ECMWF COPERNICUS REPORT

Copernicus Climate Change Service

Downscaled bioclimatic indicators for selected regions from 1950 to 2100 derived from projections

Product User Guide

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1. Introduction

1.1 Executive Summary

The dataset provides a set of bioclimatic indicators at 1 km x 1 km resolution for selected target regions (i.e. Europe, Northern Brazil and Central Africa) derived from CMIP5 climate projections. These bioclimatic indicators describe how climate affects ecosystems, the services they deliver and nature's biodiversity. They are specifically relevant for applications within the biodiversity and ecosystem services community.

The dataset is tailored to the needs of diverse biodiversity experts. The pre-computed bioclimatic indicators are based on renowned datasets, easily accessible and user-friendly, which facilitates the direct use of climate information in screening analyses or in diverse downstream applications. Stakeholders can use the dataset among others to plan conservation activities, to screen a region's climate suitability for a specific species, or to support decision making in the area of biodiversity and ecosystem services.

The dataset contains essential climate variables (such as temperature and precipitation), but also derived variables (e.g. mean diurnal range and aridity), which have been calculated based on daily or monthly CMIP5 climate projections from 10 different Global Circulation Models (GCMs). The data have been additionally bias-corrected against ERA5 reanalysis data and further downscaled to 1km x 1km resolution using state-of-the-art techniques that take into account the relationship between orography and a climate state variable. A total of 76 relevant indicators is available for the period 1950-2100 at a spatial resolution of 1km x 1km. The temporal resolution is a 20-year average.

This dataset was produced on behalf of the Copernicus Climate Change Service.

1.2 Scope of Documentation

This document provides a characterization of the dataset and a description of the methodology used to produce it. First, the background against which this dataset has been developed is given, followed by a specification of the dataset of bioclimatic indicators. Thereafter, the applied methodology to produce the dataset is described in detail.

1.3 Version History

This is the first version of the dataset.

2. Product Description

2.1 Product Target Requirements

In its 5th Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) states *with high confidence* that climate change will significantly affect biodiversity and the related services ecosystems provide to humans. Climate is obviously not the only driver of biodiversity loss in marine and terrestrial ecosystems; many other factors, including anthropogenic land use change, pollution and habitat fragmentation, also have a substantial impact. Yet, climatic changes are considered an increasingly important driver for the worldwide decline in biodiversity and ecosystem functioning. Climate change vulnerability assessments are gaining importance and are acknowledged to be critical elements in conservation strategies. Yet, while biodiversity research increasingly incorporates realistic processes underlying biological responses to climate change, progress is often hindered by the lack of climate data to drive these models. Access to customized and qualified climate information to assess species' performance or survival under climate change conditions is crucial.

The Copernicus Sectoral Information System (SIS) Biodiversity aims to fill this knowledge gap by providing operational bioclimatic indicators for the biodiversity and ecosystem services community. Based on existing datasets of the Climate Data Store (CDS), unique datasets of not less than 78 bioclimatic indicators - and six new applications deploying these datasets - have been developed within SIS Global Biodiversity to serve stakeholders in the biodiversity community. The developed datasets result from an extended co-creation trajectory involving developers at VITO and several biodiversity experts. Very specifically, the **dataset of downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections** (***BIOCLIMATE_1km_CMIP5***) offers 76 relevant bioclimatic indicators derived from CMIP5 data, bias-corrected against ERA5 reanalysis data and further downscaled. Indicators are available for Europe, Central Africa and Northern Brazil at high resolution (1km x 1km). Stakeholders can use the climate information directly to assess biodiversity loss, plan conservation or restoration activities and support decision-making in the field of biodiversity and ecosystem services.

2.2 Product Overview

2.2.1 Data Description

Characteristics of the **dataset of downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections** (***BIOCLIMATE_1km_CMIP5***) are given in Table 1. As an example, one indicator is visualized in Figure 1.

Table 1. Overview of key characteristics of the BIOCLIMATE_1km_CMIP5 dataset

Data Description	
Dataset title	Downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections (BIOCLIMATE_1km_CMIP5)
Data type	Bioclimatic indicators derived from CMIP5 climate projections
Topic category	Biodiversity
Sector	Biodiversity & ecosystem services

Keyword	biodiversity; CMIP; bioclimatic indicators; high resolution
Dataset language	English
Domain	Central Africa (15°S-25°N, 0-35°E); Europe (32-72°N, -30°W-50°E); Northern Brazil (12-20°S, 35-43°W)
Horizontal resolution	1km x 1km
Temporal coverage	1950 to 2100
Temporal resolution	20-year averages
Vertical coverage	Surface
Update frequency	No updates expected
Version	v1.0
Model (experiment)	access1-0 (r1i1p1) bcc-csm-1-m (r1i1p1) csiro-mk3-6-0 (r1i1p1) gfdl-esm2m (r1i1p1) hadgem2-cc (r1i1p1) hadgem2-es (r2i1p1) ipsl-cm5a-lr (r1i1p1) ipsl-cm5a-mr (r1i1p1) ipsl-cm5b-lr (r1i1p1) noresm1-m (r1i1p1)
Provider	Flemish Institute for Technological Research (VITO) in collaboration with Arcadis Belgium, Baltic Environmental Forum Estonia (BEF Estonia), Baltic Environmental Forum Latvia (BEF Latvia), National Institute of Aquatic Resources at the Technical University of Denmark (DTU Aqua), Bioversity International, Antwerp Zoo Society (KMDA)
Terms of Use	Licence to use Copernicus products

Annual mean temperature for Europe

2081-2100 under RCP4.5 with CMIP5 model IPSL-CM5A-MR

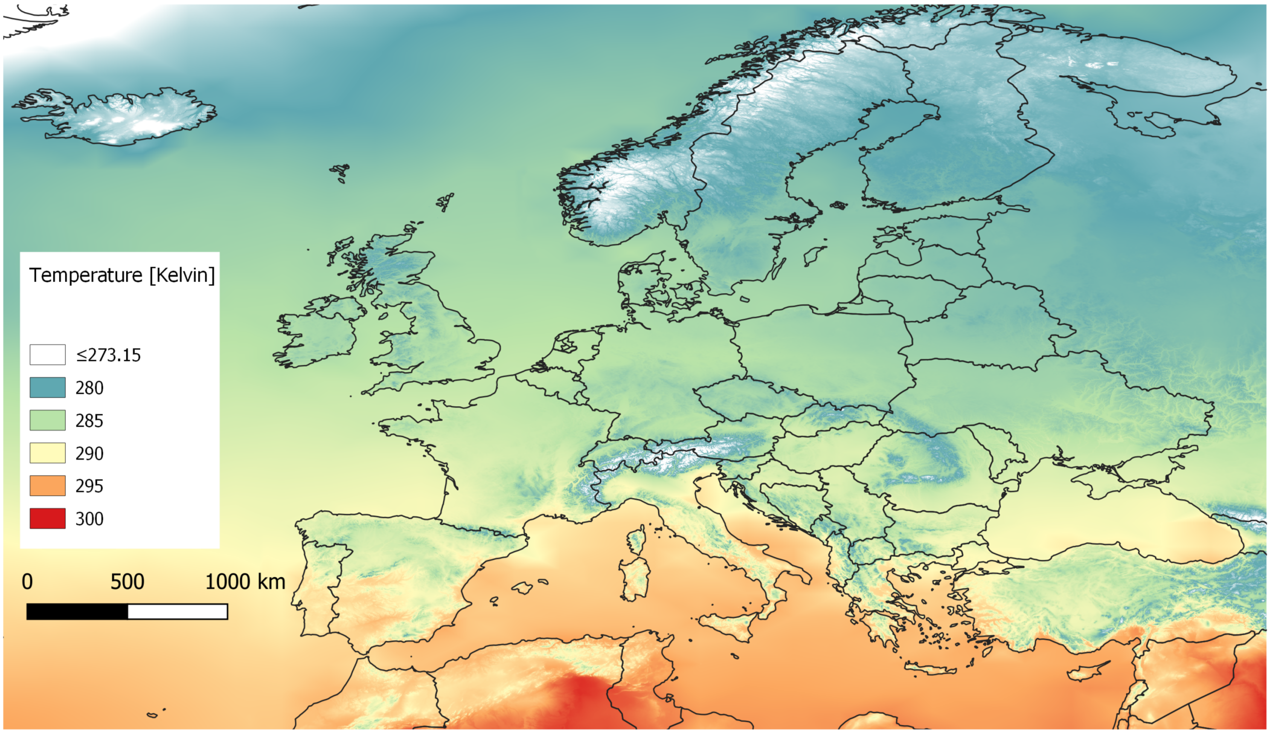

Figure 1. Annual mean temperature for Europe for the period 2081-2100 derived from IPSL-CM5A-MR

2.2.2 Variable Description

A set of 76 bioclimatic indicators was selected after consultation with a wide range of biodiversity experts active in different domains. The bioclimatic indicators were calculated by applying indicator definitions (available in Table 2) on raw daily and monthly (bias-corrected) input climate data timeseries per year. Additional details can be found in Appendix I.

Table 2. Overview and description of bioclimatic indicators

Variable	Units	Definition
Essential climate variables (12)		
Monthly mean precipitation	$m\,s^{-1}$	Monthly mean (of the daily mean) precipitation. To compute the total precipitation sum over the aggregation period, a conversion factor should be applied of 3600x24x1000x30.4 (average number of days per month).
Annual mean daily precipitation	$m\,s^{-1}$	Annual mean (of the daily mean) precipitation. To compute the total precipitation sum over the aggregation period, a conversion factor should be applied of 3600x24x1000x365 (average number of days per year).

Annual maximum daily precipitation	m s^{-1}	Annual maximum of daily precipitation. To compute the total precipitation sum over the aggregation period, a conversion factor should be applied of 3600x24x1000x365 (average number of days per year).
Annual maximum 2m temperature	K	Annual maximum (of the daily maximum) temperature at 2 m above surface.
Annual minimum 2m temperature	K	Annual minimum (of the daily minimum) temperature at 2 m above surface.
Monthly mean and annual mean 2m temperature	K	Monthly/annual mean of the daily mean temperature at 2 m above surface.
Monthly mean daily maximum 2m temperature	K	Monthly mean of the daily maximum temperature at 2 m above surface.
Monthly mean daily minimum 2m temperature	K	Monthly mean of the daily minimum temperature at 2 m above surface.
Annual mean daily maximum 2m temperature	K	Annual mean of the daily maximum temperature.
Annual mean daily maximum 2m temperature	K	Annual mean of the daily minimum temperature.
Monthly and annual water vapour pressure	Pa	Monthly and annual mean of the contribution to the total atmospheric pressure provided by the water vapour over the period 00-24h local time per unit of time.
Monthly and annual cloud cover	-	Monthly and annual mean of the cloud cover fraction.
Bioclimatic indicators as in WorldClim[1] (19)		
Annual mean temperature (BIO01)	K	Annual mean of the monthly mean temperature at 2 m above the surface. This indicator corresponds to the official BIOCLIM variable BIO01.
Mean diurnal range (BIO02)	K	Mean of the monthly maximum temperature minus the monthly minimum temperature (max temp - min temp). The data is aggregated over the months. This indicator corresponds to the official BIOCLIM variable BIO02.

[1] WorldClim offers spatially interpolated gridded climate data at a high spatial resolution (1km x 1km) for all global land areas. The data provide long-term average monthly temperature, precipitation and other climate variables, based on weather station data and satellite-derived and other covariables for interpolation. The WorldClim database identified 19 bioclimatic variables (BIO01-BIO019) derived from monthly temperature and rainfall data that have important biological meaning and can be used in species distribution modelling and related ecological modelling techniques (Fick and Hijmans, 2017; Hijmans et al., 2005). The definitions used to calculate BIO01-BIO19 in the CDS dataset are adopted from WorldClim.

Isothermality (BIO03)	%	Monthly mean diurnal range divided by temperature annual range, multiplied by 100: (monthly mean diurnal range/temperature annual range) x100. This indicator corresponds to the official BIOCLIM variable BIO03.
Temperature seasonality (BIO04)	K	Standard deviation of the monthly mean temperature multiplied by 100. This indicator corresponds to the official BIOCLIM variable BIO04.
Maximum temperature in warmest month (BIO05)	K	Maximum daily temperature averaged over the month with the highest monthly mean of daily maximum temperature. This indicator corresponds to the official BIOCLIM variable BIO05.
Minimum temperature in coldest month (BIO06)	K	Minimum daily temperature averaged over the month with the lowest monthly mean of daily minimum temperature. This indicator corresponds to the official BIOCLIM variable BIO06.
Temperature annual range (BIO07)	K	Daily maximum temperature averaged over the warmest month (BIO05) minus daily minimum temperature averaged over the coldest month (BIO06). This indicator corresponds to the official BIOCLIM variable BIO07.
Mean temperature in wettest quarter (BIO08)	K	The mean of monthly mean temperature during the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months. This indicator corresponds to the official BIOCLIM variable BIO08.
Mean temperature in driest quarter (BIO09)	K	The mean of monthly mean temperature during the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months. This indicator corresponds to the official BIOCLIM variable BIO09.
Mean temperature in warmest quarter (BIO10)	K	The mean of monthly mean temperature during the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months. This indicator corresponds to the official BIOCLIM variable BIO10.
Mean temperature of coldest quarter (BIO11)	K	The mean of monthly mean temperature during the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months. This indicator corresponds to the official BIOCLIM variable BIO11.
Annual precipitation (BIO12)	$m\ s^{-1}$	Annual mean of the monthly mean precipitation rate (both liquid and solid phases). This indicator corresponds to the official BIOCLIM variable BIO12. To compute the total precipitation sum over the year, a conversion factor should be applied of 3600x24x365x1000 mm/year.
Precipitation in wettest month (BIO13)	$m\ s^{-1}$	Maximum of the monthly precipitation. This indicator corresponds to the official BIOCLIM variable BIO13.
Precipitation in driest month (BIO14)	$m\ s^{-1}$	Minimum of the monthly precipitation. This indicator corresponds to the official BIOCLIM variable BIO14.
Precipitation seasonality (BIO15)	-	Annual coefficient of variation of the monthly precipitation. This indicator corresponds to the official BIOCLIM variable BIO15.

Precipitation in wettest quarter (BIO16)	$m\ s^{-1}$	The mean of monthly mean precipitation during the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months. To compute the total precipitation sum over the month, a conversion factor should be applied of 3600x24x91.3 (average number of days per quarter)*1000. This indicator corresponds to the official BIOCLIM variable BIO16.
Precipitation in driest quarter (BIO17)	$m\ s^{-1}$	The mean of monthly mean precipitation during the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months. To compute the total precipitation sum over the months, a conversion factor should be applied of 3600x24x91.3 (average number of days per quarter)x1000. This indicator corresponds to the official BIOCLIM variable BIO17.
Precipitation in warmest quarter (BIO18)	$m\ s^{-1}$	The mean of monthly mean precipitation during the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months. To compute the total precipitation sum over the months, a conversion factor should be applied of 3600x24x91.3 (average number of days per quarter)x1000. This indicator corresponds to the official BIOCLIM variable BIO18.
Precipitation in coldest quarter (BIO19)	$m\ s^{-1}$	The mean of the monthly mean precipitation during the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months. To compute the total precipitation sum over the months, a conversion factor should be applied of 3600x24x91.3 (average number of days per quarter)x1000. This indicator corresponds to the official BIOCLIM variable BIO19.
Drought indicators (11)		
Annual mean aridity	-	Monthly potential evaporation divided by the monthly mean precipitation averaged over the year.
Aridity in coldest quarter	-	Monthly potential evaporation divided by the monthly mean precipitation averaged over the year averaged over the over coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Aridity in warmest quarter	-	Monthly potential evaporation divided by the monthly mean precipitation averaged over the year averaged over the over warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Aridity in wettest quarter	-	Monthly potential evaporation divided by the monthly mean precipitation averaged over the year averaged over the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Aridity in driest quarter	-	Monthly potential evaporation divided by the monthly mean precipitation averaged over the year averaged over the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Dry days	days $year^{-1}$	Number of days within a year where total daily precipitation does not exceed 2 mm.

Maximum length of dry spells	days	Maximum number of consecutive days of the dry spells within a year.
Mean intensity of dry spells	days	Determine the consecutive dry days at each day in a year, then take the average of these daily values over the year.
Mean length of dry spells with min 5 days	days	Mean length of dry spells with a minimum of 5 days within a year.
Number of dry spells with min 5 days	spells $year^{-1}$	Number of dry spells with a minimum of 5 days that occur in a year.
Summer days	days $year^{-1}$	Number of days in a year for which the daily maximum temperature is not lower than 298.15 K (25°C).
Evaporation indicators (10)		
Annual mean potential evaporation	$m\ s^{-1}$	The amount of water that would evaporate and transpire if there is unlimited water supply, averaged over the year.
Potential evaporation in coldest quarter	$m\ s^{-1}$	The amount of water that would evaporate and transpire if there is unlimited water supply, averaged for the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Potential evaporation in warmest quarter	$m\ s^{-1}$	The amount of water that would evaporate and transpire if there is unlimited water supply, averaged for the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Potential evaporation in wettest quarter	$m\ s^{-1}$	The amount of water that would evaporate and transpire if there is unlimited water supply, averaged for the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Potential evaporation driest quarter	$m\ s^{-1}$	The amount of water that would evaporate and transpire if there is unlimited water supply averaged for the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Annual mean evaporative fraction	-	Monthly surface latent heat divided by the monthly total sensible and latent heat flux, averaged over the year.
Evaporative fraction in coldest quarter	-	Monthly surface latent heat flux divided by the monthly total sensible and latent heat flux, averaged over the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Evaporative fraction in warmest quarter	-	Monthly surface latent heat divided by the monthly total sensible and latent heat flux, averaged over the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Evaporative fraction in wettest quarter	-	Monthly surface latent heat divided by the monthly total sensible and latent heat flux, averaged over the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.

Evaporative fraction in driest quarter	-	Monthly surface latent heat flux divided by the monthly total sensible and latent heat flux averaged over the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Surface energy indicators (10)		
Annual mean surface latent heat flux	W m^{-2}	The transfer of latent heat (resulting from water phase changes, such as evaporation or condensation) between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the year.
Surface latent heat flux in coldest quarter	W m^{-2}	The transfer of latent heat (resulting from water phase changes, such as evaporation or condensation) between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Surface latent heat flux in warmest quarter	W m^{-2}	The transfer of latent heat (resulting from water phase changes, such as evaporation or condensation) between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Surface latent heat flux in wettest quarter	W m^{-2}	The transfer of latent heat (resulting from water phase changes, such as evaporation or condensation) between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Surface latent heat flux in driest quarter	W m^{-2}	The transfer of latent heat (resulting from water phase changes, such as evaporation or condensation) between the Earth's surface and the atmosphere through the effects of turbulent air motion averaged over the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Annual mean surface sensible heat flux	W m^{-2}	The transfer of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion.
Surface sensible heat flux in coldest quarter	W m^{-2}	The transfer of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Surface sensible heat flux in warmest quarter	W m^{-2}	The transfer of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Surface sensible heat flux in wettest quarter	W m^{-2}	The transfer of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion, averaged over the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.

Surface sensible heat flux in driest quarter	$W\ m^{-2}$	The transfer of heat between the Earth's surface and the atmosphere through the effects of turbulent air motion averaged over the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Soil indicators (5)		
Annual mean volumetric soil water layer 1	$m^3\ m^{-3}$	The volume of water in soil layer 1 (0 - 7cm, the surface is at 0cm) averaged over the year. The ECMWF Integrated Forecasting System model has a four-layer representation of soil: Layer 1: 0 - 7cm Layer 2: 7 - 28cm Layer 3: 28 - 100cm Layer 4: 100 - 289cm. The volumetric soil water is associated with the soil texture (or classification), soil depth, and the underlying groundwater level.
Volumetric soil water layer 1 in coldest quarter	$m^3\ m^{-3}$	The volume of water in soil layer 1 (0 - 7cm, the surface is at 0cm) averaged over the coldest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Volumetric soil water layer 1 in warmest quarter	$m^3\ m^{-3}$	The volume of water in soil layer 1 (0 - 7cm, the surface is at 0cm) averaged over the warmest quarter, defined as the quarter with the highest monthly mean (of the daily mean) temperature using a moving average of 3 consecutive months.
Volumetric soil water layer 1 in wettest quarter	$m^3\ m^{-3}$	The volume of water in soil layer 1 (0 - 7cm, the surface is at 0cm) averaged over the wettest quarter, defined as the quarter with the highest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Volumetric soil water layer 1 in driest quarter	$m^3\ m^{-3}$	The volume of water in soil layer 1 (0 - 7cm, the surface is at 0cm) averaged over the driest quarter, defined as the quarter with the lowest monthly mean (of the daily mean) precipitation using a moving average of 3 consecutive months.
Growing season specific indicators (6)		
Frost days	days	Monthly and annual number of days with minimum temperature below 0°C (273.15 K) .
Growing degree days	K days $year^{-1}$	Monthly and annual growing degree days (sum of daily degrees above daily mean temperature of 278.15 K (5°C)).
Growing season start	day since 1 January	First day in a year with 5 consecutive days with a mean daily temperature above 278.15 K (5°C).
Growing season end	day since 1 January	Last day in a year with 5 consecutive days with a mean daily temperature above 278.15 K (5°C).
Growing degree days during growing season	K days	Growing degree days in the growing season.
Köppen-Geiger class	-	A climate classification that divides worldwide climates into separate classes depending on temperature and precipitation thresholds.
Wind indicators (3)		
Zonal wind speed	$m\ s^{-1}$	Magnitude of the eastward component of the two-dimensional horizontal air velocity near the surface.

Meridional wind speed	m s^{-1}	Magnitude of the northward component of the two-dimensional horizontal air velocity near the surface.
Wind speed	m s^{-1}	Magnitude of the two-dimensional horizontal air velocity near the surface.

2.3 Input Data

2.3.1 CMIP5

The Climate Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) was used to provide the future climate information for biodiversity. Its raw daily and monthly raw data on single levels generated by Global Climate Models (GCMs) are the data source to calculate the **globally complete dataset of bioclimatic indicators derived from CMIP5 climate projections** (***BIOCLIMATE_CMIP5***). They include daily and monthly raw data on single levels from GCMs and are obtained from the CDS. The data originated from GCMs for two representative concentration pathways (RCPs) that provide scenarios for future climate (i.e. RCP4.5 and RCP8.5). Ten GCMs were selected (Table 3) based on data availability required for calculating all 76 indicators.

Table 3. Climate model characterization for input to *BIOCLIMATE_CMIP5*

Model name	Model centre	Ensemble member	Atmospheric grid	
			Lat (°)	Lon (°)
access1-0	CSIRO & Bureau of Meteorology, Australia	r1i1p1	1.255	1.875
csiro-mk3-6-0	CSIRO, Australia	r1i1p1	~1.855	1.875
gfdl-esm2m	NOAA, USA	r1i1p1	2.0225	2.5
hadgem2-cc	Met Office, UK	r1i1p1	1.25	1.875
hadgem2-es	Met Office, UK	r2i1p1	1.25	1.875
ipsl-cm5a-lr	IPSL, France	r1i1p1	1.89473724	3.75
ipsl-cm5a-mr	IPSL, France	r1i1p1	1.26760846	2.5
ipsl-cm5b-lr	IPSL, France	r1i1p1	1.89473724	3.75
noresm1-m	NCC, Norway	r1i1p1	1.89473684	2.5
bcc-csm-1-m	BCC, China	r1i1p1	~1.121	1.125

CMIP5 is the most recent completed phase and was used in the 5th IPCC Assessment Report in 2013. All used climate model data have been quality checked and certified by the Copernicus Climate Change Service (C3S). Its successor, CMIP phase 6, is still in its final stage of development, and it is expected that it will become available in the CDS in 2021 when the 6th IPCC Assessment Report is published. Once available, an update of the bioclimatic indicators based on CMIP6 climate projections and scenarios (the so-called Shared Socio-Economic Pathways; SSP) is possible.

2.3.2 ERA5

ERA5 (Hersbach et al., 2020) was used to provide historical climate information for biodiversity. Its hourly (aggregated to daily scale using the cdstoolbox to match the temporal resolution of CMIP5) and monthly data are used to calculate the **globally complete dataset of bioclimatic indicators derived from ERA5 reference historical climate** (***BIOCLIMATE_ERA5***). ERA5 also serves as the input for bias adjustments (see sections 2.4.2 and 2.4.5) of *BIOCLIMATE_CMIP5* to ensure consistency with the reference historical climate *BIOCLIMATE_ERA5*.

ERA5 is a state-of-the-art climate reconstruction that describes the complete state and evolution of the global atmosphere—ocean—land system. It comprehends hourly and monthly estimates of a large number of atmospheric, land and ocean climate variables. It is the war-horse of the C3S, and combines vast amounts of historical observations into global estimates using advanced modelling and data assimilation systems. The data cover the earth on a 30km x 30 km grid and resolve the atmosphere using 137 levels from the surface up to a height of 80km. Quality-assured monthly updates of ERA5 are published within 3 months of real time, including uncertainties for all variables at reduced spatial and temporal resolutions. Preliminary daily updates of the dataset are available to users within 5 days of real time. The entire ERA5 dataset starts from 1979, although an extension was provided very recently towards 1950 to present. ERA5 replaces its processor ERA-Interim, which stopped being produced on 31 August 2019.

A detailed characterization of all input datasets is given in Appendix Table 4, Table 5, Table 6 and Table 7. References to access the input datasets are given in the *Resources* section of this document.

2.4 Method

The different processing steps to calculate the customized 76 bioclimatic indicators the **dataset of downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections** (***BIOCLIMATE_1km_CMIP5***) are described here in detail. An overview of the data processing flow is given in Figure 2.

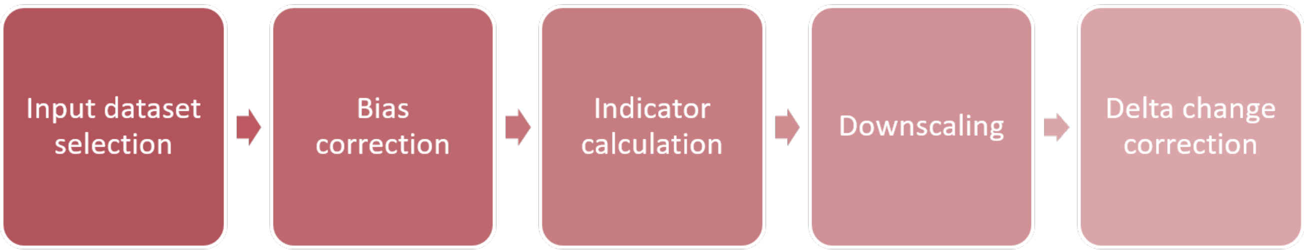

Figure 2. Overview of the processing steps used in the calculation of the bioclimatic indicators

2.4.1 Input dataset selection

CMIP5 and ERA5 daily/hourly and monthly data on single levels available in the CDS were selected as data sources. Geographical selection had to be made due to storage limitations and was based on the aim to support biodiversity challenges in specific use cases. Those use cases (including Golden-headed lion tamarin conservation in Northern Brazil, native tree restoration in Central Africa, and management of hedgerows and semi-natural grasslands in Europe) demonstrate the value of SIS

Global Biodiversity and can serve as source of inspiration for other stakeholders to apply the bioclimatic indicators in their own activities.

Raw data were pre-processed in the CDS Toolbox. In particular, hourly ERA5 data were aggregated to a daily resolution and data was geographically subset according to the area of interest.

The required input variables included:

- 2m temperature (daily mean, minimum and maximum)
- total precipitation
- total cloud cover
- 10m wind speed
- 10m zonal wind speed
- 10m meridional wind speed
- 2m specific humidity
- volumetric soil moisture
- surface pressure
- downward shortwave radiation
- surface sensible and latent heat flux
- sea surface temperature
- sea ice concentration

2.4.2 Bias correction

Consistency between observed variables and modelled climate variables is essential for reliable projections of climate suitability for species. Therefore, the raw CMIP5 ensemble climate model data was bias-corrected against ERA5 reanalysis by following the concept of quantile delta-mapping (QDM) described by Switanek et al. (2017) and Cannon et al. (2015). In essence, the bias correction method considers the bias of each quantile value of the raw model time series distribution with respect to the observed (or reanalysis) time series distribution, and subtracts these biases from the raw modelled time series (more details in the technical steps below). This was done for all raw climate variables that are required to calculate the bioclimatic indicators, and for each model grid location. The bias-correction method conserves the (absolute) climate-change signals of the quantile values distribution of each member in the model ensemble. Given the timeseries of ERA5 reanalysis x_r and the timeseries of the CMIP5 ensemble model member timeseries x_m, the bias-correction procedure involved the following technical steps:

1. Aggregate x_r to the grid of the ensemble climate model member
2. Calculate the discrete quantile function $Q_r(p)$ of x_r for each grid point of ERA5. $Q_r(p)$ yields the value of x_r such that the probability of x_r being less than or equal to that value equals the given probability p. This is done for multiple discrete p values. (By default, a uniform p profile of equidistant p values is taken. In order to discriminate in the biases among extreme precipitation values (ie., corresponding to high p values) an exponential p profile is used for precipitation with a maximum p value of 0.999)

3. Calculate the control quantile function for the climate model variable $Q_m(p)$ for the decadal timeframe corresponding to the reanalysis data, in analogy to the quantile function of the reanalysis data $Q_r(p)$ in the previous step
4. Calculate the transient quantile function for the climate model variable $Q_m(p,t)$ that changes with the 20-year time window t. $Q_m(p,t)$ is calculated by steps in t of 5 years
5. Calculate the discrete model quantile bias function $B(p) = Q_m(p) - Q_r(p)$ for each discrete p value
6. Calculate multi-decadal timeseries of model p values ($p(x_m(t),t$) by linear interpolation between the discrete p values according to the discrete $Q_m(p,t)$ values
7. Calculate the multi-decadal timeseries of model biases ($B(p(x_m,t)))$ by linear interpolation of the discrete $B(p)$ values according to the discrete p values
8. Finally, calculate the decadal bias-corrected model timeseries by subtracting the bias from the original timeseries as follows:
$$x_{m,bc}(t) = x_m(t) - B(p(x_m(t),t))$$

2.4.3 Indicator calculation

Customized bioclimatic indicators were calculated by applying indicator definitions (available in Table 2) on raw daily and monthly climate data timeseries per year. Monthly, annual and 20-year window statistics (for 1961-1980, 1981-2000, 2021-2040, 2041-2060, 2061-2080, 2081-2100) were calculated. Also median and spread (inter-quartile range) were calculated for the CMIP multi-model ensemble for each RCP scenario.

2.4.4 Downscaling

Bioclimatic indicators were further downscaled from the native coarse resolution of the climate products (several tens of km grid spacing) to a high resolution (1 km grid spacing) for selected regions using local information. This was also done for the global domain, but towards a much lower 0.5° resolution (~50km). The local information consists of the orography prescribed by the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010; Danielson & Gesch, 2011), and the downscaling itself employed a height correction of the coarse-scale indicator towards the elevation level at high resolution. This was achieved by the following steps:

1. quantify the change of the indicator with height (slope) at the native coarse resolution of the global climate model by calculating a linear regression of the surrounding pixels of 500 km x 500 km (= α_{CR})
2. Interpolate α_{CR} to the high-resolution grid using Delaunay linear interpolation. This interpolation step is done (e.g., instead of a nearest look-up of the slope parameter) to avoid discontinuities at the border of the coarse grid cells when applying the height correction in the final step)
3. Interpolate the coarse indicator (= I_{CR}) to the high-resolution grid using Delaunay linear interpolation

4. Create the coarse elevation field (= H_{CR}) corresponding to the coarse field I_{CR}. This is done by (I) aggregating the fine-scale orography to the native low resolution of the climate model and (II) interpolating it back to the high resolution
5. Finally, apply the height correction to the coarse scale indicator: correction at each high-resolution grid cell as follows:

$$I_{HR} = I_{CR} + \alpha_{CR}(h_{HR} - h_{CR})$$

Downscaling procedure evaluation

The downscaling procedure described above is consistent with the height-correction of temperature-based indicators considering a fixed adiabatic lapse rate employed in existing bioclimatic information products, including CHELSA (Karger et al., 2017) and WorldClim (Hijmans et al., 2005; Navarro-Racines et al., 2020). The added value of the applied procedure is that it considers also other height-related dependencies beyond the adiabatic lapse rate (e.g. temperature inversion). It also allowed to extend the high-resolution indicator set based on additional climate variables (such as aridity, volumetric water content or evaporative fraction) that have not been included yet in previous bioclimatic datasets such as WorldClim. Acknowledging that α_{HR} is changing only slightly in space, the linear relation assured the aggregate of the high-resolution field to approximate the original field. The above described procedure was applied to the calculated indicators after computing the decadal rolling-window statistics, which generally provides a more robust relation with the control parameters than based on single-year indicators.

It should be noted that the applied method assumed scale invariance for which the dependency of the indicators on the control parameters at the coarse spatial scale is applied to the local scale at 1km x 1km resolution. This way, dependency of the indicators on the spatial control parameters at the coarse scales - and that of the corresponding climate change signal - is extrapolated towards the local scales. The latter is also an advantage over the delta-change approach applied in other bioclimatic datasets, e.g. WorldClim that only considers for the climate-change signal at the coarse scales (Navarro-Racines et al., 2020). It should be noted, however, that the scale-invariance assumption may be problematic for some indicators like extreme precipitation. Particularly, the intensity distribution of local precipitation (at 1km x 1km) differs from the intensity distribution of precipitation averaged over large domains (i.e. several tens of km). Hence, extreme precipitation at coarse and local scales reflect variables with a distinct physical meaning. For these kind of indices, additional scale-variant corrections can improve the high-resolution indicators.

2.4.5 Indicator delta-change correction

In addition to the bias-adjustment applied on the raw CMIP5 data, a final correction — the delta-change correction — was employed on the high-resolution indicators. Despite the quantile-delta mapping employed on the climate model timeseries (that allows to get more realistic quantity distributions hence from projections), the resulting CMIP5-based indicators still differ from the ERA5-based indicators over the overlapping period 1979–2018. These discrepancies are mainly due to differences in the dynamics of atmospheric variables between the datasets (e.g. seasonality or day-to-day variation) which are mainly conserved by the first bias- correction and these differences propagate into the indicator computation. The delta-change correction is therefore applied in order to compensate for these differences. The period 1979–2018 is considered as reference and the mean values of ERA5-based indicators over this window are used as the baseline. The correction was performed by super-imposing the changes in the previously bias-adjusted CMIP5 indices, i.e. the model differences with respect to the CMIP5 averages over the reference period, on the ERA5 baseline values:

$$Index_{CMIP5dcc}(x) = Index_{ERA5}(1979\text{-}2018) + Index_{CMIP5bc}(x) - Index_{CMIP5bc}(1979\text{-}2018)$$

with x any year from 1960 to 2091.

As a result, the final set of indicators using CMIP5 raw bias-correction, indicator calculation, downscaling and delta-change correction with respect to ERA5 ensures consistency between the baseline reconstruction and the future data, while preserving the information on future climate change. For the latter however, it should be noted that the reference period covers a 40-year period whereas the scenario periods are 20-year periods.

2.4.6 Advances, uncertainties and limitations

The **dataset of downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections** (***BIOCLIMATE_1km_CMIP5***) offers substantial advances with respect to previous bioclimatic databases and climate-impact assessment datasets (e.g. Fick & Hijmans, 2017; Karger et al., 2017; Navarro-Racines et al., 2020):

- It offers an **unprecedented wealth of bioclimatic indicators,** 76 in total. The indicators provide a comprehensive description of the state and evolution of the land–atmosphere–ocean system under climate change. In addition to the common bioclimatic indicators based on temperature, precipitation and cloud cover characteristics (the BIO01-BIO19 indicators), the dataset also offer other indicators that are known to drive eco-system thresholds such as aridity (Berdugo et al., 2020), but also soil moisture, energy fluxes, evaporation, ocean variables, drought and hot spell indicators, wind fields,…. The indicators take into account both monthly and daily data from the latest ERA5 reanalysis dataset and CMIP5 climate projections.
- Bioclimatic indicators are calculated based on data from **ten global climate models and two climate scenarios.** As such, users can perform a comprehensive assessment of both bioclimatic impacts and uncertainties associated to climate change.
- The SIS Global Biodiversity offers **easy online access, exploration and screening** of the bioclimatic data through online download pages and dedicated applications. Users can download the complete data files via the CDS download page. In addition, specifically developed bioclimatic applications allow users to explore and sub-select bioclimatic indicators.
- Instead of the usually fixed future timeframes, the bioclimatic indicators are provided as **continuous trends** towards the end of this century. These trends are based on GCM information from 1950 until 2100. They are further processed with a moving window using a timespan of 20 years, which results in yearly/seasonal/monthly values from 1960 (representing the range 1950–1969) until 2091 (representing the range 2081–2100).
- Not only **climatological averages** are provided for each climate model (i.e., the ‘mean’), but also the statistical information on **annual variability**. The latter includes both **the multi-annual**

statistics of the indicators (i.e. the ‘median’ and quartile values ‘q25’ and ‘q75’), and the **non-averaged annual, seasonal and monthly time series** of the indicators for past reconstruction and future climate scenarios.

- The CMIP5 source data underneath the bioclimatic indicators are processed with a **new globally applicable and high-quality bias-correction method**. The method combines state-of-the-art bias-correction techniques (Cannon et al., 2015; Switanek et al., 2017) with state-of-the-art ERA5 climate reconstruction data used as the reference climate. Details of this bias correction method can be found in section 2.4.2.
- Finally, all bioclimatic indicators are **based on** data from **state-of-the-art climate reconstruction and climate models**, hence they incorporate the latest advances in the understanding and representation of physical processes of the atmosphere, the ocean and the land in the climate projections. These include dynamics in the biosphere and hydrosphere, but also anthropogenic factors (e.g. in the climate scenarios) including the greenhouse gas emissions, land-cover changes and their impacts on the global climate system. However, users should acknowledge the uncertainties that are inherent to model-based information. These uncertainties are at least partially covered by the range of the climate model ensemble of 10 CMIP5 models. Still, the 10 global climate models presented here may not cover the full range of climate uncertainty. Using the data and applications, one should acknowledge and investigate these uncertainties, e.g. by comparing historical trends with observations. A brief overview of the main model uncertainties associated with the bioclimatic indicators is given in section 2.4.7. The bioclimatic indicators are downscaled and provided at high resolution (1km x 1km). However, users should also acknowledge the assumptions in the downscaling procedure from the coarse to the high resolution. Particularly, the downscaling procedure employs spatial relations between indicators and land information, specifically orography, at coarse resolution (10 – 100 km), which is applied at the high resolution (1 – 10 km). High-resolution meteorological information (e.g. from atmospheric models, satellite data and any dense observational networks) may be considered to improve the high-resolution indicator set. A brief overview of the main model uncertainties associated with the bioclimatic indicators is given in section 2.4.7.

2.4.7 Validation

2.4.7.1 CMIP5 bioclimatic indicators

Uncertainties largely vary according to the considered bioclimatic indicator and location. For instance, trends in global temperature (e.g. BIO01) are considered to have a very low uncertainty under human-induced climate change. Recent advances in GCMs, accounting for more detailed physical processes of atmosphere, oceans, land-cover and sea ice, allow to reproduce reliable temperature patterns across the globe (Field et al., 2014). A comparison between CMIP5-based and ERA5-based indicators for the overlapping period 1979-2018 over Europe (not shown) indicated a good agreement for temperature (cfr. BIO01). This agreement is not only reflected in absolute temperature quantities – which highlights a consistent post-processing chain of bias correction against ERA5, indicator calculation, downscaling and delta change correction for the CMIP5-based bioclimatic indicators (see section 2.4) – but also in the warming trends in recent climate change over Europe. A similar good agreement is found for the number of hot and cold extremes (cfr. Summer frost days respectively). However, anomalies in temperature are generally found to be exaggerated in the CMIP5 models as compared to observed variables (Di Luca et al., 2020), but this exaggeration may be partially alleviated by the bias-correction described in section 2.4. This aspect is also further discussed in section 0 on ERA5 validation. The multi-model average trends of CMIP5 agree well with the observed increases in hot extremes over the past six decades, though with a tendency to slightly overestimate this trend in the majority of model members (Fischer & Knutti, 2015).

Larger uncertainties in observations, models and trends are seen in bioclimatic indicators other than temperature, including cloud cover, precipitation variability and the associated trends in drought and dryness parameters (Stocker et al., 2013). Especially, soil moisture levels have large uncertainties across the globe due to sparse observations and their changes not being robust under climate change in many regions (Stocker et al., 2013). At the same time, the representation of other surface physical characteristics like dynamic vegetation (interfering with soil moisture) and land use changes in climate models are still in early development (Arneth, 2015). As a consequence, modeled fields of land evaporation and other surface energy fluxes remain unreliable since the capability to observe them over large scales is still limited (Miralles et al., 2019).

Biases in the surface variables described above may be partially alleviated through the bias-adjustment against ERA5 reanalysis (see sections 2.4.2 and 2.4.5, and the validation of ERA5 in section 0). While the bias-correction may reduce the overall biases in the CMIP5-based bioclimatic indicators in terms of absolute values, their future trends (changes) under climate change are still model-dependent and uncertainties could not be alleviated. Users should acknowledge any uncertainties of the CMIP5-based bioclimatic indicators. It is encouraged to address them by comparing the bioclimatic indicators with observational trends, and by considering the ensemble model spread in the bioclimatic indicators.

2.4.7.2 ERA5

ERA5 reanalysis was used for as the source for calculating the bioclimatic indicators. With its higher resolution and more advanced assimilation system employing additional sources of observational data compared to its predecessor ERA-Interim, the ERA5 climate reanalysis was found to substantially reduce biases in temperature, precipitation, wind, water vapor and other near-surface meteorological parameters with respect to observations in different parts of the world. These include North-America (Tarek et al., 2020), Canada (Betts et al., 2019), Europe (Olauson, 2018), East-Africa (Gleixner et al., 2020) and the Arctic (Graham et al., 2019).

A clear benefit of ERA5 is also found for variables describing the Earth’s surface. Particularly, ERA5 offers high quality in reproducing the (partitioning between) surface-atmosphere heat exchanges and evaporation according to a range of global observational products, and offers a general improvement as compared to its predecessor ERA-Interim (Martens et al., 2020). This is in spite of today’s uncertainties in (sub)surface characteristics and processes like soil hydrology, vegetation dynamics and their interactions with the atmosphere. Finally, ERA5 integrates observed sea ice concentration and sea-surface temperature from two independent satellite-derived products (Hirahara et al., 2016), namely the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA; Donlon et al., 2012) and the Hadley Centre Sea Ice and Sea Surface Temperature data set version 2 (HadISST; Titchner & Rayner, 2014).

As a consequence, ERA5 is being adopted as the next-generation reference climate reconstruction for the globe for any climate, hydrological, eco-system and geophysics application, and for impact assessments in different sectors including energy, water and agriculture. Therefore, it is also used as a reference dataset for bias-adjustment of the CMIP5-based bioclimatic indicators.

2.4.7.3 Downscaling to high resolution

The downscaling procedure described in section 2.4.4 is consistent with the height-correction of temperature-based indicators considering a fixed adiabatic lapse rate employed in existing bioclimatic information products, including CHELSA (Karger et al., 2017) and WorldClim (Hijmans et al., 2005; Navarro-Racines et al., 2020). The added value of the applied procedure is that it considers also other height-related dependencies beyond the adiabatic lapse rate (e.g. temperature inversion). It also allowed to extend the high-resolution indicator set based on additional climate variables (such as aridity, volumetric water content or evaporative fraction) that have not been included yet in previous bioclimatic datasets such as WorldClim. Acknowledging that α_{HR} is changing only slightly in space, the linear relation assured the aggregate of the high-resolution field to approximate the original field. The above described procedure was applied to the calculated indicators after computing the decadal rolling-window statistics, which generally provides a more robust relation with the control parameters than based on single-year indicators.

It should be noted that the applied method assumed scale invariance for which the dependency of the indicators on the control parameters at the coarse spatial scale is applied to the local scale at 1km x 1km resolution. This way, dependency of the indicators on the spatial control parameters at the coarse scales - and that of the corresponding climate change signal - is extrapolated towards the local scales. The latter is also an advantage over the delta-change approach applied in other bioclimatic datasets, e.g. WorldClim that only considers for the climate-change signal at the coarse scales (Navarro-Racines et al., 2020). It should be noted, however, that the scale-invariance assumption may be problematic for some indicators like extreme precipitation. Particularly, the intensity distribution of local precipitation (at 1km x 1km) differs from the intensity distribution of precipitation averaged over large domains (i.e. several tens of km). Hence, extreme precipitation at coarse and local scales reflect variables with a distinct physical meaning. For these kind of indices, additional scale-variant corrections can improve the high-resolution indicators.

3. Concluding Remarks

The **dataset of downscaled bioclimatic indicators for selected locations derived from CMIP5 climate projections** (***BIOCLIMATE_1km_CMIP5***) provides a dataset of customized, high-resolution bioclimatic indicators relevant to the biodiversity and ecosystem services community for the past and the future for Central Africa, Europe, and Northern Brazil. The indicators are derived from renowned CMIP5 and ERA5 datasets and include a wide range of indicators that are not generally available in other datasets. The high spatial resolution (1km x 1km) responds to specific requirements when tackling biodiversity challenges. The dataset can serve the community in biodiversity related assessments, ecosystem conservation/restoration planning or decision-making.

Resources

CDS catalogue entries:

CMIP5 daily data on single levels. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip5-daily-single-levels?tab=overview

CMIP5 monthly data on single levels. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip5-monthly-single-levels?tab=eqc

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Glossary

Acronym	Description
C3S	Copernicus Climate Change Service
CDS	Climate Data Store
IPCC	Intergovernmental Panel on Climate Change
RCP	Representative Concentration Pathway
GCM	Global Circulation Model
SIS	Sectoral Information System

Appendix I

Variable Description

Köppen-Geiger classification

The indicator representing the Köppen-Geiger climate classification is determined in accordance to the existing global database for past and future global climate trends by Rubel and Kottek (2010), available at http://koeppen-geiger.vu-wien.ac.at. Therefore, the source code for class determination obtained from http://koeppen-geiger.vu-wien.ac.at/present.htm was translated to Python code. The code was used to calculate Köppen-Geiger Climate classes from the bioclimatic indicators of monthly temperature and precipitation at the climatology aggregation level (corresponding to 40-year averages of each month).

Other bioclimatic indicators

All other bioclimatic indicators are calculated from monthly and daily raw ERA5 and CMIP5 data according to the definitions listed in Table 2. They are provided as annual, seasonal, and monthly indicators that are aggregated to 20-year climatologies.

Bioclimatic indicators based on temperature, precipitation, and vapor pressure have a valid range between 0 and positive infinite although the temperature may usually not exceed 329 K (highest temperature ever recorded). Indicators reflecting fractions (cloud cover, sea ice concentration, evaporative fraction) and the aridity indicators have their valid range between 0 and 1. Surface energy fluxes (sensible heat flux, (potential) evaporation, downward shortwave radiation...) can have both positive and negative values. In order to provide consistency among the climate models using different calendar types, bioclimatic indicators reflecting number of days in a year (dry days, summer days, frost days, …) are rescaled to an average year length of 365.25 days, hence their valid range is between 0 and 365.25 days. Finally, aggregated quantities (such as growing degree days) have a valid range between 0 and positive infinite.

Since all data is obtained from ERA5 and climate models providing a global coverage, no missing data flags were assigned.

Appendix II

Input Data Description

ERA5 hourly data on single levels from 1979 to present

Table 4. Key characteristics of the ERA5 hourly data on single levels from 1979 to present

Data Description	
Main variables	Various including: 2m temperature (K); total precipitation (m s^{-1}); total cloud cover (-); 10m wind speed (m s^{-1}); 10m zonal wind speed (m s^{-1}); 10m meridional wind speed (m s^{-1}); 2m specific humidity (kg kg^{-1}); volumetric soil moisture (m^3 m^{-3}); surface pressure (Pa); downward shortwave radiation (J m^{-2}); surface sensible heat flux (J m^{-2}); surface latent heat flux (J m^{-2}); sea surface temperature (K); sea ice concentration (-)
Domain	Global
Horizontal resolution	0.25° x 0.25°
Temporal coverage	1979-01-01 to present
Temporal resolution	Hourly
Vertical coverage	Single level
Update frequency	Daily
Provider	Copernicus Climate Change Service (C3S)

ERA5 monthly averaged data on single levels from 1979 to present

Table 5. Key characteristics of ERA5 monthly data on single levels from 1979 to present

Data Description	
Main variables	Various including: 2m temperature (K); total precipitation (m s^{-1}); total cloud cover (-); 10m wind speed (m s^{-1}); 10m zonal wind speed (m s^{-1}); 10m meridional wind speed (m s^{-1}); 2m specific humidity (kg kg^{-1}); volumetric soil moisture (m^3 m^{-3}); surface pressure (Pa); downward shortwave radiation (J m^{-2}); surface sensible heat flux (J m^{-2}); surface latent heat flux (J m^{-2}); sea surface temperature (K); sea ice concentration (-)
Domain	Global
Horizontal resolution	0.25° x 0.25°
Temporal coverage	1979-01-01 to present
Temporal resolution	Monthly
Vertical coverage	Single level
Update frequency	Monthly
Provider	Copernicus Climate Change Service (C3S)

CMIP5 daily data on single levels

Table 6. Key characteristics of CMIP5 daily data on single levels

Data Description	
Main variables	Various including: 2m temperature (K); total precipitation (m s^{-1}); total cloud cover (-); 10m wind speed (m s^{-1}); 10m zonal wind speed (m s^{-1}); 10m meridional wind speed (m s^{-1}); 2m specific humidity (kg kg^{-1}); volumetric soil moisture (m^3 m^{-3}); surface pressure (Pa); downward shortwave radiation (J m^{-2}); surface sensible heat flux (J m^{-2}); surface latent heat flux (J m^{-2}); sea surface temperature (K); sea ice concentration (-)
Domain	Global
Horizontal resolution	From 0.125° x 0.125° to 5° x 5° depending on the model
Temporal coverage	1850-2300 (shorter for some experiments)
Temporal resolution	Daily
Vertical coverage	Single
Update frequency	
Provider	Copernicus Climate Change Service (C3S)

CMIP5 monthly data on single levels

Table 7. Key characteristics of CMIP5 monthly data on single levels

Data Description	
Main variables	Various including: 2m temperature (K); total precipitation (m s^{-1}); total cloud cover (-); 10m wind speed (m s^{-1}); 10m zonal wind speed (m s^{-1}); 10m meridional wind speed (m s^{-1}); 2m specific humidity (kg kg^{-1}); volumetric soil moisture (m^3 m^{-3}); surface pressure (Pa); downward shortwave radiation (J m^{-2}); surface sensible heat flux (J m^{-2}); surface latent heat flux (J m^{-2}); sea surface temperature (K); sea ice concentration (-)
Domain	Global
Horizontal resolution	From 0.125° x 0.125° to 5° x 5° depending on the model
Temporal coverage	1850-2300 (shorter for some experiments)
Temporal resolution	Monthly
Vertical coverage	Single
Update frequency	
Provider	Copernicus Climate Change Service (C3S)

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