High-resolution downscaled CMIP5 projections dataset of essential surface climate variables over Europe coherent with ERA5-Land reanalyses for climate change impact assessments

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Article Title

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Abstract

A high-resolution climate projections dataset is obtained by statistically downscaling climate projections from the CMIP5 experiment using the ERA5-Land reanalyses from the Copernicus Climate Change service. The dataset is over Europe, has a spatial resolution of 0.10° x 0.10°, comprises 21 climate models and includes 5 surface daily variables: air temperature (mean, minimum, and maximum), precipitation, and mean near-surface wind speed. Two greenhouse gas emissions scenarios are available: one with mitigation policy (RCP4.5) and one without mitigation (RCP8.5). The downscaling method is a Quantile mapping method (QM) called the Cumulative Distribution Function transform (CDF-t) method that was first used for wind values and is now referenced in dozens of peer-reviewed publications. The data processing includes quality control of meta data according to the climate modeling community standards and value checking for outlier detection.

Keywords

High-resolution, projections, CMIP5, ERA5-Land, downscaling, climate change, adaptation, impact modelling.

Specifications Table

Subject	Climatology; Global and Planetary Change
Specific subject area	Climate change; Natural disasters. Evolution of temperature, precipitation and others climate variables
Type of data	Data Cube (Raster X Time) in NetCDF
How data were acquired	CMIP5 model projections data were obtained from the Copernicus Climate Change Service and Earth System Grid Federation data nodes. A statistical downscaling trend-preserving method (CDFt) was applied using the ERA5-Land reanalysis for calibration.
Data format	Netcdf. It is a set of software libraries and self-describing, machine-independent data formats that support the creation, access, and sharing of array-oriented scientific data (use in Atmospheric and Oceanic sciences).
Parameters for data collection	Statistical downscaling with the CDFt method and ERA5-Land reanalyses historical data: 0.10° x 0.10°, spatial resolution, calibration period 1981–2010, historical and future period from 1950 to 2100 for 21 models and 2 scenarios (RCP4.5 and RCP8.5), daily temporal resolution, raster data.
Description of data collection	Simulated near-surface air Temperature (mean, minimum, maximum), precipitation, and mean near-surface wind speed data from 21 climate models downloaded at the Earth System Model Grid Federation (https://esgf-node.ipsl.upmc.fr/search/cmip5-ipsl/) and Copernicus Climate Change Service (https://cds.climate.copernicus.eu) including the ERA5 reanalysis data for the period 1981-2010 and the same variables.
Data source location	Europe scale only land surface
Data accessibility	Accessible through theclimatedatafactory.com under commercial license. Special conditions for research purposes.

Related research article	Michelangeli, P. A., Vrac, M., & Loukos, H. (2009). Probabilistic downscaling approaches: Application to wind cumulative distribution functions. Geophysical Research Letters, 36(11),GL038401.
	Vrac, M., Drobinski, P., Merlo, A., Herrmann, M., Lavaysse, C., Li, L., & Somot, S. (2012). Dynamical and statistical downscaling of the French Mediterranean climate: uncertainty assessment.Nat. Hazards Earth Syst. Sci., 12, 2769–2784.
	Vigaud, N., Vrac, M., & Caballero, Y. (2013). Probabilistic downscaling of GCM scenarios over southern India. International journal of climatology, 33(5), 1248-1263.
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	Galmarini, S., Cannon, A., Ceglar, A., Christensen, O., Dentener, F. J., de Noblet-Ducoudré, N., ... & Vrac, M. (2019). Adjusting climate model bias for agricultural impact assessment: How to cut the mustard. Climate services, 13, pp.65-69.
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	Rhoné, B., Defrance, D., Berthouly-Salazar, C., Mariac, C., Cubry, P., Couderc, M., ... & Barnaud, A. (2020). Pearl millet genomic vulnerability to climate change in West Africa highlights the need for regional collaboration. Nature Communications, 11(1), 1-9.

Value of the Data

- The high resolution, number of models and variables available in the dataset offer a great opportunity for researchers and climate change adaptation practitioners to study climate change features and feed the data into impact models for any region around the world.

- The dataset is obtained by statistically downscaling climate projections from the CMIP5 experiment using the ERA5-Land reanalyses from the Copernicus Climate Change service, a data product extensively used around the world for historical climate analysis. A great advantage of this data set is thus to provide a coherent extension of the ERA5 reanalysis into the future.

- The dataset is over Europe, has a spatial resolution of 0.10° x 0.10° (~10 km x 10 km), comprises 21 climate models allowing to address model uncertainty and includes 5 surface daily variables: air temperature (mean, minimum, and maximum), precipitation, and mean near-surface wind speed.

- To sample future climate uncertainty from anthropogenic forcing, two greenhouse gas emissions scenarios are available: one with mitigation policy (RCP4.5) and one without mitigation (RCP8.5).

1. Data Description

The high-resolution climate projections dataset covers the globe at a 0.25°x0.25° spatial resolution and at daily temporal resolution for five surface variables. It comprises 21 models (see table 1) from the CMIP5 experiment [1] with simulations for the historical period (1950-2005) and the 21st century (2006 to 2100) under two emissions scenarios: one with mitigation policy (Representative Concentration Pathway 4.5 or RCP4.5) and one with no mitigation (Representative concentration Pathway 8.5 or RCP8.5). The downscaled variables are five surface land and ocean variables: mean daily temperature, daily minimum and maximum temperature (at 2 m), total precipitation, and surface wind speed (at 10m). The combination of models and scenarios is 36 climate projections with all variables except a few models that didn't provide some (see table 1). Other variables, models and emissions scenarios could be added in the near future.

The data was produced with a statistical downscaling method using the ERA5-Land reanalyses [2] for calibration and training (see next section for details). The interest of the downscaled data is the removal of model biases at a resolution more compatible with the requirements of assessments and further modelling of the impacts of climate change. In other terms it corrects the climatology (distribution) of model values to make them comparable with a reference observational dataset [3] which in this case is the ERA5 reanalyses. We briefly illustrate below the bias removal over the historical period and the climate change signal differences at the end of century.

1.1 Differences between interpolated and downscaled data with reanalysis data

Here we compare the differences with the ERA5-Land reanalyses of both the original model (interpolated on the reanalysis grid and referred to as "interpolated") and downscaled simulations (referred to as "downscaled") over the historical period (1981-2010) for daily mean temperature, total precipitation and wind speed.

In Figure 1, we illustrate the spatial difference for the interpolated (left) and the downscaled data (right). For temperature, the ensemble mean of CMIP5 models tends to underestimate temperature over Europe. However, in the mountainous area, the temperature is overestimated from until +6°C comparable to the ERA5-Land reanalyses. This is due to the resolution of the CMIP5 models that smooth the elevation of these areas. For precipitation, there is overestimation of precipitation over Europe and underestimation in the mountainous area (Western Norwegian coast, Alps) and in the coastline of the Mediterranean Sea. Finally for wind speed, all models overestimate by more than 2 m/s. The greater overestimation is located on the northern European coastline. For the downscaled data, the difference with ERA5-Land is very limited for all variables. Values are ranged from -0.38 to -0.07 °C for temperature, from -0.24 to 0.035 mm/day for precipitation, and from -0.02 to 0.02 m/s for wind speed.

In Figure 2, the cumulative distributions are empirically estimated from monthly values averaged on Europe for the interpolated (left) and downscaled data (right). There is a spread between the ERA5-Land data and the interpolated with both overestimation and underestimation. The spread is more important for wind speed and precipitation than for the temperature. Moreover, for wind speed, we observe an overestimation of the distribution by a factor 3 for models. For downscaled data, the difference between the model curves and the observations is greatly reduced. However, for precipitation, we record differences for the low and high monthly precipitation amounts. This is due to the fact that downscaling is performed at a daily scale and grid point while CDFs are estimated and drawn on monthly and spatially averaged data. The day-to-day (temporal) and spatial variability of the model data are mostly preserved by the downscaling method but residual biases can appear on monthly and spatial averages.
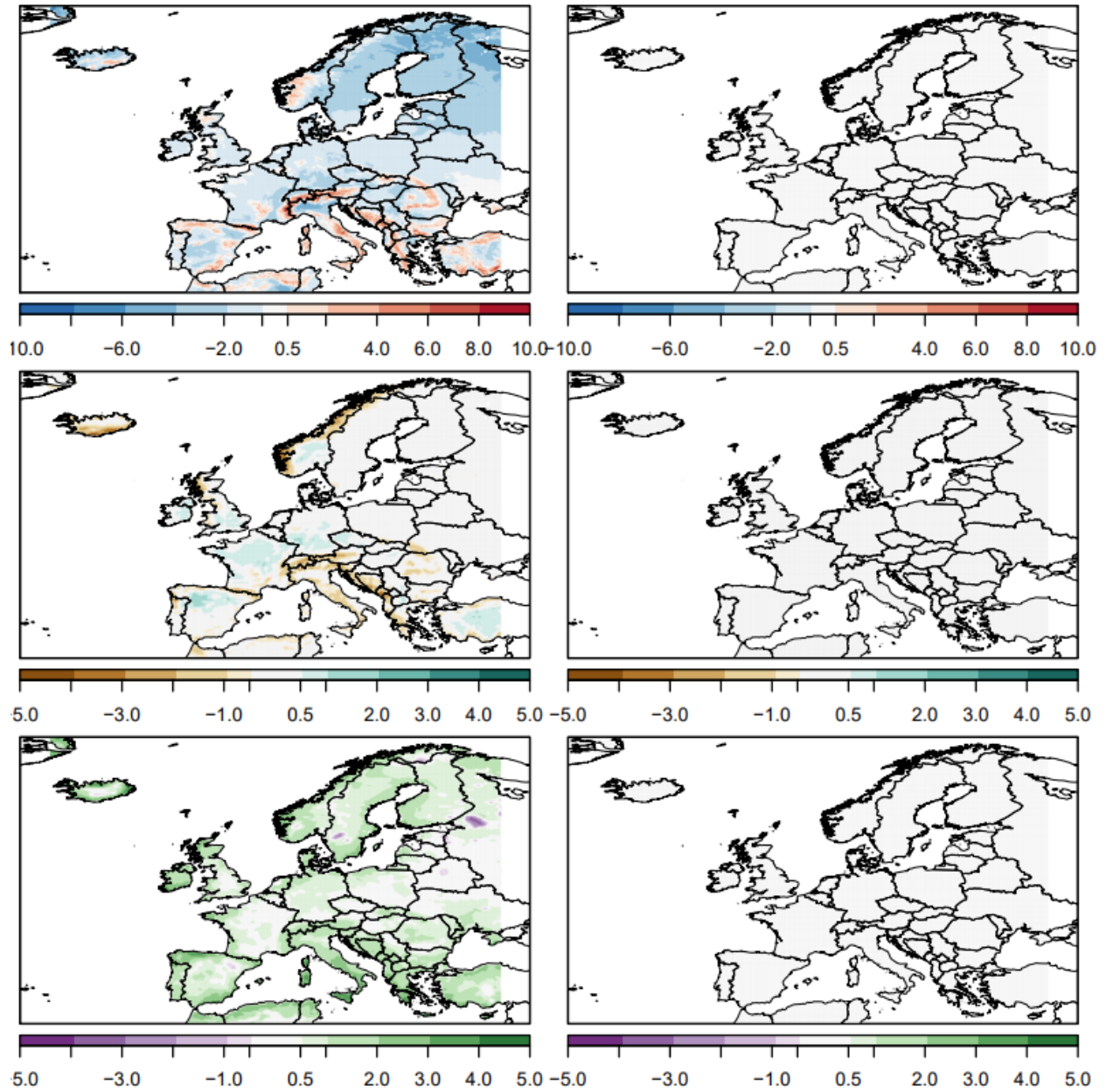
Fig 1. Comparison between the interpolated data and the downscaled data averaged over the calibration period (1981-2010), for temperature (top), for precipitation (center) and for wind speed (below). Difference between the interpolated and reanalysis data (left) and the downscaled and reanalysis data (right).
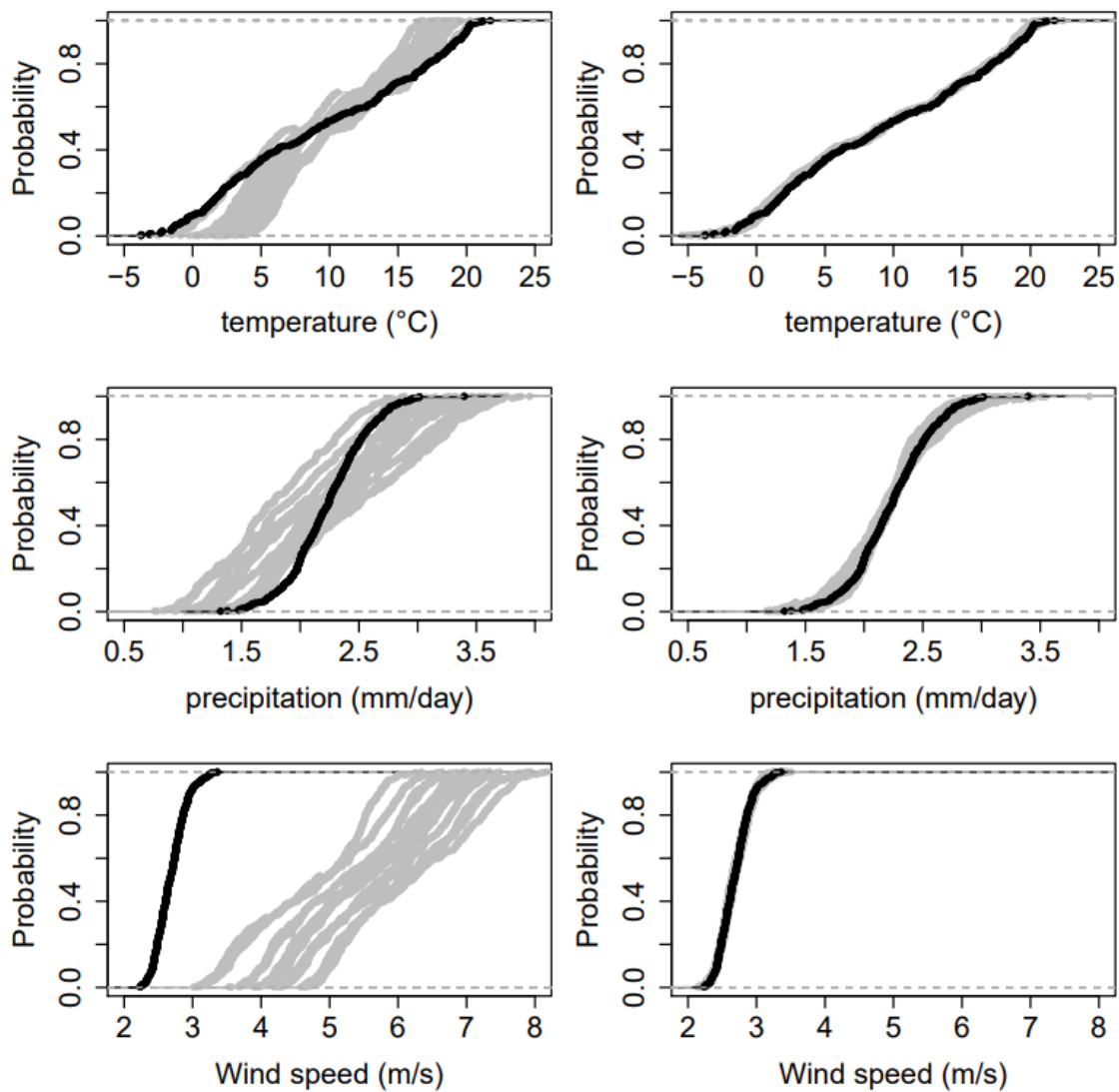
Fig 2. Cumulative distribution functions of European domain mean monthly averages over the calibration period (1981-2010), for temperature (top), for precipitation (center) and for wind speed (below). In grey the results for each model for interpolated data (left) and for downscaled data (right) and in black the ERA5-Land reanalyses.

1.2 Changes at the end of the century after downscaling

Here we illustrate values by the end of the century over the 2071-2100 period under scenario RCP8.5, comparing the interpolated and downscaled simulations. The analyses are based on daily mean temperature, total precipitation and surface wind speed.

On the map of Figure 3, we show the spatial difference between interpolated and downscaled data of the ensemble mean in the future. For temperature, the effect of downscaling leads to an increase of temperature except for mountainous areas where we find lower temperature than in the interpolated data. For precipitation, we can see differences in the South of Europe with more precipitations (about +2 mm/day) and in the mountainous areas (Western Norwegian coast, alps). As in figure 1, the coarse resolution is a major factor explaining the largest differences between raw and downscaled data. For wind speed, we obtain lower values with downscaled data. The differences are mainly observed on the coastline.

In Figure 4, we now illustrate the difference between interpolated and downscaled data in terms of time series of annual averages. For all variables, a general reduction of the ensemble envelope is shown on future period by reducing the inter-model differences (on the left interpolated and on the right downscaled) that is quantified by the distribution shown on the boxplots. Moreover, the model trends are preserved with the downscaled time series. For temperature, we observe a greater inter-annual variability and an increase of temperature by the end of the 21st century higher than raw data. For precipitation, there is no trend for the 21st century and the downscaled data offer the reduction of the envelope-curve with an increase of the interannual variability. For wind speed, we have a general overestimation by a factor of 2. With the downscaled data, the bias between models in the historical period and the ERA5-Land observation is small and for the future, the uncertainty is greatly reduced in comparison with the other variables. Moreover, for both the raw and downscaled data, there is little variability between years and between models, which is shown a smooth envelope with small differences. Because the downscaling method is applied to daily data at each grid point and not globally to annual data, it does not affect the interannual variability of model data. There is also a spatial and temporal averaging smoothing effect because those characteristics are less pronounced at smaller scales (e.g. monthly point data).
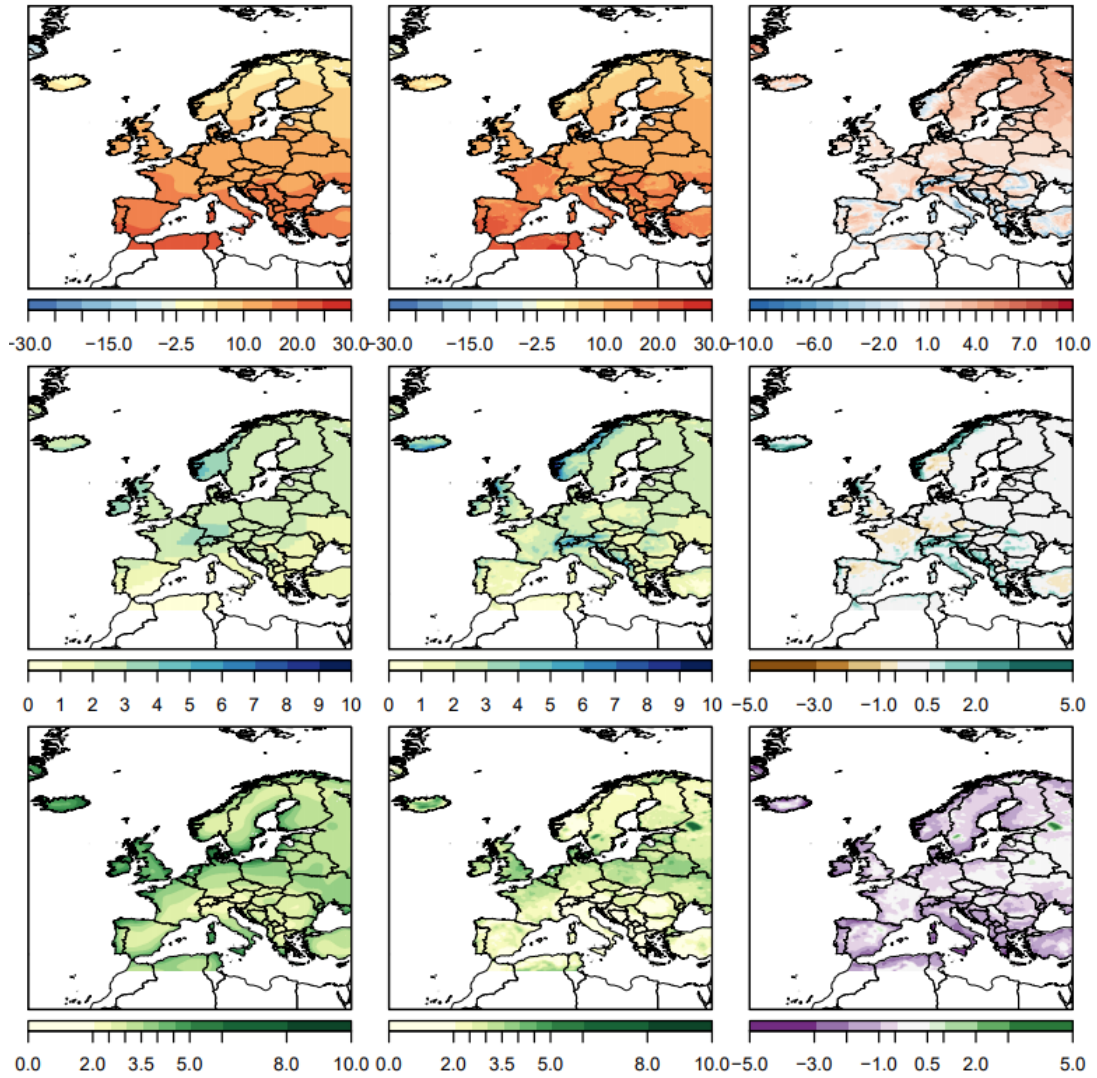
Fig 3. Values of the ensemble mean averaged over the end of the century (2071-2100), for temperature (top), precipitation (center), and wind speed (below). Interpolated data (left), downscaled data (center), and differences between downscaled and interpolated data (right).
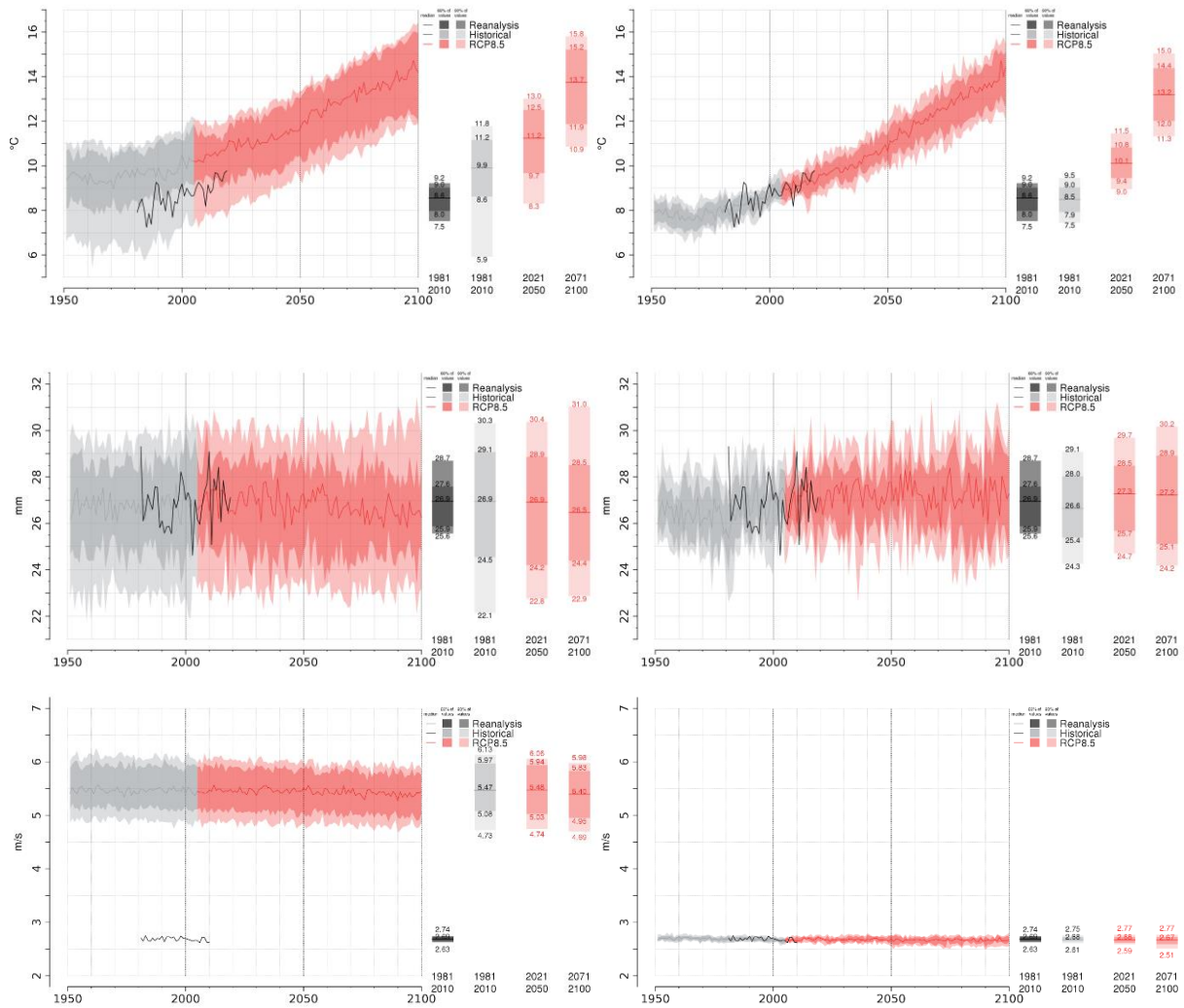
Fig 4. Time series of spatially averaged annual mean model results (1950-2100) and ERA5-Land reanalyses (1979-2020) for temperature (top), precipitation (center) and wind speed (below). The interpolated data (left) and downscaled data (right). Envelope of model results are in shades of grey over the historical period (1950-2005) and of red over the projection period (2006-2100). Median of model results is in plain line and ERA5-Land reanalysis data is plotted for comparison as a plain black line. Boxplots representing the distribution of values are also plotted.

2. Experimental Design, Materials and Methods

Four datasets are used in this work:
- The reanalysis data that is used as reference for calibrating the statistical algorithm over a training period. The reanalysis grid sets the final resolution of the downscaled projections.
- The original model climate projections that come in a variety of spatial resolutions (typically between 2°x2° and 0,75°x0,75°) and referred to as "raw".
- The raw data interpolated on the reanalysis grid and referred to as "interpolated".
- The downscaled data obtained from the interpolated data and the reanalysis data used for statistical calibration (both on the same grid) and referred as "downscaled".

The raw and reanalysis data are input data that need to be sourced. The interpolated data is just an intermediary dataset needed by the methodology while the downscaled data is the final dataset. These datasets correspond to the four steps process (data sourcing, remapping, downscaling, quality control) described below.

2.1 Data Sourcing

The reanalysis data is the ERA5-Land reanalyses [2]. ERA5-Land is the latest climate reanalyses being produced by ECMWF as part of implementing the EU- funded Copernicus Climate Change Service (C3S), providing hourly data on atmospheric, land-surface and sea-state parameters together with estimates of uncertainty. ERA5-Land data are available on the C3S Climate Data Store on regular latitude-longitude grids at 0.25° x 0.25° resolution. We compute the daily data from the ERA5-Land hourly data for all necessary variables.

The climate simulations are from The Coupled Model Intercomparison Project Phase 5 (CMIP5) experiment [1]. They support the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC). We use projections from 2 emissions scenarios RCP4.5 (moderate mitigation policy scenario) and RCP8.5 (a no mitigation policy scenario). Daily data of necessary variables are extracted from the Copernicus Climate Change Service that hosts a subset of the CMIP5 archive. The data covers the period from 1 January 1950 to 31 December 2100. All models have different spatial resolutions ranging between 0.75° to 3°. All models are shown on Table 1.

Table 1: The CMIP5 models list with the availability of the essential surface variables: temperature (minimum –tasmin-, maximum –tasmax-, and daily mean –tas-), precipitation –pr- and wind speed -sfcWind-).

GCM	Historical	RCP4.5	RCP8.5
inmcm4 (INM, Russia)	**No sfcWind**	**No sfcWind**	**No sfcWind**
ACCESS1-0 (BoM-CSIRO, Australia)	All	All	All
ACCESS1-3 (BoM-CSIRO, Australia)	All	All	All
bcc-csm1-1 (BCC, China)	**No sfcwind**	**No sfcWind**	**No pr, sfcWind**
bcc-csm1-1-m (BCC, China)	**No sfcWind**	**No sfcWind**	**No sfcWind**
BNU-ESM (BNU, China)	All	All	All
CMCC-CM (CMCC, Italy)	**No sfcWind**	**No sfcWind**	**No pr and sfcWind**
CMCC-CMS (CMCC. Italy)	All	**none**	All
CNRM-CM5 (CNRM-CERFACS, France)	All	All	**None**
GFDL-CM3 (NOAA, USA)	All	All	All
GFDL-ESM2G (NOAA, USA)	All	All	All
GFDL-ESM2M (NOAA, USA)	All	All	All
HadGEM2-CC (UK Met Office, UK)	All	All	All
HadGEM2-ES (UK Met Office, UK)	All	Only tas	Only tasmin
IPSL-CM5A-LR (IPSL, France)	**No tas, tasmin, pr**	**All**	**All**
IPSL-CM5A-MR (IPSL, France)	All	All	All
IPSL-CM5B-LR (IPSL, France)	All	All	All
MIROC5 (UTCCSR, Japan)	All	**No sfcWind**	All
MPI-ESM-LR (MPI, Germany)	All	All	All
MPI-ESM-MR (MPI, Germany)	All	All	All
NorESM1-M (NCC, Norway)	**No sfcWind**	**No sfcwind**	**No sfcWind**

2.2 Remapping

Remapping is a preliminary task required by the downscaling methodology. It consists in spatially interpolating the raw simulations (between 0.75° and 3° resolution) onto the ERA5-Land grid (0.25° x 0.25°). We use the Climate Data Operators (CDO, 2016) software from the Max Planck Institute that gathers various algorithms for interpolation used by the scientific community. Daily temperature (mean, minimum, maximum) and daily wind speed are interpolated with a bicubic method while daily precipitation is interpolated sequentially (to 1.5°, then to 0.75°, and then 0.25°) with a conservative method.

2.3 Downscaling

The downscaling method used here is a Quantile mapping-based method (QM) called the Cumulative Distribution Function transform (CDF-t) method [4–8]. CDF-t was first developed for wind values and is now referenced in dozens of peer-reviewed publications to downscale different sets of data and variables (e.g. [9–11]). QM methods relate the cumulative distribution function of a climate variable at large scale (e.g., from the GCM) to the CDF of the same variable at a local scale (e.g., from the reanalyses) and are increasingly popular in climate applications although bias correction methods have received criticism (e.g. [12]). For a review of recent QM methods see [3]. Here the variables are downscaled at a daily resolution over the 1951-2100 period using 1981-2010 as calibration period. The precipitation variable is downscaled with a specific version of CDF-t referred to as "Singularity Stochastic Removal" (SSR) which considers rainfall occurrence and intensity challenges [13].

2.4 Quality control

We conduct two types of quality control. The first one is technical and consists in verifying data compliance with climate community's standards, data consistency and metadata. Doing quality control is crucial for the data publication process and data re-use. The second quality control is a value check to check for outlier values in the downscaled data.

Technical quality control

We use the Quality Assurance tool (QA-DKRZ, https://readthedocs.org/projects/qa-dkrz) developed by the Deutsches Klimarechenzentrum (DKRZ) to check conformance of meta-data of climate simulations given in NetCDF format with conventions and rules of projects. During the Quality Assurance process of the DKRZ, the following criteria are checked:

1. Number of datasets is correct and > 0
2. Size of every dataset is > 0
3. The datasets and corresponding metadata are accessible
4. The data sizes are controlled and correct
5. The spatial-temporal coverage description "metadata" is consistent with the data,
6. Time steps are correct and the time coordinate is continuous
7. The format is correct
8. Variable description and data are consistent

Value quality control

The value quality control is built with CDO and NCO tools and consists in:

- Analyzing the difference between the downscaled values and the observations over the reference period.
- Analyzing the time evolution difference between downscaled and original model.

Difference between downscaled model and observations

First, we estimate two quantities:

- The average for each month over the reference period of the observations.
- The average for each month over the reference period of the downscaled model.

We then estimate the difference between these two quantities for every month. For each month we take the 10th and 90th quantiles. That gives 12 values for each quantile.

Finally, we verify that these 12 values are comprised in the following ranges (unpublished, R. Vautard personal communication):

- temperature between [-1 ; 1] in K,
- precipitation between [-0.5 ; 0.5] in mm.day-1,
- surface wind speed between [-0.5 ; 0.5] in m.s-1.

These values are relatively small and allow only low discrepancies since modifications should be small over the historical period (inherently over the calibration period). If values are outside the range, the script raises an error and the simulation is rejected and thus not included in the dataset.

Difference of evolutions between downscaled model and original model

First, we estimate four quantities:

- Average for each season in the reference period for the original model.
- Average for each season in the reference period for the downscaled model.
- Average for each season in the future period (2071-2100) for the original model.
- Average for each season in the future period (2071-2100) for the downscaled model.

Then, for each season, we compute the evolution between future and reference periods for the original and downscaled model. We estimate the difference between them and get 4 files in output (one per season). For each season (i.e. for each file), we take the 10th and 90th quantiles of the differences. That gives 4 values for each quantile.

Finally, we control these 4 values are comprised in the following range (unpublished, R. Vautard and personal communication):

- temperature between [-2 ; 2] in K,
- precipitation between [-1 ; 1] in mm.day-1,
- surface wind speed between [-1 ; 1] in m.s-1.

In this case, values are higher than previously to account for higher discrepancies but small enough to avoid unrealistic changes. If values are outside the range, the quality control raises an error and the simulation is rejected and thus not included in the dataset.

CRediT author statement

T.N.: methodology, software, data curation; H.L.: Supervision, funding acquisition, writing revue and editing; D.D.: writing original draft, visualization; M.V.: methodology, writing revue and editing; G.L.: resources, software.

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