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CHclim25 - a spatially and temporally very high-resolution climatic dataset for Switzerland

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Abstract

CHclim25 is a climatic dataset with a 25 m resolution for Switzerland that includes daily, monthly and yearly layers for temperature, precipitation, relative sunshine duration, growing degree-days, potential evapotranspiration, bioclimatic variables and aridity. The dataset is downscaled from a daily 1 km resolution dataset from the Swiss federal agency for meteorology using local regressions with an elevation model to better account for local topography and complex local climatic phenomena. Climatic layers are provided for individual years, 1981-2010 baseline period and future periods 2020-2049, 2045-2074, and 2070-209. Future layers incorporate three regional/global circulation models and three representative concentration pathways. We compare our predictions with values observed at independent weather stations and show that errors are minimal in comparison to the original dataset at 1 km resolution, and that the dataset is more accurate than available climatic global datasets at 30' resolution, especially at high elevation. CHclim25 improves the temporal and spatial accuracy of climatic data available for Switzerland and enables new studies at very high resolution in ecology and environmental sciences.

1 Introduction

Several climatic datasets are now freely and easily available globally that provide gridded monthly temperature and precipitation variables at a resolution up to 30' (~1 km at temperate latitudes) for individual recent years (e.g. 1979 to 2019 for Chelsa; (Karger et al., 2021)) or averages for reference time periods (e.g. 1970-2000 for Worldclim2; (Fick and Hijmans, 2017). These datasets include future climate projections derived from various regional/global circulation models (RCM/GCM; (Di Luca et al., 2016)) for different time periods and representative concentration pathways (RCPs; (Moss et al., 2010)). They have been shown to be vital inputs for many scientific studies of climate change impact, in conservation planning or in ecology.

However, while a 1 km resolution may be appropriate for many areas with mild topography, for areas with highly rugged terrain such as the European Alps, climatic conditions may strongly vary at a much finer scale. For example, on a 40% slope

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(i.e. usually considered as the maximum steepness for walking without equipment), walking 450 m uphill results in a temperature change of 1°C assuming an adiabatic rate of 6°C/km (Seidel and Free, 2003). Moreover, the distribution of surface temperature in the Alps shows considerable deviation from linear vertical dependence (i.e. adiabatic rate) depending on the slope, geometry, land cover and topographic shading of the valleys (Frei, 2014). For example, cold air pools frequently form in specific mountain valleys in winter as a result of night-time radiative cooling, resulting in inversions in the altitudinal temperature profile (Lareau et al., 2013). Furthermore, the smaller air volume in small valleys can lead to exacerbated thermal contrasts, with highest maximum summer temperatures observed in inner alpine valleys rather than the flatland (Whiteman, 1990). Finally, strong downslope winds (foehn) can lead to warm and dry anomalies at the foothills of the Alps (Jansing et al., 2022). Global datasets based on monthly climatologies cannot capture the complexity of these local phenomena. For these reasons, the Swiss federal agency for meteorology and climate (MeteoSwiss) produces daily 1 km resolution gridded temperature maps using spatial interpolations of daily temperature from station measurements built on nonlinear parametric function to model nonlinearities in the vertical thermal profile at the scale of major basins, coupled with a non-Euclidean distance weighting to account for local effects[6].

While the Meteoswiss dataset is optimal to deal with temporal complexities of the climate of the Swiss alps, the spatial resolution of the data is still not optimal for applications such as the prediction of the distribution of plants or sessile or dispersal-limited animals and associated conservation management plans. Here we aim to build on the MeteoSwiss daily dataset at 1km resolution to produce a climatic dataset that provides up-to-date daily climatic data at a resolution of 25m for Switzerland for the period 1981-2010, which is the reference period recommended by the World Meteorological Organization (Arguez and Vose, 2011). The dataset is thus compatible with the 5th assessment report of the IPCC (IPCC, 2014). We further calculate future climatic layers for three general circulation models (GCMs), 3 time slices and 2 representative concentration pathways (RCPs).

2 Methods

2.1 Downscaling of daily variables from 1 km to 25 m

Owing to air temperature profiles that can change on a daily basis, we produced downscaled temperature maps for every day between January 1st 1981 and December 31st 2010. This allows for instance taking into account days when temperature profiles are inverted in internal valleys (cold air pools). The input data for the downscaling was the dataset of daily MeteoSwiss Grid-Data Products at 1 km resolution for 1981-2017 (MeteoSwiss, 2022) that include daily mean, maximum and minimum temperatures (TaveD, Tmin, Tmax), daily sum of precipitation (PrecD), and daily relative sunshine duration (SrelD)(Fig. 1).

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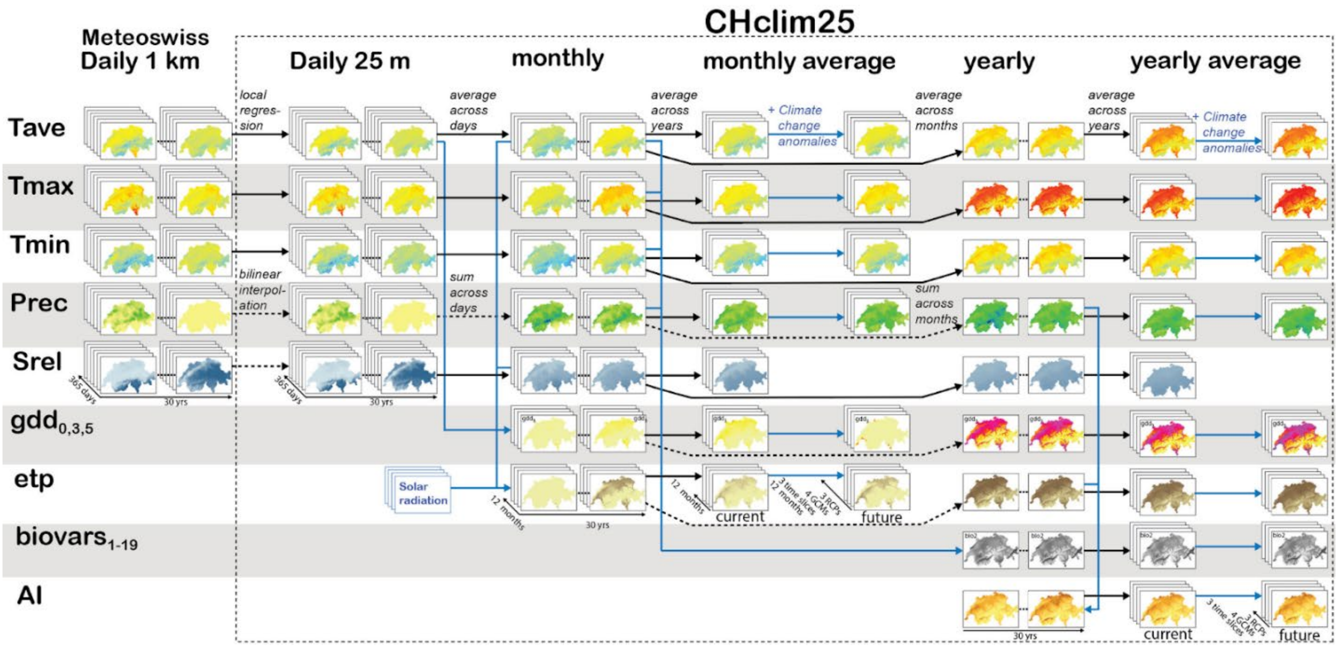

Figure 1: Flow chart of relationships between variables and how they are calculated. Black arrows correspond to direct aggregations of variables from lower to higher time resolutions. Blue arrows indicate integrations of several variables.

The downscaling method for temperature is based on the adiabatic relationship between temperature and elevation. Local linear regressions were performed in each pixel of a rectangular moving window of 5 km x 5 km (using a customized function based on function *focal* of the R package *raster*) to calculate the intercept and slope of temperature with elevation at 1 km :

$$T_{1km} = a_{1km} + b_{1km} \cdot E_{1km}$$, where T =temperature, E =elevation, a=intercept, b=slope for each 1 km pixel

The 5 km x 5 km window was chosen to coincide to the average extent of valleys in the Alps. Intercepts a_{1km} and slopes b_{1km} are then disaggregated at 25 m (using the *resample* function with argument method="nbg") and smoothed spatially using function *focal* with a conic moving window of 1 km where weights are inversely proportional to the distance to the focal pixel. We thus obtain intercept a_{25m} and slope b_{25m} at 25 m resolution. Finally, the air temperature at 25 m resolution can be calculated using these intercepts and slopes and an elevation map at 25 m :

$$T_{25m} = a_{25m} + b_{25m} \cdot E_{25m}$$, where T =temperature, E =elevation, a=intercept, b=slope for each 25m pixel

The procedure was applied for daily mean temperature (TaveD), minimum temperature (TminD) and maximum temperature (TmaxD). Daily precipitation (PrecD) and relative sunshine duration (SrelD) showed no relationship with elevation. For the latters, we thus applied simple bilinear interpolation to downscale the grids from 1 km to 25 m.

2.2 Monthly and yearly data

We aggregated daily grids to obtain monthly and yearly grids for each variable. For monthly temperatures, we calculated the monthly (TaveM, TminM and TmaxM) and yearly (TaveY, TminY and TmaxY) averages of daily temperatures (TaveD, TminD and TmaxD) for every individual year. For precipitation (PrecM), we calculated the monthly (PrecM) and yearly (PrecY) sum of daily precipitation for every individual year. We then calculated averages of monthly and yearly temperature and precipitation for the periode 1981-2010 as the average of individual years between 1981 and 2010. For comparison, we also calculated monthly and yearly 1981-2010 temperature averages based on one single downscaling from 1 km to 25 m based on the 30 year average values using the same local linear regressions described above. This approach smoothens the temporal complexities of daily air temperature profiles but corresponds more closely to the approach taken in other datasets (e.g. worldclim; (Fick and Hijmans, 2017)).

2.3 Future data

For future layers, we used as inputs the transient daily time series of gridded climate scenarios of temperature and precipitation between 1981-2099 at 0.02°D (~2.2 km) provided by the CH2018 initiative (CH2018 Project Team, 2018). Anomalies between monthly temperature for 1981-2010 and monthly temperature for the future period at 2.2 km were downscaled at 25 m using bilinear interpolation (using function resample). These anomalies were then added to 1981-2010 average monthly variables (TaveM, TminM, TmaxM, PrecM). We calculated future climatic layers for 4 RCM/GCM regional/global models (CLMCOM-CCLM4/HADGEM, DMI-HIRHAM/ECEARTH, MPICSC-REMO2/MPIESM, and SMHI-RCA/IPSL), 3 time slices (2020-2049, 2045-2074, and 2070-2099) and 3 representative concentration pathways (RCP 2.6, 4.5 and 8.5). The 4 RCM/GCM models were chosen because they were the only models made available by the CH2018 initiative (CH2018 Project Team, 2018) that implemented a EURO-CORDEX simulation at the finer resolution of 0.11 degree (EUR-11, ~12.5 km) for RCP 4.5 and 8.5. For RCP 2.6, only DMI-HIRHAM/ECEARTH and MPICSC-REMO2/MPIESM models were available.

2.4 Extended climate variables

We calculated monthly or/and yearly layers for a series of extended climatic variables derived mainly from precipitation and temperature. Monthly and yearly number of growing degree days (gddM and gddY) were calculated for three base temperatures (0, 3 and 5°C). gdd3M corresponds for instance to the monthly sum of degree days above 3°C. Potential evapotranspiration (etp) was calculated according to the Turc method (Turc, 1961) taking into account solar radiation (Srad) calculated at 25m for Switzerland (Zimmermann, 2022):

$$etp\left[\frac{mm}{day}\right] = \frac{0.4}{30} \cdot \left(23.9 \cdot srad\left[\frac{MJ}{day}\right] + 50\right) \cdot \frac{T[°C]}{T[°C] + 15}$$

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We further calculated 19 bioclimatic variables with the function biovars from package dismo. They represent mean and seasonal annual temperature and precipitation trends or limiting variables such as temperature of the coldest month, or precipitation of the dry quarters. These variables, originally provided by the Worldclim data set (Fick and Hijmans, 2017), are biologically meaningful as they represent the same climatic features in both hemispheres and are for this reason often used in species distribution models (Guisan et al.). The aridity index (AI) was calculated as in the CGIAR/CSI dataset (Zomer et al., 2022).

3 Validation

To assess the accuracy of the basic variable (Prec, Tave, Tmin and Tmax) of our dataset, we compared observed values from weather stations to values from our dataset extracted at the coordinates of the stations. Observed values were extracted from the IDAWEB web portal (gate.meteoswiss.ch/idaweb). We used 3 sets of weather stations: stations from the Swiss National basic climatological Network (NBCN; 90, 67, 68, and 65 stations for Prec, Tave, Tmin, Tmax, respectively), from the institute for Avalanche Research (SLF; 77, 169, 169 and 168 stations for Prec, Tave, Tmin, Tmax, respectively) and from the National Air Pollution Monitoring Network (NABEL; 8, 7, 7 and 7 stations for Prec, Tave, Tmin, Tmax, respectively). We selected stations to have complete climatologies between 1981 and 2010 (i.e. no missing data). The NBCN dataset constitutes the bulk of the input data used for the modeling of the daily MeteoSwiss Grid-Data Products at 1 km (MeteoSwiss, 2022) and thus is not an independent dataset, but covers the country homogeneously. The SLF dataset is an independent dataset collected mostly at high elevation sites to monitor avalanches (mean elevation = 2467 ± 388 m). The NABEL dataset is an independent dataset collected mostly near the main cities of the Swiss plateau to monitor pollution (mean elevation = 580 ± 221 m).

For each basic variable, we calculated the root-square mean error (RMSE) between the monthly averages observed at the three sets of weather stations and the monthly average values extracted from our dataset. This was done for individual years between 1981 and 2010 (Fig. 2, gray shaded areas), and for monthly averages for the 1981-2010 period (Fig. 2, black lines). To assess the influence of the choice of the size of the moving window (i.e. 5 km radius in the daily dataset) in the downscaling procedure, we further recalculated monthly datasets for each variable based on a downscaling of 1981-2010 averages with moving windows of increasing radii of 5, 10 and 25 km (i.e. one downscaling procedure is performed on data averaged at 1 km resolution, instead of daily downscalings then averaged across 30 years) and assessed the error to values observed at weather stations (Fig. 2, color lines). We further compared the accuracy of the CHclim25 dataset to the MeteoSwiss (MeteoSwiss, 2022), Chelsa (Karger et al., 2021) and Worldclim2 (Fick and Hijmans, 2017) datasets (Fig. 3).

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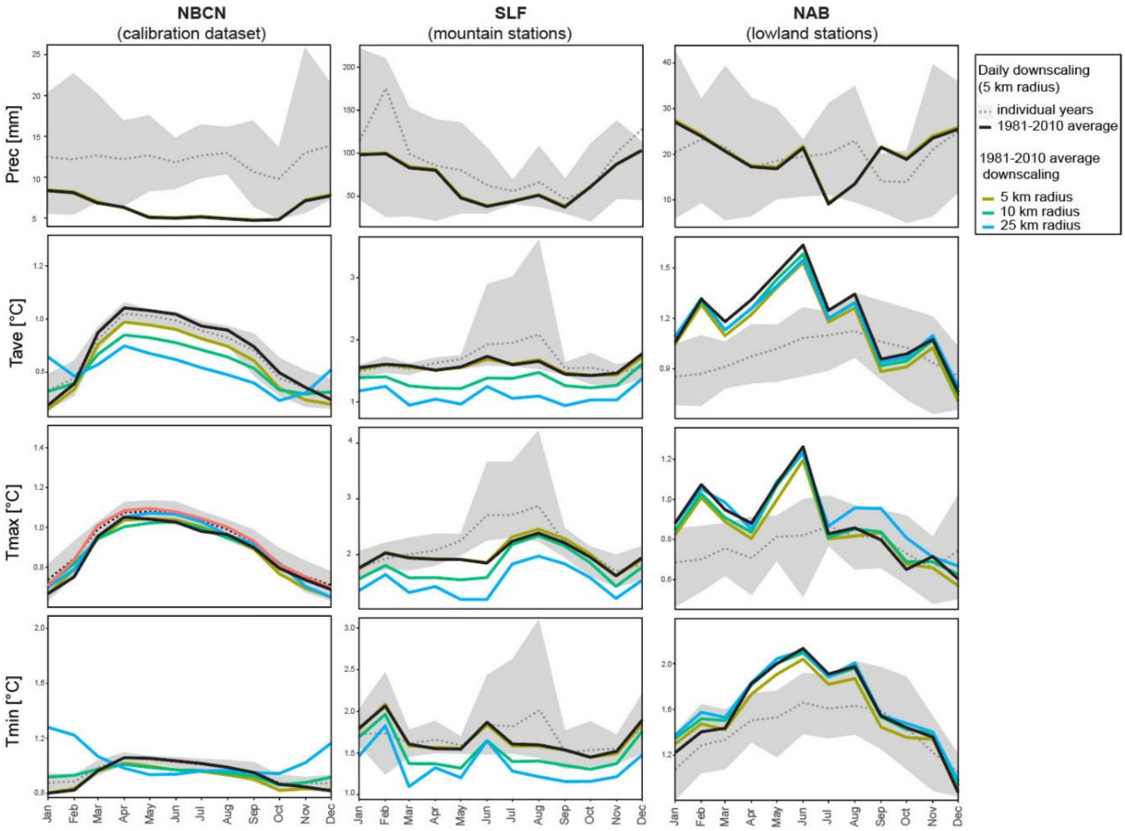

Figure 2: Monthly deviations between calculated values and values observed at weather stations. For each variable (Prec, Tave, Tmax and Tmin, in row) and each set of weather stations (NBCN, SLF and NABEL, in column), the error (rmse) between observed and calculated values is represented for individual years (gray areas; 10 and 90% quantiles of 1981-2010 values) and 1981-2010 averages (solid lines). The black line corresponds to the daily downscaling dataset presented in the paper. Color lines correspond to datasets based on 1981-2010 averages downscaling with moving windows of radii of 5, 10 and 25 km.

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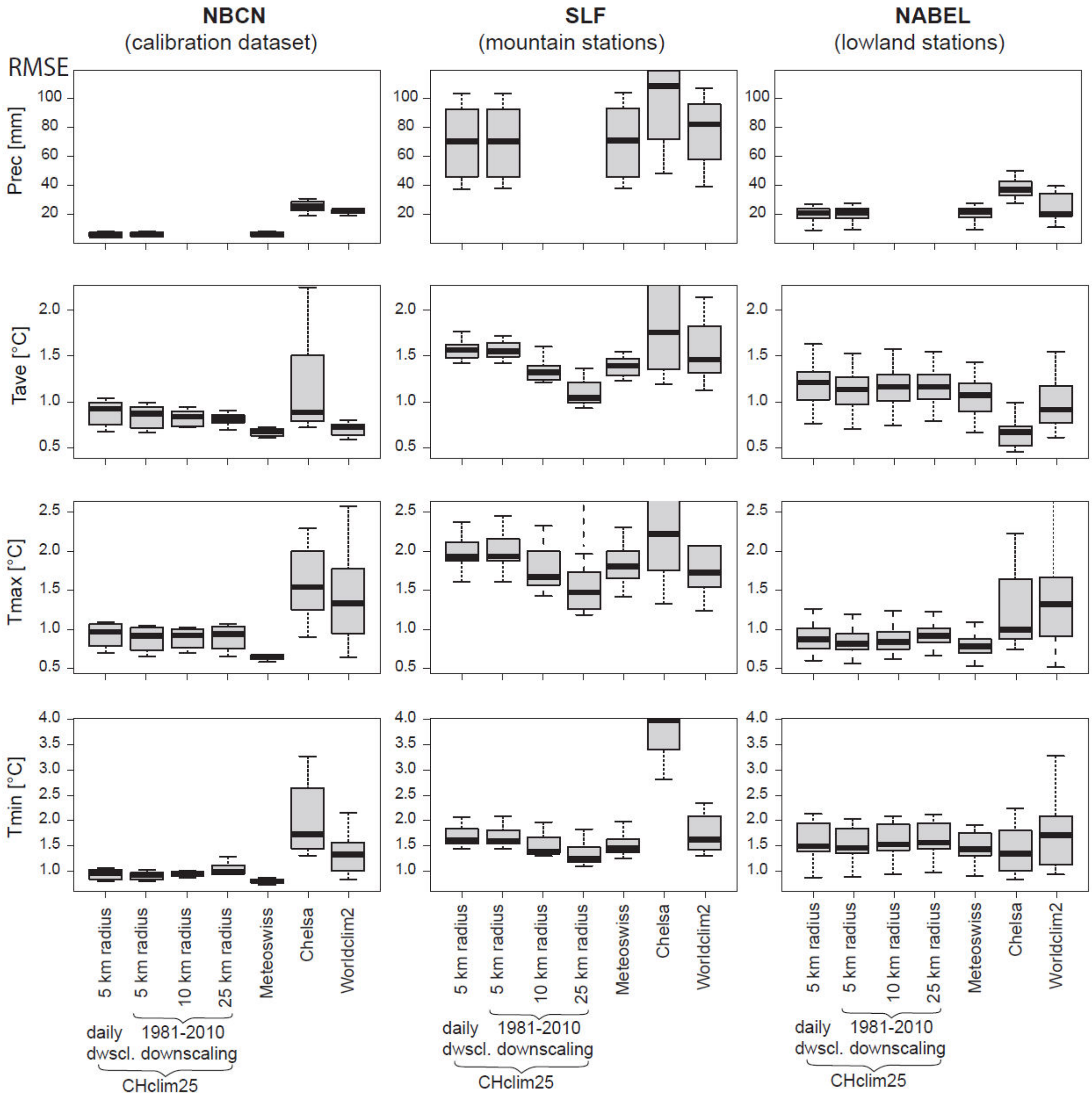

Figure 3 – Comparison of monthly deviations between CHclim25 and other datasets. For each variable (Prec, Tave, Tmax and Tmin, in row) and each set of weather stations (NBCN, SLF and NABEL, in column), boxplot of root-mean-square error (RMSE) between observed and calculated values is shown for CHclim25, MeteoSwiss, Chelsea and Worldclim2. For CHclim25, we show RMSE for the integration of daily downscaling in a 5 km radius, as well as the 1981-2010 downscaling with 5, 10 and 25 km moving window radii.

Deviations to observed values are higher at high elevation sites than lowland sites (Fig. 2, Fig. 3). The deviations are fairly constant throughout the year, but lead to slightly more accurate calculations for Prec during summer, while calculations are

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more accurate for Tave, Tmax and Tmin during winter months for lowland stations (Fig. 2). Interestingly, errors on 30 year monthly averages for the high elevation sites are lower than errors for separate years, indicating that interannual variability is accounted for when considering 30 year averages. Deviations between datasets calculated by aggregation of daily downscaled layers and datasets calculated by first aggregation values at 1km and then performing one downscaling do not show significant differences, indicating that the order of the data aggregation does not matter (Fig. 2, Fig. 3). Differences in deviation can be noticed however depending on the choice of the radius of the moving window in the downscaling process. Although these differences are small, our results indicate that radii of 10 and 25 km provide more accurate estimates for temperature variables at high elevation (but not at low elevation), which are more accurate than the initial MeteoSwiss dataset (Fig. 3). In comparison to Chelsa and Wordclim2, CHclim25 provides overall more accurate estimates (and lower variance in the estimates) for all variables and sets of independent sites (except Tmax from Worldclim 2 at high elevation sites).

Discussion

CHclim25 dataset represents a significant advancement in the availability of high-resolution climatic data in Switzerland. This dataset offers a high spatial resolution of 25 meters with daily, monthly, and yearly climatic layers for the period 1981-2010, as well as three future projections up to 2099. The downscaling process employed, using local regressions with elevation models, enhances the dataset's ability to capture complex local climatic phenomena, especially in regions with rugged terrain. The validation of CHclim25 demonstrates its accuracy, with minimal errors compared to both original datasets at 1 km resolution and global datasets at 30' resolution. This increased accuracy is particularly notable at high elevations where microclimatic variations strongly influence ecological patterns and dynamics.

Incorporating very high-resolution climatic maps, such as the CHclim25 dataset proposed in this study, is pivotal for advancing our understanding of microclimate-species interactions and their implications for ecological modelling. These maps offer crucial information for mapping species temperature preferences, microclimate heterogeneity, and microclimate refugia in much greater detail. The ability to consider microclimatic conditions at fine scales facilitates a more realistic, organism-cantered perspective when analysing climate–species interactions (Lembrechts et al., 2019; De Frenne et al., 2021). The limitations of macro-climatic datasets such as Worldclim (Fick and Hijmans, 2017) or Chelsa (Karger et al., 2021), which fail to capture the spatiotemporal variability in microclimate influenced by terrain, wind, and vegetation, have raised concerns about the accuracy of species distribution models (SDMs) (Patiño et al., 2023). The coarse spatial resolution of these dataset and the differences in local elevation and topographic complexity contribute to a mismatch between actual microclimatic conditions experienced by organisms and the macroclimate. In mountainous regions such as Switzerland, characterized by rugged terrain, this discrepancy is particularly pronounced, with microclimate varying noticeably over short distances (Graae et al., 2018).

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Recent studies have emphasized the importance of fine-scale climate data in SDMs when forecasting the impact of climate change on the distribution of species (e.g. Patiño et al., 2023). Fine-scale climatic data are crucial for identifying microrefugia, small sheltered areas against changing climates, which play a significant role in the survival of warm- and drought-sensitive organisms (Finocchiaro et al., 2023; Hylander et al., 2015; Suggitt et al., 2018). Macro-climatic datasets tend to homogenize climatic gradients driven by elevation and topography, overlooking rare microclimates in the landscape (Moudrý et al., 2023). For instance, using SDM predictions based on a microclimate dataset, Patino et al. (2023) identified a higher number of microrefugia across mid-elevation ridges, emphasizing the relevance of high-resolution climatic datasets for predicting species responses to environmental changes.

In conclusion, the CHclim25 dataset represents a valuable contribution in addressing the limitations of macro-climatic data, enabling more accurate analyses and forecasting of species distributions, range dynamics, and the identification of microrefugia during climate change. The dataset is not only relevant to fundamental and applied ecology but also holds significance for agriculture and forestry in the face of climate change.

Data availability

The layer files are stored on the Zenodo repository in the chclim25 community (https://zenodo.org/communities/chclim25). The data is stored as sub-datasets with individual DOI for each variable (Broennimann, 2023b, f, e, j, i, d, g, a, c). Monthly and yearly average layers for the 1981-2010 period and future periods are available online (Table 1). Daily layers for individual years can be provided on request.
The layer files are stored in compressed GeoTIFF format with the "deflate" algorithm with option "predictor2" from the GDAL. This format has the advantage to enable a high compression ratio (i.e. save storage space) while allowing direct import in most GIS softwares. All the maps are projected in the Swiss coordinate system CH 1903+ LV95 (epsg:2056) with a resolution of 25x25m using the extent of the digital height model DHM25 of the Swiss office for topography (swisstopo).

Table 1: description of variables, with availability of daily, monthly and yearly layers. A sub-dataset for each variable is available on Zenodo with a specific DOI (e.g. for Prec: doi.org/10.5281/zenodo.7868383, final numbers of the DOIs for all variables are provided in the table). Symbols indication layers availability: calculation not possible or not relevant : ×, not calculated : o, available on request : ✓, available online : ✓✓

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Variable	description	units	DOI	Daily layers	Monthly layers					Yearly layers				
			10.5281/ zenodo.x	individual years	individual years	1981-2010 average	2020-2049 average	2045-2074 average	2070-2099 average	individual years	1981-2010 average	2020-2049 average	2045-2074 average	2070-2099 average
Prec	sum of precipitation	mm	7868383	✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
Srel	duration of daily sunshine	%	7870977	✓	✓✓	✓✓	x	x	x	✓✓	✓✓	x	x	x
Tave	daily average temperature	°C	7859252	✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
Tmax	daily maximum temperature	°C	7861894	✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
Tmin	daily minimum temperature	°C	7861921	✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
gdd	sum of growing degree-days above 0°C, 3°C or 5°C	°C	7870203	x	o	✓✓	✓✓	✓✓	✓✓	o	✓✓	✓✓	✓✓	✓✓
etp	evapotranspiration using Turc method	mm	7870918	x	o	✓✓	✓✓	✓✓	✓✓	o	✓✓	✓✓	✓✓	✓✓
biovars	bioclimatic variables	-	7871116	x	x	x	x	x	x	✓✓	✓✓	✓✓	✓✓	✓✓
AI	index of aridity	ratio	7871030	x	o	o	o	o	o	✓✓	✓✓	✓✓	✓✓	✓✓

Code availability

The R code to generate the local regressions, to aggregate daily layers into monthly and yearly layers as well as the code to generate extended climatic variables is available on https://doi.org/10.5281/zenodo.7898915 (Broennimann, 2023h).

Author Contributions

Olivier Broennimann (OB) and Antoine Guisan (AG) developed together the idea of the downscaling approach. OB developed the code, ran the calculations on the HPC cluster, performed the technical evaluation of the dataset and wrote the manuscript. AG provided the funding and supervised the writing of the final version of the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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References

Arguez, A. and Vose, R. S.: The Definition of the Standard WMO Climate Normal: The Key to Deriving Alternative Climate Normals, Bulletin of the American Meteorological Society, 92, 699–704, https://doi.org/10.1175/2010BAMS2955.1, 2011.

Broennimann, O.: CHclim25 - aridity index (AI) (1.1), https://doi.org/10.5281/ZENODO.7871029, 2023a.

Broennimann, O.: CHclim25 - average temperature (Tave) (1.1), https://doi.org/10.5281/ZENODO.7859252, 2023b.

Broennimann, O.: Chclim25 - bioclimatic variables (biovars) (1.1), https://doi.org/10.5281/ZENODO.7871115, 2023c.

Broennimann, O.: CHclim25 - growing degree days (gdd) (1.1), https://doi.org/10.5281/ZENODO.7870202, 2023d.

Broennimann, O.: CHclim25 - maximum temperature (Tmax) (1.1), https://doi.org/10.5281/ZENODO.7861893, 2023e.

Broennimann, O.: CHclim25 - minimum temperature (Tmin) (1.1), https://doi.org/10.5281/ZENODO.7861920, 2023f.

Broennimann, O.: CHclim25 - potential evapotranspiration (etp) (1.1), https://doi.org/10.5281/ZENODO.7870917, 2023g.

Broennimann, O.: CHclim25 - R scripts, , https://doi.org/10.5281/ZENODO.7898914, 2023h.

Broennimann, O.: CHclim25 - relative sunshine duration (Srel) (1.1), https://doi.org/10.5281/ZENODO.7870976, 2023i.

Broennimann, O.: CHclim25 - sum of precipitation (Prec) (1.1), https://doi.org/10.5281/ZENODO.7868382, 2023j.

CH2018 Project Team: CH2018 - Climate Scenarios for Switzerland, National Centre for Climate Services, doi: 10.18751/Climate/Scenarios/CH2018/1.0, 2018.

De Frenne, P., Lenoir, J., Luoto, M., Scheffers, B. R., Zellweger, F., Aalto, J., Ashcroft, M. B., Christiansen, D. M., Decocq, G., De Pauw, K., Govaert, S., Greiser, C., Gril, E., Hampe, A., Jucker, T., Klinges, D. H., Koelemeijer, I. A., Lembrechts, J. J., Marrec, R., Meeussen, C., Ogée, J., Tyystjärvi, V., Vangansbeke, P., and Hylander, K.: Forest microclimates and climate change: Importance, drivers and future research agenda, Global Change Biology, 27, 2279–2297, https://doi.org/10.1111/gcb.15569, 2021.

Di Luca, A., Argüeso, D., Evans, J. P., Elía, R., and Laprise, R.: Quantifying the overall added value of dynamical downscaling and the contribution from different spatial scales, J. Geophys. Res. Atmos., 121, 1575–1590, https://doi.org/10.1002/2015JD024009, 2016.

Fick, S. E. and Hijmans, R. J.: WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas, International Journal of Climatology, 37, 4302–4315, https://doi.org/10.1002/joc.5086, 2017.

Finocchiaro, M., Médail, F., Saatkamp, A., Diadema, K., Pavon, D., and Meineri, E.: Bridging the gap between microclimate and microrefugia: A bottom-up approach reveals strong climatic and biological offsets, Global Change Biology, 29, 1024–1036, https://doi.org/10.1111/gcb.16526, 2023.

Frei, C.: Interpolation of temperature in a mountainous region using nonlinear profiles and non-Euclidean distances, International Journal of Climatology, 34, 1585–1605, https://doi.org/10.1002/joc.3786, 2014.

Graae, B. J., Vandvik, V., Armbruster, W. S., Eiserhardt, W. L., Svenning, J.-C., Hylander, K., Ehrlén, J., Speed, J. D. M., Klanderud, K., Bråthen, K. A., Milbau, A., Opedal, Ø. H., Alsos, I. G., Ejrnæs, R., Bruun, H. H., Birks, H. J. B.,

https://doi.org/10.5194/essd-2024-79
Preprint. Discussion started: 8 April 2024

Westergaard, K. B., Birks, H. H., and Lenoir, J.: Stay or go – how topographic complexity influences alpine plant population and community responses to climate change, Perspectives in Plant Ecology, Evolution and Systematics, 30, 41–50, https://doi.org/10.1016/j.ppees.2017.09.008, 2018.

Guisan, A., W., T., and E., Z. N.: Habitat suitability and distribution models.

Hylander, K., Ehrlén, J., Luoto, M., and Meineri, E.: Microrefugia: Not for everyone, Ambio, 44, 60–68, 2015.

IPCC: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Geneva, Switzerland, 2014.

Jansing, L., Papritz, L., Dürr, B., Gerstgrasser, D., and Sprenger, M.: Classification of Alpine south foehn based on 5 years of kilometre-scale analysis data, Weather and Climate Dynamics, 3, 1113–1138, https://doi.org/10.5194/wcd-3-1113-2022, 2022.

Karger, D. N., Wilson, A. M., Mahony, C., Zimmermann, N. E., and Jetz, W.: Global daily 1 km land surface precipitation based on cloud cover-informed downscaling, Sci Data, 8, 307, https://doi.org/10.1038/s41597-021-01084-6, 2021.

Lareau, N. P., Crosman, E., Whiteman, C. D., Horel, J. D., Hoch, S. W., Brown, W. O. J., and Horst, T. W.: The Persistent Cold-Air Pool Study, Bulletin of the American Meteorological Society, 94, 51–63, https://doi.org/10.1175/BAMS-D-11-00255.1, 2013.

Lembrechts, J. J., Nijs, I., and Lenoir, J.: Incorporating microclimate into species distribution models, Ecography, 42, 1267–1279, https://doi.org/10.1111/ecog.03947, 2019.

MeteoSwiss: MeteoSwiss Spatial Climate Analyses: Documentation of Datasets for Users, https://www.meteoswiss.admin.ch/climate/the-climate-of-switzerland/spatial-climate-analyses.html, 2022.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J.: The next generation of scenarios for climate change research and assessment, Nature, 463, 747–756, https://doi.org/10.1038/nature08823, 2010.

Moudrý, V., Keil, P., Gábor, L., Lecours, V., Zarzo-Arias, A., Barták, V., Malavasi, M., Rocchini, D., Torresani, M., Gdulová, K., Grattarola, F., Leroy, F., Marchetto, E., Thouverai, E., Prošek, J., Wild, J., and Šímová, P.: Scale mismatches between predictor and response variables in species distribution modelling: A review of practices for appropriate grain selection, Progress in Physical Geography: Earth and Environment, 47, 467–482, https://doi.org/10.1177/03091333231156362, 2023.

Patiño, J., Collart, F., Vanderpoorten, A., Martin-Esquivel, J. L., Naranjo-Cigala, A., Mirolo, S., and Karger, D. N.: Spatial resolution impacts projected plant responses to climate change on topographically complex islands, Diversity and Distributions, 29, 1245–1262, https://doi.org/10.1111/ddi.13757, 2023.

Seidel, D. J. and Free, M.: Comparison of Lower-Tropospheric Temperature Climatologies and Trends at Low and High Elevation Radiosonde Sites, Climatic Change, 59, 53–74, https://doi.org/10.1023/A:1024459610680, 2003.

https://doi.org/10.5194/essd-2024-79
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Suggitt, A. J., Wilson, R. J., Isaac, N. J. B., Beale, C. M., Auffret, A. G., August, T., Bennie, J. J., Crick, H. Q. P., Duffield, S., Fox, R., Hopkins, J. J., Macgregor, N. A., Morecroft, M. D., Walker, K. J., and Maclean, I. M. D.: Extinction risk from climate change is reduced by microclimatic buffering, Nature Clim Change, 8, 713–717, https://doi.org/10.1038/s41558-018-0231-9, 2018.

Turc, L.: Water requirements assessment of irrigation, potential evapotranspiration: Simplified and updated climatic formula, Annales Agronomiques, 12, 13–49, 1961.

Whiteman, C. D.: Observations of Thermally Developed Wind Systems in Mountainous Terrain, in: Atmospheric Processes over Complex Terrain, edited by: Banta, R. M., Berri, G., Blumen, W., Carruthers, D. J., Dalu, G. A., Durran, D. R., Egger, J., Garratt, J. R., Hanna, S. R., Hunt, J. C. R., Meroney, R. N., Miller, W., Neff, W. D., Nicolini, M., Paegle, J., Pielke, R. A., Smith, R. B., Strimaitis, D. G., Vukicevic, T., Whiteman, C. D., and Blumen, W., American Meteorological Society, Boston, MA, 5–42, https://doi.org/10.1007/978-1-935704-25-6_2, 1990.

Zimmermann, N. E.: solrad.aml, https://www.wsl.ch/staff/niklaus.zimmermann/programs/aml1_6.html, 2022.

Zomer, R. J., Xu, J., and Trabucco, A.: Version 3 of the Global Aridity Index and Potential Evapotranspiration Database, Sci Data, 9, 409, https://doi.org/10.1038/s41597-022-01493-1, 2022.