecology & Evolution*, **21**, 123-129.

Prentice, I. C., Cramer, W., Harrison, S. P., Leemans, R., Monserud, R. A. & Solomon, A. M. (1992) A global biome model based on plant physiology and dominance, soil properties and climate. *Journal of Biogeography*, **19**, 117-134.

Regato, P., Castejón, M., Tella, G., Giménez, S., Barrera, I. & Elena-Rosselló, R. (1999) Cambios recientes en los paisajes de los sistemas forestales de España. *Investigación Agraria. Sistemas y Recursos Forestales*, **1**, 383-398.

Rikli, M. 1933. Erica arborea L. In: Pflanzenareale, 3 (8), Map 79/80. Fischer, Jena.

Sanderson, M. (1999) The Classification of Climates from Pythagoras to Koeppen. *Bulletin of the American Meteorological Society*, **80**, 669-673.

Sayre, R., Bow, J., Josse, C., Sotomayor, L. & Touval, J. (2008) Terrestrial Ecosystems of South America. *North America Land Cover Summit-A Special Issue of the Association of American Geographers* (ed. by J.C. Campbell & K. Bruce Jones & J.H. Smith ).

Sayre, R., Comer, P., Warner, H. & Cress, J. (2009) A new map of standardized terrestrial ecosystems of the conterminous United States: U.S. Geological Survey Professional Paper 1768. pp 17. U.S. Geological Survey, Reston, Virginia.

Scholes, R. J., Mace, G. M., Turner, W., Geller, G. N., Jurgens, N., Larigauderie, A., Muchoney, D., Walther, B. A. & Mooney, H. A. (2008) ECOLOGY: Toward a Global Biodiversity Observing System. *Science*, **321**, 1044-1045.

Sitch, S., Smith, B., Prentice, I. C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J. O., Levis, S., Lucht, W., Sykes, M. T., Thonicke, K. & Venevsky, S. (2003) Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ Dynamic Vegetation Model. *Global Change Biology*, **9**, 161-185.

Tappan, G. G., Sall, M., Wood, E. C. & Cushing, M. (2004) Ecoregions and land cover trends in Senegal. *Journal of Arid Environments*, **59**, 427-462.

Thornthwaite, C. W. (1943) Problems in the classification of climates. *Geographical Review*, **33**, 233-255.

Thornthwaite, C. W. (1948) An Approach toward a Rational Classification of Climate. *Geographical Review*, **38**, 55-94.

Thuiller, W., Lavorel, S., Araãº Jo, M. B., Sykes, M. T. & Prentice, I. C. (2005) Climate change threats to plant diversity in Europe. *Proceedings of the National Academy of Sciences of the United States of America*, **102**, 8245-8250.

Tou, J. T. & Conzalez, R. C. (1974) *Pattern Recognition Principles*, edn. Addison-Wesley Publishing Company, Reading, Massachusetts.

Trabucco, A., Zomer, R. J., Bossio, D. A., Van Straaten, O. & Verchot, L. V. (2008) Climate change mitigation through afforestation/reforestation: A global analysis of hydrologic impacts with four case studies. *Agriculture, Ecosystems & Environment*, **126**, 81-97.

Udvardy, M. D. F. (1975) A Classification of Biogeographical Provinces of the World. *IUCN Occasional Paper*, Gland.

Visser, H. & De Nijs, T. (2006) The Map Comparison Kit. *Environmental Modelling & Software*, **21**, 346-358.

Von Humboldt, A. (1867) Ideeen zu einem Geographie der Pflanzen nebst einem naturgemälde der Tropenländer., edn. F.G. Cotta, Tübingen.

Walter, H. & Lieth, H. (1964) Klimadiagramm Weltatlas. VEB Gustaf Fischer Verlag, Jena.

Zomer, R. J., Trabucco, A., Bossio, D. A. & Verchot, L. V. (2008) Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. *Agriculture, Ecosystems & Environment*, **126**, 67-80.

# Appendix 1

Description of the eighteen newly calculated bioclimate variables. Although some indicators could be easily extracted from the available data sets, others required more elaborate calculations.

**ind_12, Temperature sums when mean monthly temperature is above 0°C**

Calculated by summation of mean monthly temperature for all months with a mean temperature greater than 0°C, and multiplying by the total number of days in those months.

**ind_13, Temperature sums when mean monthly temperature is above 5°C**

Calculated by summation of mean monthly temperature for all months with a mean temperature greater than 5°C, and multiplying by the total number of days in those months.

**ind_14, Mean temperature of the coldest month**
**ind_15, Mean temperature of the warmest month**
**ind_16, Maximum temperature of coldest month**
**ind_17, Minimum temperature of warmest month**

Extracted relevant value from WorldClim monthly temperature data.

**ind_18, Number of months with a mean temperature > 10°C**

Count of the number of months for which mean temperature > 10°C

**ind_19, Thermicity index**

Indicator used by Sayre *et al.* (2008; 2009) to define isoclimate regions, which is a summation of the Annual mean temperature range (ind_1), the minimum temperature of the coldest month (ind_6) and the maximum temperature of coldest month (ind_16).

**ind_28, Minimum June July August precipitation**
**ind_29, Maximum June July August precipitation**
**ind_30, Minimum December January February precipitation**
**ind_31, Maximum December January February precipitation**

Relevant values were extracted from the WorldClim monthly precipitation data.

**ind_32, Total precipitation for months with a mean monthly temperature is above 0°C**

Summation of mean monthly precipitation for months with a mean temperature > 10°C

**ind_35, Coefficient of annual moisture availability**

Used by Pretice *et al.* (1992) and Sitch *et al.* (2003) to reflect the annual amount of growth-limiting drought stress on plants, who refer to it as the Priestley-Taylor coefficient *alpha*. It is calculated as the ratio between the annual actual evapotranspiration (ind_33) and the annual potential evapotranspiration (ind_34).

**ind_37, PET seasonality**

Calculated as 100 * the standards deviation of the monthly values for the potential evapotranspiration.

**ind_38, Thornthwaite humidity index**

An index of the degree of water surplus over water need as defined by Thornthwaite (1948):

humidity index = $100s / n$

where $s$ (the water surplus) is the sum of the monthly differences between precipitation and potential evapotranspiration for those months when the normal precipitation exceeds the latter, and $n$ (the water need) is the sum of monthly potential evapotranspiration for those months of surplus. The humidity index has two uses in

**ind_39, Thornthwaite aridity index**

An index of the degree of water deficit below water need as defined by Thornthwaite (1948):

aridity index = $100d / n$

where $d$ (the water deficit) is the sum of the monthly differences between precipitation and potential evapotranspiration for those months when the normal precipitation is less than the normal potential evapotranspiration; and where $n$ is the sum of monthly values of potential evapotranspiration for the deficient months.

**ind_40, Emberger Q**

Emberger's pluviothermic quotient ($Q$) was calculated using the formula provided by Daget (1977):

$Q = 2000\, P / (M + m + 546.4)\,(M - m)$

where $P$ is the mean annual precipitation in mm (ind_20), $M$ the mean maximum temperature of the warmest month (ind_17), and $m$ is the mean minimum temperature of the coldest month (ind_6).

# Appendix 2

Pearson correlation matrix for the forty-two bioclimate variables listed in Table 1, showing high correlations between many variables. Those variables with a correlation of 1.00 are presented in Table 2.

| Indicator | | var_1 | var_2 | var_3 | var_4 | var_5 | var_6 | var_7 | var_8 | var_9 | var_10 | var_11 | var_12 | var_13 | var_14 | var_15 | var_16 | var_17 | var_18 | var_19 | var_20 | var_21 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **var_1** | Annual mean T | 1.00 | 0.53 | 0.84 | -0.83 | 0.90 | 0.97 | -0.73 | 0.81 | 0.94 | 0.93 | 0.98 | 0.96 | 0.94 | 0.98 | 0.91 | 0.98 | 0.92 | 0.95 | 0.99 | 0.37 | 0.45 |
| **var_2** | Mean diurnal range | 0.53 | 1.00 | 0.39 | -0.22 | 0.71 | 0.36 | 0.01 | 0.53 | 0.44 | 0.62 | 0.43 | 0.48 | 0.46 | 0.42 | 0.63 | 0.47 | 0.51 | 0.47 | 0.45 | -0.24 | -0.10 |
| **var_3** | Isothermality | 0.84 | 0.39 | 1.00 | -0.89 | 0.61 | 0.89 | -0.83 | 0.64 | 0.81 | 0.66 | 0.89 | 0.85 | 0.84 | 0.89 | 0.62 | 0.89 | 0.62 | 0.84 | 0.88 | 0.56 | 0.58 |
| **var_4** | T seasonality | -0.83 | -0.22 | -0.89 | 1.00 | -0.51 | -0.94 | 0.97 | -0.50 | -0.86 | -0.58 | -0.93 | -0.80 | -0.78 | -0.93 | -0.54 | -0.92 | -0.57 | -0.79 | -0.91 | -0.55 | -0.57 |
| **var_5** | Maximum T of the warmest month | 0.90 | 0.71 | 0.61 | -0.51 | 1.00 | 0.77 | -0.36 | 0.84 | 0.79 | 0.99 | 0.80 | 0.86 | 0.84 | 0.78 | 0.99 | 0.80 | 0.96 | 0.85 | 0.82 | 0.11 | 0.23 |
| **var_6** | Minimum T of the coldest month | 0.97 | 0.36 | 0.89 | -0.94 | 0.77 | 1.00 | -0.88 | 0.70 | 0.95 | 0.82 | 1.00 | 0.93 | 0.92 | 1.00 | 0.79 | 0.99 | 0.82 | 0.92 | 0.99 | 0.48 | 0.52 |
| **var_7** | Annual T range | -0.73 | 0.01 | -0.83 | 0.97 | -0.36 | -0.88 | 1.00 | -0.39 | -0.78 | -0.46 | -0.85 | -0.71 | -0.70 | -0.86 | -0.41 | -0.84 | -0.46 | -0.70 | -0.83 | -0.61 | -0.59 |
| **var_8** | Mean T of wettest quarter | 0.81 | 0.53 | 0.64 | -0.50 | 0.84 | 0.70 | -0.39 | 1.00 | 0.61 | 0.86 | 0.73 | 0.80 | 0.79 | 0.72 | 0.86 | 0.73 | 0.86 | 0.79 | 0.75 | 0.25 | 0.37 |
| **var_9** | Mean T of driest quarter | 0.94 | 0.44 | 0.81 | -0.86 | 0.79 | 0.95 | -0.78 | 0.61 | 1.00 | 0.83 | 0.95 | 0.90 | 0.88 | 0.95 | 0.81 | 0.94 | 0.81 | 0.88 | 0.95 | 0.37 | 0.41 |
| **var_10** | Mean T of warmest quarter | 0.93 | 0.62 | 0.66 | -0.58 | 0.99 | 0.82 | -0.46 | 0.86 | 0.83 | 1.00 | 0.85 | 0.91 | 0.89 | 0.84 | 1.00 | 0.85 | 0.99 | 0.89 | 0.87 | 0.19 | 0.30 |
| **var_11** | Mean T of coldest quarter | 0.98 | 0.43 | 0.89 | -0.93 | 0.80 | 1.00 | -0.85 | 0.73 | 0.95 | 0.85 | 1.00 | 0.95 | 0.93 | 1.00 | 0.82 | 1.00 | 0.83 | 0.93 | 1.00 | 0.45 | 0.51 |
| **var_12** | T sums when mean monthly T > 0°C | 0.96 | 0.48 | 0.85 | -0.80 | 0.86 | 0.93 | -0.71 | 0.80 | 0.90 | 0.91 | 0.95 | 1.00 | 1.00 | 0.94 | 0.89 | 0.95 | 0.90 | 1.00 | 0.95 | 0.38 | 0.47 |
| **var_13** | T sums when mean monthly T > 5°C | 0.94 | 0.46 | 0.84 | -0.78 | 0.84 | 0.92 | -0.70 | 0.79 | 0.88 | 0.89 | 0.93 | 1.00 | 1.00 | 0.93 | 0.87 | 0.93 | 0.89 | 1.00 | 0.93 | 0.38 | 0.47 |
| **var_14** | Mean T of the coldest month | 0.98 | 0.42 | 0.89 | -0.93 | 0.78 | 1.00 | -0.86 | 0.72 | 0.95 | 0.84 | 1.00 | 0.94 | 0.93 | 1.00 | 0.81 | 1.00 | 0.82 | 0.93 | 1.00 | 0.46 | 0.51 |
| **var_15** | Mean T of the warmest month | 0.91 | 0.63 | 0.62 | -0.54 | 0.99 | 0.79 | -0.41 | 0.86 | 0.81 | 1.00 | 0.82 | 0.89 | 0.87 | 0.81 | 1.00 | 0.82 | 0.99 | 0.87 | 0.84 | 0.17 | 0.28 |
| **var_16** | Maximum T of coldest month | 0.98 | 0.47 | 0.89 | -0.92 | 0.80 | 0.99 | -0.84 | 0.73 | 0.94 | 0.85 | 1.00 | 0.95 | 0.93 | 1.00 | 0.82 | 1.00 | 0.82 | 0.93 | 1.00 | 0.43 | 0.50 |
| **var_17** | Minimum T of warmest month | 0.92 | 0.51 | 0.62 | -0.57 | 0.96 | 0.82 | -0.46 | 0.86 | 0.81 | 0.99 | 0.83 | 0.90 | 0.89 | 0.82 | 0.99 | 0.82 | 1.00 | 0.89 | 0.85 | 0.23 | 0.33 |
| **var_18** | Number of months with mean T > 10°C | 0.95 | 0.47 | 0.84 | -0.79 | 0.85 | 0.92 | -0.70 | 0.79 | 0.88 | 0.89 | 0.93 | 1.00 | 1.00 | 0.93 | 0.87 | 0.93 | 0.89 | 1.00 | 0.94 | 0.37 | 0.47 |
| **var_19** | Thermicity index | 0.99 | 0.45 | 0.88 | -0.91 | 0.82 | 0.99 | -0.83 | 0.75 | 0.95 | 0.87 | 1.00 | 0.95 | 0.93 | 1.00 | 0.84 | 1.00 | 0.85 | 0.94 | 1.00 | 0.44 | 0.50 |
| **var_20** | Annual precipitation | 0.37 | -0.24 | 0.56 | -0.55 | 0.11 | 0.48 | -0.61 | 0.25 | 0.37 | 0.19 | 0.45 | 0.38 | 0.38 | 0.46 | 0.17 | 0.43 | 0.23 | 0.37 | 0.44 | 1.00 | 0.90 |
| **var_21** | Precipitation of the wettest month | 0.45 | -0.10 | 0.58 | -0.57 | 0.23 | 0.52 | -0.59 | 0.37 | 0.41 | 0.30 | 0.51 | 0.47 | 0.47 | 0.51 | 0.28 | 0.50 | 0.33 | 0.47 | 0.50 | 0.90 | 1.00 |
| **var_22** | Precipitation of the driest month | 0.05 | -0.38 | 0.22 | -0.24 | -0.14 | 0.16 | -0.34 | -0.07 | 0.10 | -0.08 | 0.12 | 0.02 | 0.02 | 0.12 | -0.10 | 0.09 | -0.04 | 0.02 | 0.10 | 0.70 | 0.39 |
| **var_23** | Precipitation seasonality | 0.37 | 0.51 | 0.28 | -0.19 | 0.43 | 0.27 | -0.07 | 0.45 | 0.26 | 0.41 | 0.32 | 0.43 | 0.44 | 0.31 | 0.41 | 0.35 | 0.39 | 0.43 | 0.33 | -0.17 | 0.14 |
| **var_24** | Precipitation of wettest quarter | 0.44 | -0.12 | 0.58 | -0.57 | 0.21 | 0.52 | -0.59 | 0.35 | 0.40 | 0.28 | 0.50 | 0.46 | 0.46 | 0.51 | 0.26 | 0.49 | 0.32 | 0.46 | 0.49 | 0.92 | 0.99 |
| **var_25** | Precipitation of driest quarter | 0.08 | -0.37 | 0.25 | -0.27 | -0.13 | 0.19 | -0.37 | -0.05 | 0.13 | -0.06 | 0.15 | 0.05 | 0.05 | 0.15 | -0.08 | 0.12 | -0.02 | 0.05 | 0.13 | 0.74 | 0.43 |
| **var_26** | Precipitation of warmest quarter | 0.22 | -0.20 | 0.35 | -0.33 | 0.02 | 0.28 | -0.38 | 0.25 | 0.15 | 0.09 | 0.26 | 0.20 | 0.19 | 0.26 | 0.07 | 0.25 | 0.14 | 0.20 | 0.25 | 0.80 | 0.74 |
| **var_27** | Precipitation of coldest quarter | 0.25 | -0.24 | 0.43 | -0.40 | 0.05 | 0.35 | -0.47 | 0.07 | 0.30 | 0.11 | 0.31 | 0.24 | 0.24 | 0.32 | 0.09 | 0.28 | 0.13 | 0.24 | 0.30 | 0.75 | 0.58 |
| **var_28** | Minimum June July August precipitation | 0.16 | -0.22 | 0.22 | -0.23 | 0.03 | 0.21 | -0.28 | 0.16 | 0.11 | 0.08 | 0.19 | 0.15 | 0.15 | 0.19 | 0.07 | 0.17 | 0.12 | 0.15 | 0.18 | 0.71 | 0.72 |
| **var_29** | Maximum June July August precipitation | 0.21 | -0.17 | 0.25 | -0.26 | 0.09 | 0.25 | -0.30 | 0.21 | 0.16 | 0.14 | 0.24 | 0.22 | 0.22 | 0.24 | 0.13 | 0.22 | 0.18 | 0.21 | 0.23 | 0.68 | 0.78 |
| **var_30** | Minimum December January February precipitation | 0.33 | -0.11 | 0.52 | -0.50 | 0.10 | 0.42 | -0.54 | 0.17 | 0.36 | 0.15 | 0.40 | 0.33 | 0.32 | 0.41 | 0.13 | 0.39 | 0.16 | 0.33 | 0.39 | 0.72 | 0.57 |
| **var_31** | Maximum December January February precipitation | 0.37 | -0.12 | 0.56 | -0.54 | 0.13 | 0.47 | -0.58 | 0.21 | 0.39 | 0.20 | 0.44 | 0.37 | 0.37 | 0.45 | 0.17 | 0.43 | 0.21 | 0.37 | 0.43 | 0.75 | 0.63 |
| **var_32** | Total precipitation for months with a mean monthly T is above 0°C | 0.51 | -0.10 | 0.67 | -0.61 | 0.28 | 0.59 | -0.64 | 0.41 | 0.47 | 0.35 | 0.56 | 0.51 | 0.50 | 0.57 | 0.33 | 0.54 | 0.39 | 0.50 | 0.55 | 0.97 | 0.90 |
| **var_33** | Annual actual evapotranspiration | 0.49 | -0.09 | 0.66 | -0.59 | 0.27 | 0.56 | -0.61 | 0.43 | 0.43 | 0.34 | 0.54 | 0.48 | 0.47 | 0.54 | 0.32 | 0.52 | 0.37 | 0.47 | 0.53 | 0.89 | 0.83 |
| **var_34** | Annual potential evapotranspiration | 0.96 | 0.67 | 0.83 | -0.76 | 0.91 | 0.90 | -0.63 | 0.80 | 0.89 | 0.92 | 0.93 | 0.97 | 0.96 | 0.92 | 0.90 | 0.94 | 0.88 | 0.96 | 0.94 | 0.25 | 0.36 |
| **var_35** | Coefficient of annual moisture availability | -0.47 | -0.77 | -0.22 | 0.15 | -0.66 | -0.33 | -0.01 | -0.42 | -0.44 | -0.60 | -0.38 | -0.45 | -0.43 | -0.37 | -0.60 | -0.40 | -0.53 | -0.44 | -0.40 | 0.53 | 0.37 |
| **var_36** | Aridity Index | -0.35 | -0.52 | -0.19 | 0.02 | -0.54 | -0.22 | -0.09 | -0.54 | -0.20 | -0.50 | -0.25 | -0.28 | -0.25 | -0.24 | -0.51 | -0.26 | -0.46 | -0.26 | -0.27 | 0.27 | 0.14 |
| **var_37** | PET seasonality | -0.06 | 0.46 | -0.43 | 0.46 | 0.30 | -0.24 | 0.57 | 0.06 | -0.09 | 0.21 | -0.21 | -0.18 | -0.22 | -0.23 | 0.24 | -0.21 | 0.16 | -0.21 | -0.18 | -0.54 | -0.53 |
| **var_38** | Thornthwaite 1948 humidity index | -0.32 | -0.44 | -0.19 | 0.02 | -0.49 | -0.20 | -0.07 | -0.52 | -0.17 | -0.45 | -0.23 | -0.25 | -0.22 | -0.22 | -0.47 | -0.23 | -0.43 | -0.23 | -0.25 | 0.18 | 0.08 |
| **var_39** | Thornthwaite 1948 aridity index | 0.30 | 0.66 | 0.07 | 0.01 | 0.52 | 0.16 | 0.15 | 0.29 | 0.28 | 0.45 | 0.21 | 0.30 | 0.29 | 0.20 | 0.46 | 0.23 | 0.39 | 0.30 | 0.23 | -0.64 | -0.47 |
| **var_40** | Emberger's pluviothermic quotient | 0.40 | -0.21 | 0.64 | -0.56 | 0.15 | 0.51 | -0.63 | 0.28 | 0.40 | 0.23 | 0.48 | 0.43 | 0.43 | 0.48 | 0.20 | 0.45 | 0.27 | 0.43 | 0.46 | 0.93 | 0.79 |
| **var_41** | Annual solar radiation | 0.95 | 0.58 | 0.89 | -0.83 | 0.82 | 0.92 | -0.72 | 0.76 | 0.88 | 0.85 | 0.94 | 0.91 | 0.89 | 0.94 | 0.82 | 0.95 | 0.82 | 0.90 | 0.94 | 0.41 | 0.49 |
| **var_42** | Altitude | -0.19 | 0.17 | 0.02 | -0.05 | -0.29 | -0.14 | -0.01 | -0.34 | -0.10 | -0.32 | -0.12 | -0.23 | -0.24 | -0.12 | -0.34 | -0.09 | -0.39 | -0.24 | -0.14 | -0.08 | -0.06 |

| Indicator | | var_22 | var_23 | var_24 | var_25 | var_26 | var_27 | var_28 | var_29 | var_30 | var_31 | var_32 | var_33 | var_34 | var_35 | var_36 | var_37 | var_38 | var_39 | var_40 | var_41 | var_42 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **var_1** | Annual mean T | 0.05 | 0.37 | 0.44 | 0.08 | 0.22 | 0.25 | 0.16 | 0.21 | 0.33 | 0.37 | 0.51 | 0.49 | 0.96 | -0.47 | -0.35 | -0.06 | -0.32 | 0.30 | 0.40 | 0.95 | -0.19 |
| **var_2** | Mean diurnal range | -0.38 | 0.51 | -0.12 | -0.37 | -0.20 | -0.24 | -0.22 | -0.17 | -0.11 | -0.12 | -0.10 | -0.09 | 0.67 | -0.77 | -0.52 | 0.46 | -0.44 | 0.66 | -0.21 | 0.58 | 0.17 |
| **var_3** | Isothermality | 0.22 | 0.28 | 0.58 | 0.25 | 0.35 | 0.43 | 0.22 | 0.25 | 0.52 | 0.56 | 0.67 | 0.66 | 0.83 | -0.22 | -0.19 | -0.43 | -0.19 | 0.07 | 0.64 | 0.89 | 0.02 |
| **var_4** | T seasonality | -0.24 | -0.19 | -0.57 | -0.27 | -0.33 | -0.40 | -0.23 | -0.26 | -0.50 | -0.54 | -0.61 | -0.59 | -0.76 | 0.15 | 0.02 | 0.46 | 0.02 | 0.01 | -0.56 | -0.83 | -0.05 |
| **var_5** | Maximum T of the warmest month | -0.14 | 0.43 | 0.21 | -0.13 | 0.02 | 0.05 | 0.03 | 0.09 | 0.10 | 0.13 | 0.28 | 0.27 | 0.91 | -0.66 | -0.54 | 0.30 | -0.49 | 0.52 | 0.15 | 0.82 | -0.29 |
| **var_6** | Minimum T of the coldest month | 0.16 | 0.27 | 0.52 | 0.19 | 0.28 | 0.35 | 0.21 | 0.25 | 0.42 | 0.47 | 0.59 | 0.56 | 0.90 | -0.33 | -0.22 | -0.24 | -0.20 | 0.16 | 0.51 | 0.92 | -0.14 |
| **var_7** | Annual T range | -0.34 | -0.07 | -0.59 | -0.37 | -0.38 | -0.47 | -0.28 | -0.30 | -0.54 | -0.58 | -0.64 | -0.61 | -0.63 | -0.01 | -0.09 | 0.57 | -0.07 | 0.15 | -0.63 | -0.72 | -0.01 |
| **var_8** | Mean T of wettest quarter | -0.07 | 0.45 | 0.35 | -0.05 | 0.25 | 0.07 | 0.16 | 0.21 | 0.17 | 0.21 | 0.41 | 0.43 | 0.80 | -0.42 | -0.54 | 0.06 | -0.52 | 0.29 | 0.28 | 0.76 | -0.34 |
| **var_9** | Mean T of driest quarter | 0.10 | 0.26 | 0.40 | 0.13 | 0.15 | 0.30 | 0.11 | 0.16 | 0.36 | 0.39 | 0.47 | 0.43 | 0.89 | -0.44 | -0.20 | -0.09 | -0.17 | 0.28 | 0.40 | 0.88 | -0.10 |
| **var_10** | Mean T of warmest quarter | -0.08 | 0.41 | 0.28 | -0.06 | 0.09 | 0.11 | 0.08 | 0.14 | 0.15 | 0.20 | 0.35 | 0.34 | 0.92 | -0.60 | -0.50 | 0.21 | -0.45 | 0.45 | 0.23 | 0.85 | -0.32 |
| **var_11** | Mean T of coldest quarter | 0.12 | 0.32 | 0.50 | 0.15 | 0.26 | 0.31 | 0.19 | 0.24 | 0.40 | 0.44 | 0.56 | 0.54 | 0.93 | -0.38 | -0.25 | -0.21 | -0.23 | 0.21 | 0.48 | 0.94 | -0.12 |
| **var_12** | T sums when mean monthly T > 0°C | 0.02 | 0.43 | 0.46 | 0.05 | 0.20 | 0.24 | 0.15 | 0.22 | 0.33 | 0.37 | 0.51 | 0.48 | 0.97 | -0.45 | -0.28 | -0.18 | -0.25 | 0.30 | 0.43 | 0.91 | -0.23 |
| **var_13** | T sums when mean monthly T > 5°C | 0.02 | 0.44 | 0.46 | 0.05 | 0.19 | 0.24 | 0.15 | 0.22 | 0.32 | 0.37 | 0.50 | 0.47 | 0.96 | -0.43 | -0.25 | -0.22 | -0.22 | 0.29 | 0.43 | 0.89 | -0.24 |
| **var_14** | Mean T of the coldest month | 0.12 | 0.31 | 0.51 | 0.15 | 0.26 | 0.32 | 0.19 | 0.24 | 0.41 | 0.45 | 0.57 | 0.54 | 0.92 | -0.37 | -0.24 | -0.23 | -0.22 | 0.20 | 0.48 | 0.94 | -0.12 |
| **var_15** | Mean T of the warmest month | -0.10 | 0.41 | 0.26 | -0.08 | 0.07 | 0.09 | 0.07 | 0.13 | 0.13 | 0.17 | 0.33 | 0.32 | 0.90 | -0.60 | -0.51 | 0.24 | -0.47 | 0.46 | 0.20 | 0.82 | -0.34 |
| **var_16** | Maximum T of coldest month | 0.09 | 0.35 | 0.49 | 0.12 | 0.25 | 0.28 | 0.17 | 0.22 | 0.39 | 0.43 | 0.54 | 0.52 | 0.94 | -0.40 | -0.26 | -0.21 | -0.23 | 0.23 | 0.45 | 0.95 | -0.09 |
| **var_17** | Minimum T of warmest month | -0.04 | 0.39 | 0.32 | -0.02 | 0.14 | 0.13 | 0.12 | 0.18 | 0.16 | 0.21 | 0.39 | 0.37 | 0.88 | -0.53 | -0.46 | 0.16 | -0.43 | 0.39 | 0.27 | 0.82 | -0.39 |
| **var_18** | Number of months with mean T > 10°C | 0.02 | 0.43 | 0.46 | 0.05 | 0.20 | 0.24 | 0.15 | 0.21 | 0.33 | 0.37 | 0.50 | 0.47 | 0.96 | -0.44 | -0.26 | -0.21 | -0.23 | 0.30 | 0.43 | 0.90 | -0.24 |
| **var_19** | Thermicity index | 0.10 | 0.33 | 0.49 | 0.13 | 0.25 | 0.30 | 0.18 | 0.23 | 0.39 | 0.43 | 0.55 | 0.53 | 0.94 | -0.40 | -0.27 | -0.18 | -0.25 | 0.23 | 0.46 | 0.94 | -0.14 |
| **var_20** | Annual precipitation | 0.70 | -0.17 | 0.92 | 0.74 | 0.80 | 0.75 | 0.71 | 0.68 | 0.72 | 0.75 | 0.97 | 0.89 | 0.25 | 0.53 | 0.27 | -0.54 | 0.18 | -0.64 | 0.93 | 0.41 | -0.08 |
| **var_21** | Precipitation of the wettest month | 0.39 | 0.14 | 0.99 | 0.43 | 0.74 | 0.58 | 0.72 | 0.78 | 0.57 | 0.63 | 0.90 | 0.83 | 0.36 | 0.37 | 0.14 | -0.53 | 0.08 | -0.47 | 0.79 | 0.49 | -0.06 |
| **var_22** | Precipitation of the driest month | 1.00 | -0.52 | 0.42 | 0.99 | 0.55 | 0.67 | 0.47 | 0.37 | 0.57 | 0.54 | 0.61 | 0.52 | -0.07 | 0.55 | 0.40 | -0.29 | 0.32 | -0.63 | 0.72 | 0.05 | -0.07 |
| **var_23** | Precipitation seasonality | -0.52 | 1.00 | 0.10 | -0.52 | -0.10 | -0.27 | -0.09 | 0.06 | -0.17 | -0.14 | -0.06 | -0.09 | 0.48 | -0.52 | -0.32 | -0.04 | -0.26 | 0.49 | -0.14 | 0.43 | 0.15 |
| **var_24** | Precipitation of wettest quarter | 0.42 | 0.10 | 1.00 | 0.46 | 0.76 | 0.61 | 0.73 | 0.76 | 0.61 | 0.66 | 0.92 | 0.86 | 0.34 | 0.41 | 0.16 | -0.53 | 0.09 | -0.50 | 0.81 | 0.48 | -0.06 |
| **var_25** | Precipitation of driest quarter | 0.99 | -0.52 | 0.46 | 1.00 | 0.58 | 0.70 | 0.49 | 0.39 | 0.58 | 0.57 | 0.65 | 0.56 | -0.05 | 0.56 | 0.40 | -0.31 | 0.32 | -0.64 | 0.75 | 0.08 | -0.07 |
| **var_26** | Precipitation of warmest quarter | 0.55 | -0.10 | 0.76 | 0.58 | 1.00 | 0.37 | 0.63 | 0.58 | 0.57 | 0.59 | 0.77 | 0.75 | 0.11 | 0.53 | 0.20 | -0.38 | 0.11 | -0.64 | 0.68 | 0.28 | -0.02 |
| **var_27** | Precipitation of coldest quarter | 0.67 | -0.27 | 0.61 | 0.70 | 0.37 | 1.00 | 0.54 | 0.50 | 0.49 | 0.53 | 0.71 | 0.61 | 0.14 | 0.39 | 0.25 | -0.37 | 0.19 | -0.46 | 0.77 | 0.25 | -0.09 |
| **var_28** | Minimum June July August precipitation | 0.47 | -0.09 | 0.73 | 0.49 | 0.63 | 0.54 | 1.00 | 0.93 | 0.10 | 0.13 | 0.68 | 0.58 | 0.05 | 0.45 | 0.20 | -0.30 | 0.12 | -0.51 | 0.61 | 0.18 | -0.06 |
| **var_29** | Maximum June July August precipitation | 0.37 | 0.06 | 0.76 | 0.39 | 0.58 | 0.50 | 0.93 | 1.00 | 0.06 | 0.10 | 0.66 | 0.56 | 0.11 | 0.38 | 0.16 | -0.31 | 0.10 | -0.43 | 0.57 | 0.23 | -0.06 |
| **var_30** | Minimum December January February precipitation | 0.57 | -0.17 | 0.61 | 0.58 | 0.57 | 0.49 | 0.10 | 0.06 | 1.00 | 0.96 | 0.70 | 0.68 | 0.26 | 0.34 | 0.21 | -0.42 | 0.15 | -0.43 | 0.70 | 0.36 | -0.05 |
| **var_31** | Maximum December January February precipitation | 0.54 | -0.14 | 0.66 | 0.57 | 0.59 | 0.53 | 0.13 | 0.10 | 0.96 | 1.00 | 0.73 | 0.71 | 0.29 | 0.34 | 0.18 | -0.44 | 0.12 | -0.43 | 0.73 | 0.40 | -0.07 |
| **var_32** | Total precipitation for months with a mean monthly T is above 0°C | 0.61 | -0.06 | 0.92 | 0.65 | 0.77 | 0.71 | 0.68 | 0.66 | 0.70 | 0.73 | 1.00 | 0.93 | 0.39 | 0.39 | 0.05 | -0.48 | -0.03 | -0.50 | 0.92 | 0.54 | -0.14 |
| **var_33** | Annual actual evapotranspiration | 0.52 | -0.09 | 0.86 | 0.56 | 0.75 | 0.61 | 0.58 | 0.56 | 0.68 | 0.71 | 0.93 | 1.00 | 0.37 | 0.45 | 0.00 | -0.48 | -0.10 | -0.56 | 0.81 | 0.53 | -0.15 |
| **var_34** | Annual potential evapotranspiration | -0.07 | 0.48 | 0.34 | -0.05 | 0.11 | 0.14 | 0.05 | 0.11 | 0.26 | 0.29 | 0.39 | 0.37 | 1.00 | -0.59 | -0.36 | -0.04 | -0.31 | 0.43 | 0.30 | 0.94 | -0.12 |
| **var_35** | Coefficient of annual moisture availability | 0.55 | -0.52 | 0.41 | 0.56 | 0.53 | 0.39 | 0.45 | 0.38 | 0.34 | 0.34 | 0.39 | 0.45 | -0.59 | 1.00 | 0.48 | -0.50 | 0.36 | -0.95 | 0.40 | -0.45 | -0.05 |
| **var_36** | Aridity Index | 0.40 | -0.32 | 0.16 | 0.40 | 0.20 | 0.25 | 0.20 | 0.16 | 0.21 | 0.18 | 0.05 | 0.00 | -0.36 | 0.48 | 1.00 | -0.38 | 0.99 | -0.51 | 0.19 | -0.31 | 0.26 |
| **var_37** | PET seasonality | -0.29 | -0.04 | -0.53 | -0.31 | -0.38 | -0.37 | -0.30 | -0.31 | -0.42 | -0.44 | -0.48 | -0.48 | -0.04 | -0.50 | -0.38 | 1.00 | -0.32 | 0.49 | -0.55 | -0.13 | -0.10 |
| **var_38** | Thornthwaite 1948 humidity index | 0.32 | -0.26 | 0.09 | 0.32 | 0.11 | 0.19 | 0.12 | 0.10 | 0.15 | 0.12 | -0.03 | -0.10 | -0.31 | 0.36 | 0.99 | -0.32 | 1.00 | -0.38 | 0.12 | -0.29 | 0.28 |
| **var_39** | Thornthwaite 1948 aridity index | -0.63 | 0.49 | -0.50 | -0.64 | -0.64 | -0.46 | -0.51 | -0.43 | -0.43 | -0.43 | -0.50 | -0.56 | 0.43 | -0.95 | -0.51 | 0.49 | -0.38 | 1.00 | -0.49 | 0.26 | 0.00 |
| **var_40** | Emberger's pluviothermic quotient | 0.72 | -0.14 | 0.81 | 0.75 | 0.68 | 0.77 | 0.61 | 0.57 | 0.70 | 0.73 | 0.92 | 0.81 | 0.30 | 0.40 | 0.19 | -0.55 | 0.12 | -0.49 | 1.00 | 0.44 | -0.09 |
| **var_41** | Annual solar radiation | 0.05 | 0.43 | 0.48 | 0.08 | 0.28 | 0.25 | 0.18 | 0.23 | 0.36 | 0.40 | 0.54 | 0.53 | 0.94 | -0.45 | -0.31 | -0.13 | -0.29 | 0.26 | 0.44 | 1.00 | 0.06 |
| **var_42** | Altitude | -0.07 | 0.15 | -0.06 | -0.07 | -0.02 | -0.09 | -0.06 | -0.06 | -0.05 | -0.07 | -0.14 | -0.15 | -0.12 | -0.05 | 0.26 | -0.10 | 0.28 | 0.00 | -0.09 | 0.06 | 1.00 |