Global maps of soil temperature

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Abstract

Research in global change ecology relies heavily on global climatic grids derived from estimates of air temperature in open areas at around 2 m above the ground. These climatic grids thus fail to reflect conditions below vegetation canopies and near the ground surface, where critical ecosystem functions are controlled and most terrestrial species reside. Here we provide global maps of soil temperature and bioclimatic variables at a 1-km^2 resolution for 0–5 and 5–15 cm depth. These maps were created by calculating the difference (i.e., offset) between *in-situ* soil temperature measurements, based on time series from over 1200 1-km^2 pixels (summarized from 8500 unique temperature sensors) across all of the world's major terrestrial biomes, and coarse-grained air temperature estimates from ERA5-Land (an atmospheric reanalysis by the European Centre for Medium-Range Weather Forecasts). We show that mean annual soil temperature differs markedly from the corresponding 2 m gridded air temperature, by up to 10°C (mean = 3.0 ± 2.1°C), with substantial variation across biomes and seasons. Over the year, soils in cold and/or dry biomes are substantially warmer (3.6 ± 2.3°C warmer than gridded air temperature), whereas soils in warm and humid environments are on average slightly cooler (0.7 ± 2.3°C cooler). The observed substantial and biome-specific offsets underpin that the projected impacts of climate and climate change on biodiversity and ecosystem functioning are inaccurately assessed when air rather than soil temperature is used, especially in cold environments. The global soil-related bioclimatic variables provided here are an important step forward for any application in ecology and related disciplines. Nevertheless, we highlight the need to fill remaining global gaps by collecting more *in-situ* measurements of microclimate conditions to further enhance the spatiotemporal resolution of global soil temperature products for ecological applications.

Keywords: microclimate, bioclimatic variables, soil temperature, global maps, temperature offset, soil-dwelling organisms, near-surface temperatures

Introduction

With the rapidly increasing availability of big data on species distributions, functional traits and ecosystem functioning (Bond-Lamberty & Thomson, 2018, Bruelheide *et al.*, 2018, Kissling *et al.*, 2018, Kattge *et al.*, 2019, Lenoir *et al.*, 2020), we can now study biodiversity and ecosystem responses to global changes in unprecedented detail (Senior *et al.*, 2019, Steidinger *et al.*, 2019, Van Den Hoogen *et al.*, 2019, Antão *et al.*, 2020). However, despite this increasing availability of ecological data, most spatially-explicit studies of ecological, biophysical and biogeochemical processes still make use of the same global gridded temperature data (Soudzilovskaia *et al.*, 2015, Van Den Hoogen *et al.*, 2019, Du *et al.*, 2020). Most of these gridded air temperature datasets are based on long-term climatologies of rather coarse spatiotemporal resolutions: monthly and annual means, or bioclimatic derivatives, based on 30-yr time series averaged within 1 km to 50 km grid cells. Additionally, these coarse temperature grids are constructed based on measurements from standard meteorological stations that record free-air temperature inside well-ventilated protective shields placed up to 2 m above-ground in open, shade-free habitats, where abiotic conditions may differ substantially from those actually experienced by most organisms (World Meteorological Organization, 2008, Lembrechts *et al.*, 2020).

Ecological patterns and processes often relate more directly to below-canopy soil temperature rather than to well-ventilated air temperature inside a weather station. Near-surface, rather than air, temperature better predicts ecosystem functions like biogeochemical cycling (e.g., organic matter decomposition, soil respiration and other aspects of the global carbon balance) (Schimel *et al.*, 2004, Pleim & Gilliam, 2009, Portillo-Estrada *et al.*, 2016, Hursh *et al.*, 2017, Gottschall *et al.*, 2019, Davis *et al.*, 2020, Perera-Castro *et al.*, 2020). Similarly, the use of soil temperature in correlative analyses or predictive models may improve predictions of climate impacts on organismal physiology and behaviour, as well as on population and community dynamics and species distributions (Körner & Paulsen, 2004, Schimel *et al.*, 2004, Ashcroft *et al.*, 2008, Kearney *et al.*, 2009, Scherrer *et al.*, 2011, Opedal *et al.*, 2015, Berner *et al.*, 2020, Zellweger *et al.*, 2020). Given the key role of soil-related processes for both aboveground and belowground parts of the ecosystem and their feedbacks to the atmosphere (Crowther *et al.*, 2016), adequate soil temperature data are critical for a broad range of fields of study, such as ecology, biogeography, biogeochemistry, agronomy, soil science and climate system dynamics. Nevertheless, existing global soil temperature products such as those from ERA5-Land (Copernicus Climate Change Service (C3S), 2019), with a resolution of 0.08 × 0.08 degrees (≈ 9 × 9 km at the equator), remain too coarse for most ecological applications.

The direction and magnitude of the – often multi-degree – difference or *offset* between *in-situ* soil temperature and coarse-gridded air temperature products result from a combination of two factors: (i) the (vertical) microclimatic difference between air and soil temperature, and (ii) the (horizontal) mesoclimatic difference between air temperature in flat, cleared areas (i.e., where meteorological stations are located) and air temperature within different vegetation types (e.g., below a dense canopy of trees) or topographies (e.g., within a ravine or on a ridge) (Lembrechts *et al.*, 2020, De Frenne *et al.*, 2021). In essence, the offset is thus the combination of both the vertical and horizontal differences that result from factors affecting the energy budget at the Earth's surface, principally radiative energy: the ground absorbs radiative energy, which is transferred to the air by convective heat exchange, evaporation and spatial variation in net radiation, and lower convective conductance near the Earth's surface results in horizontal and vertical variation in temperature (Richardson, 1922, Geiger, 1950). Both these vertical and horizontal differences in temperature vary significantly across the globe and in time as a result of environmental conditions affecting the radiation budget (e.g., as a result of topographic orientation, canopy cover or surface albedo), convective heat exchange and evaporation (e.g., foliage density, variation in the degree of wind shear caused by surface friction) and the capacity for the soil to store and conduct heat (e.g., water content and soil structure and texture) (Geiger, 1950, Zhang *et al.*, 2008, Way & Lewkowicz, 2018, De Frenne *et al.*, 2019).

While the physics of soil temperatures have long been well-understood (Richardson, 1922, Geiger, 1950), the creation of high-resolution global gridded soil temperature products has not been feasible before, amongst others due to the absence of detailed global *in-situ* soil temperature measurements (Lembrechts & Lenoir, 2019, Lembrechts *et al.*, 2020). Recently, however, the call for microclimate temperature data with spatiotemporal resolutions relevant to the studied organism and, most importantly, values representative of *in-situ* conditions (i.e., microhabitat) as experienced by these organisms has become more urgent (Bramer *et al.*, 2018), while global data availability has rapidly increased (Lembrechts *et al.*, 2020). In this paper, we mainly address the point on the representativeness of *in-situ* conditions by generating global gridded maps of below-canopy and near-surface soil temperature at 1-km² resolution (in line with most existing global air temperature products). These maps are representative of the habitat conditions experienced by organisms living under vegetation canopies, in the topsoil or near the soil surface. They were created using the abovementioned offset between gridded air temperature data and *in-situ* soil temperature measurements. We expect these soil temperature maps to be substantially more representative of actual microclimatic conditions than existing products – even though still at a relatively coarse spatial resolution of 1-km² and summarizing multi-decadal averages – as they capture relevant near- and below-ground abiotic conditions where ecosystem functions and processes operate (Daly, 2006, Bramer *et al.*, 2018, Körner & Hiltbrunner, 2018). Indeed, the offset between free-air (macroclimate) and soil (microclimate) temperature, and between cleared areas and other habitats, can easily reach up to ±10°C annually, even at the coarse 1-km² spatial resolution used here (Zhang *et al.*, 2018, Lembrechts *et al.*, 2019, Wild *et al.*, 2019).

To create the global gridded soil temperature maps introduced above, we used over 8500 time series of soil temperature measured *in-situ* across the world's major terrestrial biomes, compiled and stored in the SoilTemp database (Lembrechts *et al.*, 2020) (Fig. 1a, Supplementary Material Fig. S1) and averaged into 1200 (or 1000 for the second soil layer) unique 1-km² pixels. First, to illustrate the magnitude of the studied effect, we visualized the global and biome-specific patterns in the mean annual offset between *in-situ* soil temperature (topsoil: 0–5 cm and second layer: 5–15 cm depth) and coarse-scale interpolated air temperature from ERA5-Land (soil temperature minus air temperature, hereafter called the *temperature offset,* sensu (De Frenne *et al.*, 2021); elsewhere called the *surface offset* (Smith & Riseborough, 1996, Smith & Riseborough, 2002)) using the average within 1 × 1 km grid cells. Next, we used a machine learning approach with 31 environmental explanatory variables (including macroclimate, soil, topography, reflectance, vegetation and anthropogenic variables) to model the spatial variation in monthly temperature offsets at a 1 × 1 km resolution for all continents except Antarctica (as absent in many of the used predictor variable layers). Using these offsets, we then calculated relevant soil-related bioclimatic variables (SBIO), mirroring the existing global bioclimatic variables for air temperature.

Finally, we compare our new global soil temperature product with a similar one calculated using coarser-resolution soil temperature data from ERA5-Land (Copernicus Climate Change Service (C3S), 2019).

Methods

Data acquisition

Analyses are based on SoilTemp, a global database of microclimate time series (Lembrechts *et al.*, 2020). We compiled soil temperature measurements from 9362 unique sensors (mean duration 2.9 years, median duration 1.0 year, ranging from 1 month to 41 years) from 60 countries, using both published and unpublished data sources (Fig. 1, Supplementary Material Fig. S1). Each sensor corresponds to one independent time series.

We used time series spanning a minimum of one month, with a temporal resolution of four hours or less. Sensors of any type were included (Supplementary Material Table S1), as long as they measured *in situ*. Sensors in experimentally manipulated plots, i.e., plots in which microclimate has been manipulated, were excluded. Most data (> 90%) came from low-cost rugged microclimate loggers such as iButtons (Maxim Integrated, USA) or TMS4-sensors (Wild *et al.*, 2019), with measurement errors of around 0.5–1°C (note that we are using °C over K throughout, for ease of understanding), while in a minority of cases sensors with higher meteorological specifications such as industrial or scientific grade thermocouples and thermistors (measurement errors of less than 0.5°C) were used. Contributing datasets mostly consisted of short-term regional networks of microclimate measurements, yet also included a set (< 5%) of soil temperature sensors from long-term research networks equipped with weather stations (e.g., Pastorello *et al.*, 2017). By combining these two types of data, a much higher spatial density of sensors and broader distribution of microhabitats could be obtained than by using weather station data only.

About 68% of sensors measured in time intervals located between 2010 and 2020 and 93% between 2000 and 2020; we thus focus on the latter period in our analyses. Additionally, given the relatively short time frame covered by most individual sensors, we were not able to test for systematic differences in the temperature offset between old and recent data sets, and thus we did not correct for this in our models. We strongly urge future studies to assess such temporal dynamics in the offset, once long-term microclimate data have become sufficient and more available.

For each of the individual 9362 time series, we calculated monthly mean, minimum (5% percentile of all monthly values) and maximum (95% percentile) temperature, after checking all time series for plausibility and erroneous data. These monthly values, while perhaps not fully intercomparable between the northern and southern hemisphere, are those that have traditionally been used to calculate bioclimatic variables (Fick & Hijmans, 2017). Months with more than one day of missing data, either at the beginning or end of the measurement period, or due to logger malfunctioning during measurement, were excluded, resulting in a final subset of 380 676 months of soil temperature time series that were used for further analyses. For each sensor with more than twelve months of data, we calculated moving averages of annual mean temperature, using each consecutive month as a starting month and calculating the mean temperature including the next eleven months. We used these moving averages to make maximal use of the full temporal extent covered by each sensor, because each time series spanned a different time period, often including parts of calendar years only. Next, these moving averages were further summarized to one mean annual average per 1-km² pixel (see below, under '*Global and biome-level analyses*').

The selected dataset contained sensors installed strictly belowground, measuring temperature at depths between 0 and 200 cm below the ground surface. Sensors recording several measurements at the same site but located at different (vertical) depths were included separately (the 9362 unique sensors thus came from 7251 unique loggers).

Sensors were grouped in different soil depth categories (0–5, 5–15, 15–30, 30–60, 60–100, 100–200 cm, Supplementary Material Table S2) to incorporate the effects of soil temperature dampening. We limited our analyses to the topsoil (0–5 cm) and the second soil layer (5–15 cm), as we currently lack sufficient global coverage to make trustworthy models at deeper soil depths (8519 time series, about 91%, came from the two upper depth layers). Due to uncertainty in identification of these soil depths between studies (e.g., due to litter layers), no finer categorisation is used.

We tested for potential bias in temporal resolution (i.e., measurement interval) by calculating mean, minimum and maximum temperature for a selection of 2000 months for data measured every 15 minutes, and the same data aggregated to 30, 60, 90, 120 and 240 minutes. Monthly mean, minimum and maximum temperature calculated with any of the aggregated datasets differed on average less than 0.2°C from the ones with the highest temporal resolution. We were thus confident that pooling data with different temporal resolutions of 4 hours or finer would not significantly affect our results.

Temperature offset calculation

For each monthly value at each sensor location (see Supplementary Material Table S3 for number of data points per month), we extracted the corresponding monthly means of the 2 m air temperature from the European Centre for Medium-Range Weather (ECMWF) Forecast's 5th reanalysis (ERA5) (from 1979–1981) and ERA5-Land from 1981–2020 (Copernicus Climate Change Service (C3S), 2019), hereafter called ERA5L. The latter dataset models the global climate with a spatial resolution of 0.08 × 0.08 degrees (≈ 9 × 9 km at the equator) with an hourly resolution, converted into monthly means using daily means for the whole month. Similarly, monthly minima and maxima were obtained from TerraClimate (Abatzoglou *et al.*, 2018) for the period 2000 to 2020 at a 0.04 × 0.04 degrees (≈ 4 × 4 km at the equator) resolution. Monthly means for TerraClimate were not available, we therefore estimated them by averaging the monthly minima and maxima. Finally, we also obtained monthly mean temperatures from CHELSA (Karger *et al.*, 2017a, Karger *et al.*, 2017b) for the period 2000 to 2013 at a 30 × 30 arc second (≈ 1 × 1 km at the equator) resolution. In our modelling exercises (see section *'Integrative modelling'* below), we opted to use the mean temperature offsets as calculated based on ERA5L rather than on CHELSA. While CHELSA's higher spatial resolution is definitely an advantage, its time period (stopping in 2013) insufficiently overlapped with the time period covered by our *in-situ* measurements (2000 to 2020), so temperature offsets based on the CHELSA dataset were only used for comparative purposes. We used TerraClimate to model offsets in monthly minimum and maximum temperature.

We calculated moving annual averages of the gridded air temperature data similar to those we computed for soil temperature. These were used to create annual temperature offset values following the same approach as above.

The offset between the *in situ* measured soil temperature in the SoilTemp database and the 2 m free-air temperature obtained from the air-temperature grids (ERA5L, TerraClim and CHELSA, hereafter called 'gridded air temperature') was calculated by subtracting the monthly or annual mean air temperature from the monthly or annual mean soil temperature. Positive offset values indicate a measured soil temperature higher than gridded air temperature, while negative offset values represent cooler soils. Similarly, monthly minimum and maximum air temperature were subtracted from minimum and maximum soil temperature, respectively. Monthly minima and maxima of the soil temperature were calculated as, respectively, the 5% lowest and highest instantaneous measurement in that month, to correct for outliers, which can be especially pronounced at the soil surface (Speak *et al.*, 2020). As a result, patterns in minima and maxima are more conservative estimates than if we had used the absolute lowest and highest values.

Importantly, the temperature offset calculated here is a result of three key groups of drivers: (1) height effects (2 m versus 0–15 cm below the soil surface); (2) environmental or habitat effects (e.g., spatial variability in vegetation, snow or topography); and (3) spatial scale effects (resolution of gridded air temperature) (Lembrechts *et al.*, 2020). We investigated the potential role of scale effects by comparing gridded air temperature data sources with different resolutions (ERA5L, TerraClimate and CHELSA, see below). Height effects and environmental effects are however not disentangled here, as the offset we propose incorporates both the difference between air and soil temperature (vertically), as well as the difference between free-air macroclimate and *in situ* microclimate (horizontally) in one measure (Lembrechts *et al.*, 2020). While it can be argued that it would be better to treat both vertical and horizontal effects separately, this would require a similar database of coupled *in-situ* air and soil temperature measurements, which is not yet available. Using *in situ* measured air temperature could also solve spatial mismatches (i.e., spatially averaged air temperature represents the whole 1 to 81 km² pixel, depending on pixel size, not only the exact location of the sensor). However, coupled air and soil temperature measurements are not only rare, but the air temperature measurements also have large measurement errors, especially in open habitats. These errors can be up to several degrees in open habitats when using non-standardized sensors, loggers and shielding (Maclean *et al.*, 2021). Hence, using *in situ* measured air temperature without correcting for these measurement errors would be misleading.

Global and biome-level analyses

For the purpose of visualization, annual offsets were first averaged in hexagons with a resolution of approximately 70 000 km^2, using the dggridR-package in R (Barnes *et al.*, 2017) (Fig. 1). Next, we plotted mean, minimum and maximum annual soil temperature as a function of corresponding gridded air temperature from ERA5, TerraClimate and CHELSA and used generalized additive models (GAMs, package mgcv; Wood, 2012) to visualise deviations from the 1:1-line (i.e., temperature offsets deviating from zero, Supplementary Figs. S4-5).

All annual and monthly values within each soil depth category and falling within the same 1-km^2 pixel were aggregated as a mean, resulting in a total of c. 1200 unique pixels at 0–5 cm, and c. 1000 unique pixels at 5–15 cm each month, across the globe (Supplementary Material Table S3). This averaging includes summarizing the data over space, i.e., multiple sensors within the same 1-km^2 pixel, and time, i.e., data from multi-year time series from a certain sensor, to reduce spatial and temporal autocorrelation and sampling bias. We assigned these 1-km^2 averages to the corresponding Whittaker biome of their georeferenced location, using the package *plotbiomes* in R (Fig. 1 c, d, Supplementary Material Table S4-5 (Stefan & Levin, 2018)). We ranked biomes based on their offset and compared this with the mean annual precipitation in each biome (Fig. 1b). This was done separately for each air temperature data source (ERA5L, TerraClimate and CHELSA), soil depth (0–5 cm, 5–15 cm) and timeframe (ERA5L 1979–2020, 2000–2020), as well as for the offset between monthly minimum and maximum soil temperature and the minimum and maximum gridded air temperature from TerraClimate. Our analyses showed that patterns were robust to variation in spatial resolution, sensor depth, climate interpolation method and temporal scale (Supplementary Material Figs. S2–5).

Acquisition of global predictor variables

To create spatial predictive models of the offset between *in-situ* soil temperature and gridded air temperature, we first sampled a stack of global map layers at each of the logger locations within the dataset. These layers included long-term macroclimatic conditions, soil texture and physiochemical information, vegetation, radiation and topographic indices as well as anthropogenic variables. Details of all layers, including descriptions, units, and source information, are described in Supplementary Data S1. In short, information about soil texture, structure and physiochemical properties was obtained from SoilGrids (version 1 (Hengl *et al.*, 2017)), limited to the upper soil layer (top 5 cm). Long-term averages of macroclimatic conditions (i.e., monthly mean, maximum and minimum temperature, monthly precipitation) was obtained from CHELSA (version 2017 (Karger *et al.*, 2017a)), which includes climate data averaged across 1979–2013, and from WorldClim (version 2 (Fick & Hijmans, 2017)). Monthly snow probability is based on a pixel-wise frequency of snow occurrence (snow cover >10%) in MODIS daily snow cover products (MOD10A1 & MYD10A1 (Hall *et al.*, 2002)) in 2001–2019. Spectral vegetation indices (i.e., averaged MODIS NDVI product MYD13Q1) and surface reflectance data (i.e., MODIS MCD43A4) were obtained from the Google Earth Engine Data Catalog (developers.google.com/earth-engine/datasets) and averaged from 2015 to 2019. Landcover and topographic information were obtained from EarthEnv (Amatulli *et al.*, 2018). Aridity index (AI) and potential evapotranspiration (PET) layers were obtained from CGIAR (Zomer *et al.*, 2008). Anthropogenic information (population density) was obtained from the EU JRC (ghsl.jrc.ec.europa.eu/ghs_pop2019.php). Aboveground biomass data were obtained from GlobBiomass (Santoro, 2018). Resolved ecoregion classifications were used to categorize sampling locations into biomes (Dinerstein *et al.*, 2017). With this set of predictor variables, we included information on all different categories of drivers of soil temperature. An important variable that had to be excluded was snow depth, due to the lack of a relevant 1-km² resolution global product. The final set of predictor variables included 24 'static' variables and eight monthly layers (i.e., maximum, mean and minimum temperature, precipitation, cloud cover, solar radiation, water vapour pressure, and snow cover). As cloud cover estimates were not available for high-latitude regions in the Northern Hemisphere in January and December due to a lack of daylight, we excluded cloud cover as an explanatory variable for these months (i.e., 'EarthEnvCloudCover_MODCF_monthlymean_XX', with XX representing the months in two-digit form Supplementary Data S1).

All variable map layers were reprojected and resampled to a unified pixel grid in EPSG:4326 (WGS84) at 30 arc-sec resolution (≈ 1 × 1 km at the equator). Areas covered by permanent snow or ice (e.g., the Greenland ice cap or glaciated mountain ranges, identified using SoilGrids) were excluded from the analyses. Antarctic sampling points were excluded from the modelling data set owing to the limited coverage of several covariate layers in the region.

Integrative modelling

To generate global maps of monthly temperature offsets (Fig. 2), we trained random forest (RF) models for each month, using the temperature offsets as the response variables and the global variable layers as predictors. We used a geospatial RF modelling pipeline as developed by van den Hoogen *et al.* (2021). RF models are particularly valuable here due to their capacity to uncover nonlinear relationships (e.g., due to increased decoupling of soil from air temperature in colder and thus snow-covered areas) and their ability to capture complex interactions among covariates (e.g., between snow and vegetation cover) (Olden *et al.*, 2008).

We performed a grid search procedure to tune the RF models across a range of 122 hyperparameter settings (variables per split: 2–12, minimum leaf population: 2–12). During this procedure, we assessed each model's performance using k-fold cross-validation (k = 10; folds assigned randomly, stratified per biome), for each of the 122 models. The models' mean and standard deviation values were the basis for choosing the best of all evaluated models. This procedure was repeated for each month separately for the two soil depth layers (0–5 cm, 5–15 cm), for offsets in mean, minimum and maximum temperature. The importance of explanatory variables was assessed using the variable importance and ordered by mean variable importance across all models. This variable importance adds up the decreases in the impurity criterion (i.e., the measure on which the local optimal condition is chosen) at each split of a node for each individual variable over all trees in the forest (van den Hoogen *et al.*, 2021).

Soil bioclimatic variables

The resulting global maps of the annual and monthly offsets between mean, minimum and maximum soil and air temperature were used to calculate relevant bioclimatic variables following the definition used in CHELSA, BIOCLIM, ANUCLIM and WorldClim (Xu & Hutchinson, 2011, Booth *et al.*, 2014, Fick & Hijmans, 2017, Karger *et al.*, 2017a) (Fig. 3–4). We calculated 11 soil bioclimatic layers (SBIO, Table 1). First, we calculated monthly soil mean, maximum and minimum temperature by adding monthly temperature offsets to the respective CHELSA monthly mean, maximum and minimum temperature (Karger *et al.*, 2017a). Next, we used these soil temperature layers to compute the SBIO layers (O'Donnell & Ignizio, 2012). Wettest and driest quarters were identified for each pixel based on CHELSA's monthly values.

Table 1: Overview of soil bioclimatic variables as calculated in this study.

Bioclimatic variable	Meaning
SBIO1	annual mean temperature
SBIO2	mean diurnal range (mean of monthly (max temp - min temp))
SBIO3	isothermality (SBIO2/SBIO7) (×100)
SBIO4	temperature seasonality (standard deviation ×100)
SBIO5	max temperature of warmest month
SBIO6	min temperature of coldest month
SBIO7	temperature annual range (SBIO5-SBIO6)
SBIO8	mean temperature of wettest quarter
SBIO9	mean temperature of driest quarter
SBIO10	mean temperature of warmest quarter
SBIO11	mean temperature of coldest quarter

Model uncertainty

To assess the uncertainty in the monthly models, we performed a stratified bootstrapping procedure, with total size of the bootstrap samples equal to the original training data (van den Hoogen *et al.*, 2021). Using biomes as a stratification category, we ensured the samples included in each of the bootstrap training collections were proportionally representative of each biome's total area. Next, we trained RF models (with the same hyperparameters as selected during the grid-search procedure) using each of 100 bootstrap iterations. Each of these trained RF models was then used to classify the covariate layer stack, to generate per-pixel 95% confidence intervals and standard deviation for the modelled monthly offsets (Fig. 5a, Supplementary Material Fig. S6a). The mean R^2 value of the RF models for the monthly mean temperature offset was 0.70 (from 0.64 to 0.78) at 0–5 cm and 0.76 (0.63–0.85) at 5 to

15 cm across all twelve monthly models. Mean RMSE of the models was 2.20°C (1.94–2.51°C) at 0–5 cm, and 2.06°C (1.67–2.35°C) at 5–15 cm.

Importantly, model uncertainty as reported in Fig. 5a and Supplementary Material Fig. S6a comes on top of existing uncertainties in (1) *in-situ* soil temperature measurements and (2) the ERA5L macroclimate models as used in our models. However, both of those are usually under 1°C (Copernicus Climate Change Service (C3S), 2019, Wild *et al.*, 2019).

To assess the spatial extent of extrapolation, which is necessary due to the incomplete global coverage of the training data, we first performed a Principal Component Analysis (PCA) on the full environmental space covered by the monthly training data, including all explanatory variables as used in the models, and then transformed the composite image into the same PC spaces as of the sampled data (Van Den Hoogen *et al.*, 2019). Next, we created convex hulls for each of the bivariate combinations from the first 10 to 12 PCs, covering at least 90% of the sample space variation, with the number of PCs depending on the month. Using the coordinates of these convex hulls, we assessed whether each pixel fell within or outside each of these convex hulls, and calculated the percentage of bivariate combinations for which this was the case (Fig. 5b, Supplementary Material Fig. S6b). This process was repeated for each month, and for each of the two soil depths separately.

These uncertainty maps are important because one should be careful with extrapolation beyond the range of conditions covered by the environmental variables included in the original calibration dataset, especially in the case of non-linear patterns such as modelled here. The maps are provided as spatial masks to remove or reduce the weighting of the pixels for which predictions are beyond the range of values covered by the models during calibration. To assess this further, we used a spatial leave-one-out cross-validation analysis to test for spatial autocorrelation in the data set (Supplementary Material Fig. S7) (van den Hoogen *et al.*, 2021). This approach trains a model for each sample in the data set on all remaining samples, excluding data points that fall within an increasingly large buffer around that focal sample. Results show lowest confidence for May to September at 5–15 cm, likely driven by uneven global coverage of data points.

Finally, we compared the modelled mean annual temperature (SBIO1, topsoil layer) with a similar product based on monthly ERA5L topsoil (0–7 cm) temperature with a spatial resolution of 0.1 × 0.1 degrees (Copernicus Climate Change Service (C3S), 2019). The corresponding SBIO1 based on ERA5L was calculated using the means of the monthly averages for each month over the period 1981 to 2016, and averaging these 12 monthly values into one annual product. We then visualized spatial differences between SBIO1 and ERA5, as well as differences across the macroclimatic gradient, to identify mismatches between both datasets.

All geospatial modelling was performed using the Python API in Google Earth Engine (Gorelick *et al.*, 2017). The R statistical software, version 4.0.2 (R Core Team, 2020), was used for data visualisations. All maps were plotted using the Mollweide projection (which preserves relative areas) to avoid large distortions at high latitudes.

Sources of uncertainty

There is a temporal mismatch between the period covered by CHELSA (1979-2013) and our *in-situ* measurements (2000-2020), which prevented us from directly using CHELSA climate to calculate the temperature offsets used in our models. This temporal mismatch might affect the offsets calculated here because the relationship between temperature offset and macroclimate will change through time as the climate warms. However, we are confident that our results are sufficiently robust to withstand this mismatch, given that we found high consistency in offset patterns between the different timeframes and air temperature datasets examined (Supplementary Material Figs. S2–5). Nevertheless, we strongly urge future research to disentangle these potential temporal dynamics, especially given the increasing rate at which the climate is warming (Xu *et al.*, 2018, GISTEMP Team, 2021).

Similarly, a potential bias could result from the mismatch in method and resolution between ERA5L – used to calculate the temperature offsets – and CHELSA, which was used to create the bioclimatic variables. However, even though temperature offsets have slightly larger variation when based on the coarser-grained ERA5L-data than on the finer-grained CHELSA-data, Supplementary Material Figs. S2–5 show that relationships between soil and air temperature are largely consistent in all biomes and across the whole global temperature gradient. Therefore, the larger offsets created additional random scatter, yet no consistent bias.

Finally, we acknowledge that the 1-km² resolution gridded products might not be representative of conditions at the *in-situ* measurement locations within each pixel. This issue could be particularly significant for different vegetation types (here proxied at the pixel level using total aboveground biomass (unit: tons/ha i.e., Mg/ha, for the year 2010; Santoro, 2018) and NDVI (MODIS NDVI product MYD13Q1, averaged over 2015–2019)). To verify this, we compared a pixel's estimated aboveground biomass with the dominant *in-situ* habitat (forest versus open) surrounding the sensors in that pixel (Supplementary Table S6). Importantly, all sensors installed in forests fell indeed in pixels with more than 1 ton/ha aboveground biomass. Similarly, 75% or more of sensors in open terrain fell in pixels with biomass estimates of less than 1 ton/ha. Only in the temperate woodland biome was the match between *in-situ* habitat estimates and pixel-level aboveground biomass lower, with less than 95% of sensors in forested locations correctly placed in pixels with more than 1 ton/ha biomass, and less than 50% of open terrain sensors in pixels with less than 1 ton/ha biomass. While our predictions will thus not be accurate for locations within a pixel that largely deviate from average conditions (e.g., open terrain in pixels identified as largely forested, or vice versa), they should be largely representative for those pixel-level averages.

Results

Biome-wide patterns in the temperature offset

We found positive and negative temperature offsets of up to 10°C between *in situ* measured mean annual topsoil temperature and gridded air temperature (mean = 3.0 ± 2.1°C standard deviation, Fig. 1, 0–5 cm depth; 5–15 cm is available in Supplementary Material Figs. S2, 5). The magnitude and direction of these temperature offsets varied considerably within and across biomes. Mean annual topsoil temperature was on average 3.6 ± 2.3°C higher than gridded air temperature in cold and/or dry biomes, namely tundra, boreal forests, temperate grasslands and subtropical deserts. In contrast, offsets were slightly negative in warm and wet biomes (tropical savannas, temperate forests and tropical rainforests) where soils were, on average, 0.7 ± 2.7°C cooler than gridded air temperature (Fig. 1b, Supplementary Material

Figs. S2 and 5; note, however, the lower spatial coverage in these biomes in Fig. 1a, c, d, Supplementary Material Table S4). Temperature offsets in annual minimum and maximum temperature amounted to c. 10°C maximum. While annual soil temperature minima were on average higher than corresponding gridded air temperature minima in all biomes, temperature offsets of annual maxima followed largely the same biome-related trends as seen for the annual means, albeit with the higher variability expected for temperature extremes (Supplementary Material Figs. S2g, h, S4g, h). Using different air temperature data sources did not alter the annual temperature offset and biome-related patterns (see Methods and Supplementary Material Figs. S2–5).

Soils in the temperate seasonal forest biome were on average 0.8°C (± 2.2°C) cooler than air temperature within 1-km^2 grid cells of forested habitats, and 1.0°C (± 4.0°C) warmer than the air within 1-km^2 grid cells of non-forested habitats, resulting in a biome-wide average of 0.5°C (Supplementary Material Table S7). Similar patterns were observed in other biomes.

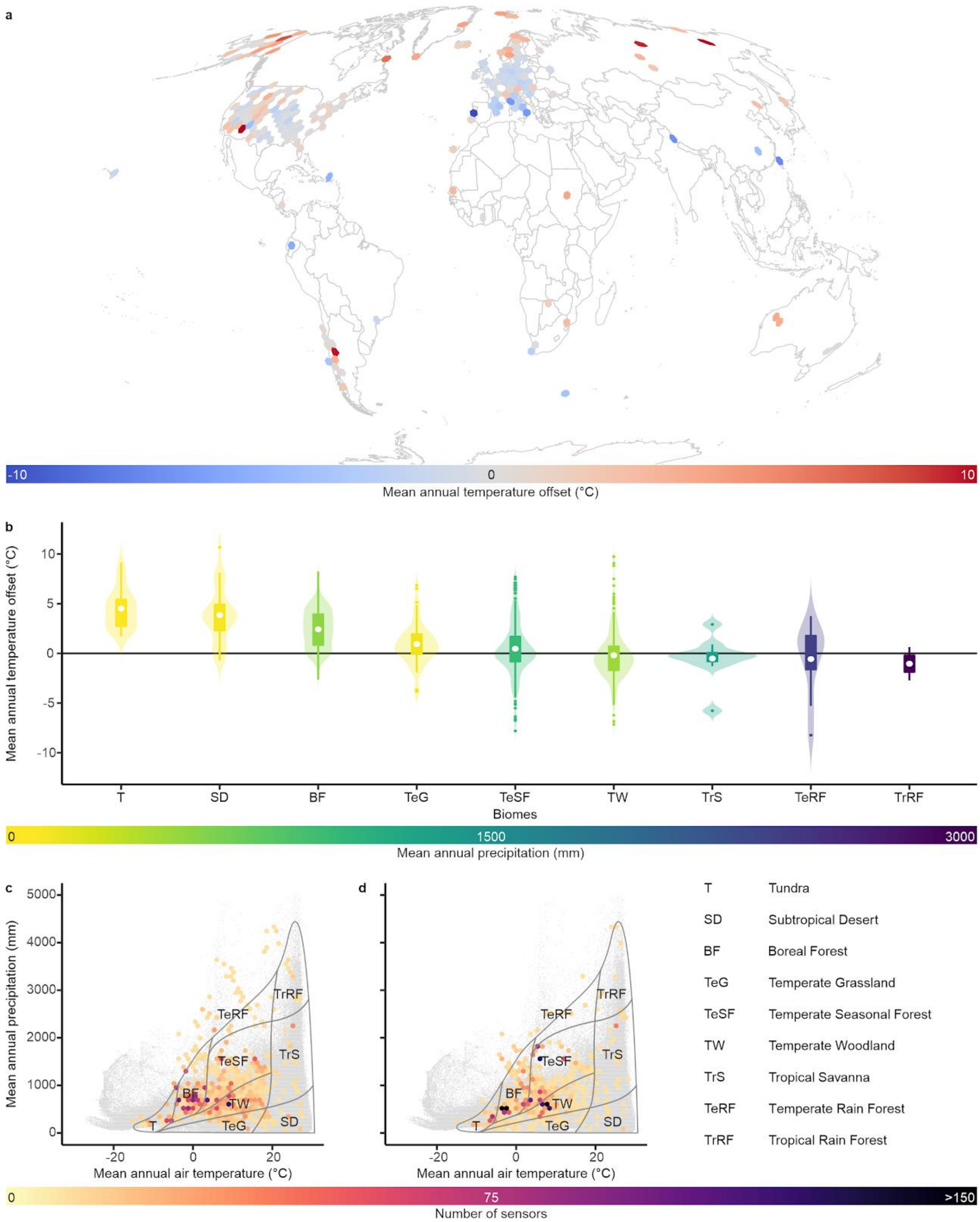

Figure 1: Temperature offsets between soil and air temperature differed significantly among biomes. *(a) Distribution of in-situ measurement locations across the globe, coloured by the mean annual temperature offset (in °C) between in situ measured soil temperature (topsoil, 0–5 cm depth) and gridded air temperature (ERA5L). Offsets were averaged per hexagon, each with a size of approximately 70,000 km². Mollweide projection. (b) Mean annual temperature offsets per Whittaker biome (adapted from Whittaker 1970, based on geographic location of sensors averaged at 1 km²; 0–5 cm depth), ordered by mean temperature offset and coloured by mean annual precipitation. (c–d) Distribution of sensors in 2D climate space for the topsoil (c, 0–5 cm depth, N = 4530) and the second*

layer (d, 5–15 cm depth, N = 3989). Colours of hexagons indicate the number of sensors at each climatic location, with a 40 × 40 km resolution. Grey dots in the background represent the global variation in climatic space (obtained by sampling 1 000 000 random locations from the CHELSA world maps). Overlay with grey lines depicts a delineation of Whittaker biomes.

Temporal and spatial variation in temperature offsets

Our random forest modelling approach highlighted a strong seasonality in monthly temperature offsets, especially towards higher latitudes (Fig. 2). High-latitude soils were found to be several degrees warmer than the air (monthly offsets of up to 25°C) during their respective winter months, and cooler (up to 10°C) in summer months, both at 0–5 cm (Fig. 2) and 5–15 cm (Supplementary Material Fig. S8) soil depths. In the tropics and subtropics, soils in dry biomes (e.g., in the Sahara desert or southern Africa) were predicted to be warmer than air throughout most of the year, whilst soils in mesic biomes (e.g., tropical biomes in South America, central Africa and Southeast Asia) were modelled to be consistently cooler, at both soil depths. These global gridded products were then used to create temperature-based global bioclimatic variables for soils (SBIO, Fig. 3, Supplementary Material Fig. S9).

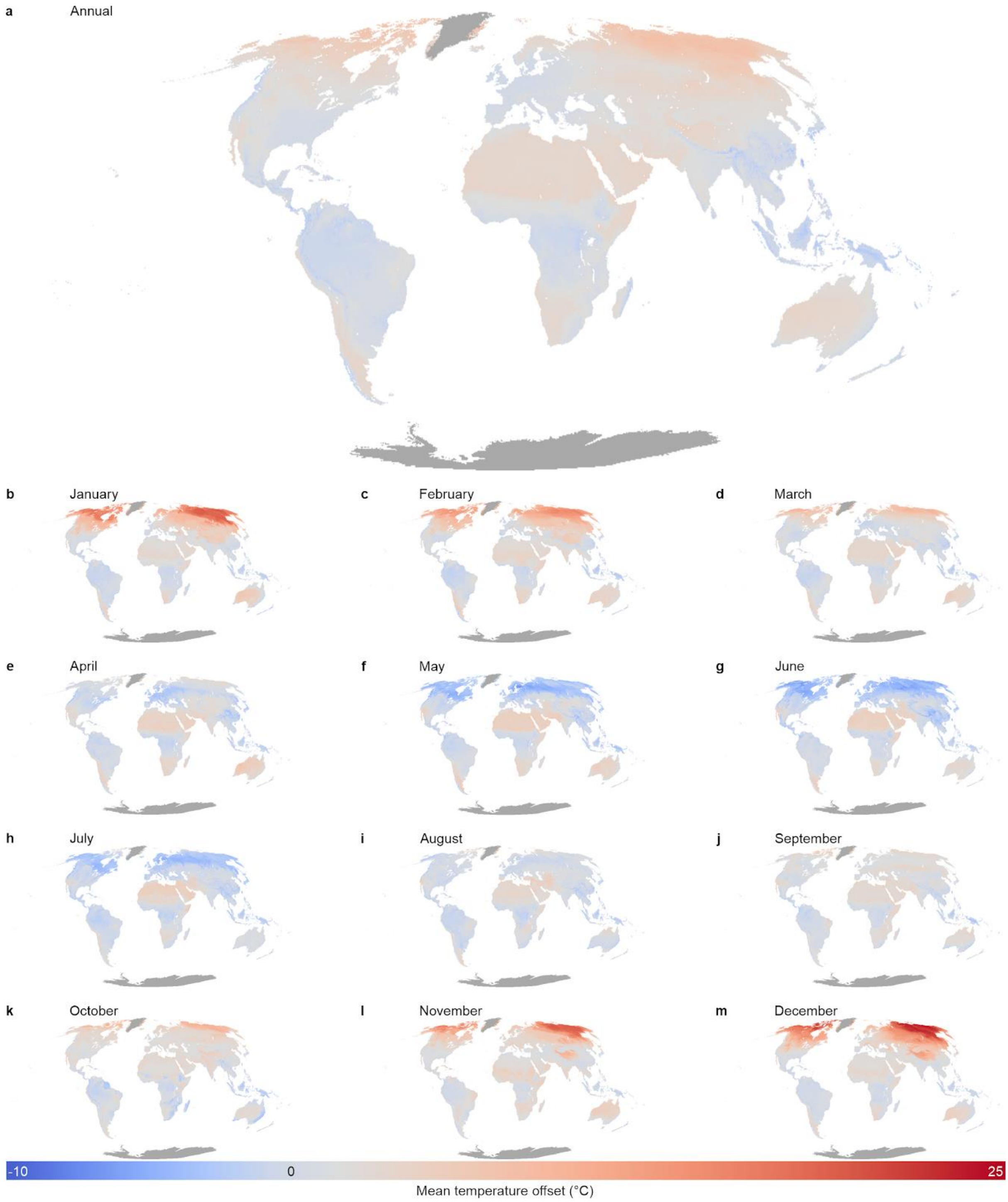

Figure 2: Global modelled temperature offsets between soil and air temperature show strong spatiotemporal variation across months. *Modelled annual (a) and monthly (b–m) temperature offset (in °C) between in situ measured soil temperature (topsoil, 0–5 cm) and gridded air temperature. Positive (red) values indicate soils that are warmer than the air. Dark grey represents regions outside the modelling area.*

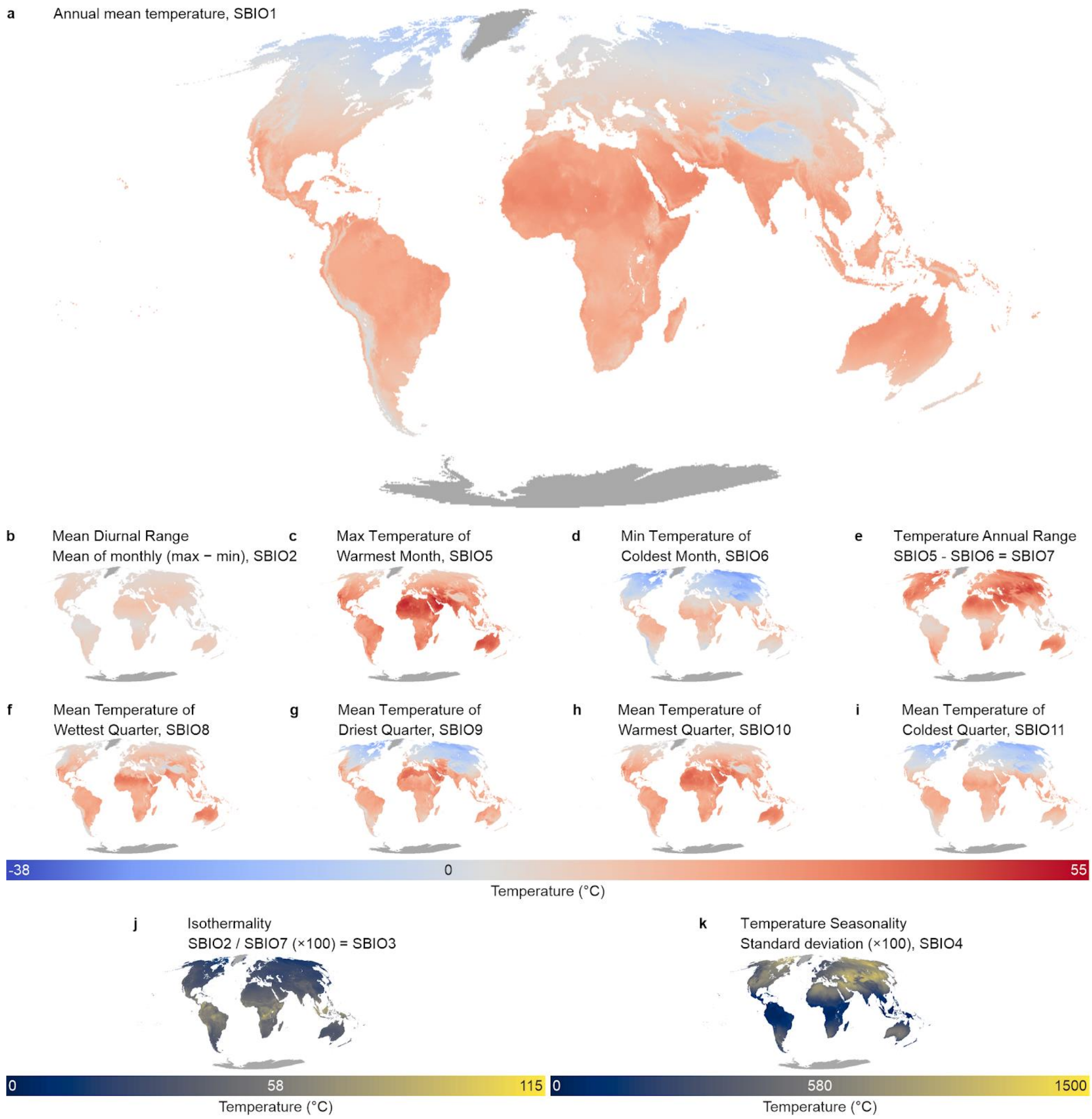

Figure 3: Soil bioclimatic variables. *Global maps of bioclimatic variables for topsoil (0–5 cm depth) climate, calculated using the maps of monthly soil climate (see Fig. 2), and the bioclimatic variables for air temperature from CHELSA.*

Global variation in soil temperature

We observed 17% less spatial variation in mean annual soil temperature globally (expressed by the standard deviation) than in air temperature, largely driven by the positive offset between soil and air temperature in cold environments (Fig. 4). Importantly, our machine learning models slightly (up to 1°C, or around 10% of variation) underestimated temperature offsets at both extremes of the temperature gradient at the 1-km² resolution (Supplementary Material Fig. S10) and likely even more in comparison with finer-resolution products. Estimates of the reduction in variation across space are thus conservative, especially in the coldest biomes. The reduction in spatial temperature variation was observed in all cold and cool biomes, with tundra and boreal forests having both a significant positive mean temperature offset and a reduction of 20% and 22% in variation, respectively (Fig. 4c). In the warmest biomes (e.g., tropical savanna and subtropical desert), however, we found an increase in variation of, on average, 10%.

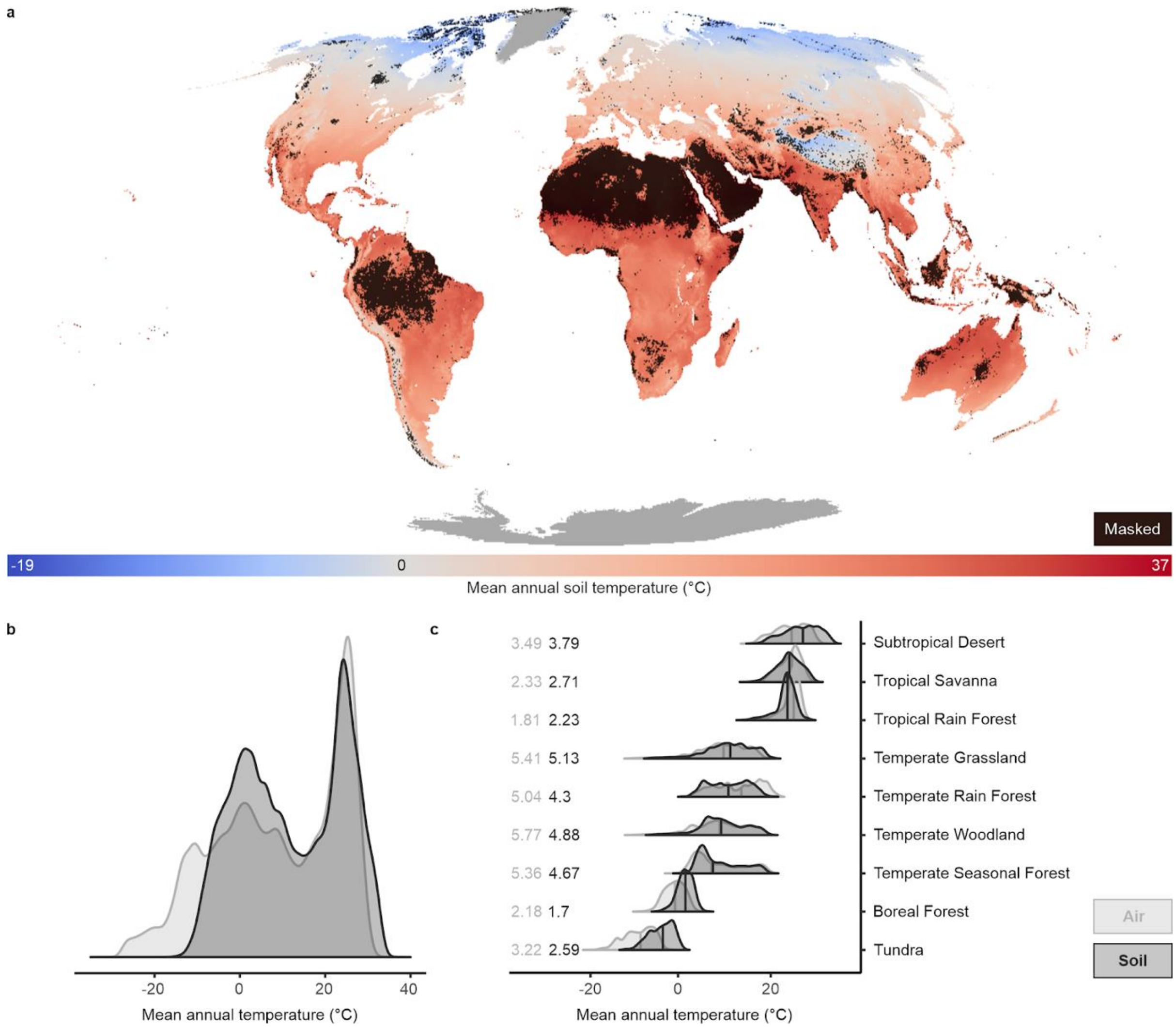

Figure 4: Mean annual soil temperature shows significantly lower spatial variability than air temperature. *(a) Global map of mean annual topsoil temperature (SBIO1, 0–5 cm depth, in °C), created by adding the monthly offset between soil and air temperature for the period 2000–2020 (Fig. 2) to the monthly air temperature from CHELSA. A black mask is used to exclude regions where our models are extrapolating (i.e., interpolation values in Fig. 5 are < 0.9, 18% of pixels). Dark grey represents regions outside the modelling area. (b–c) Density plots of mean annual soil temperature across the globe (b) and for each Whittaker biome separately (c) for SBIO1 (dark grey, soil temperature),*

compared with BIO1 from CHELSA (light grey, air temperature), created by extracting 1 000 000 random points from the 1-km² gridded bioclimatic products. The numbers in (c) represent the standard deviations of air temperature (light grey) and soil temperature (dark grey). Biomes are ordered according to the median annual soil temperature values from the highest temperature (subtropical desert) to the lowest (tundra).

Our bootstrap approach to validate modelled monthly offsets indicated high consistency among the outcomes of 100 bootstrapped models (Fig. 5, Supplementary Material Fig. S6a), with standard deviations in most months and across most parts of the globe around or below ±1°C. One exception to this was the temperature offset at high latitudes of the northern hemisphere during winter months (standard deviation up to ±5°C in the 0–5 cm layer). Predictive performance was comparable across biomes, although with large variation in data availability (Supplementary Material Fig. S11).

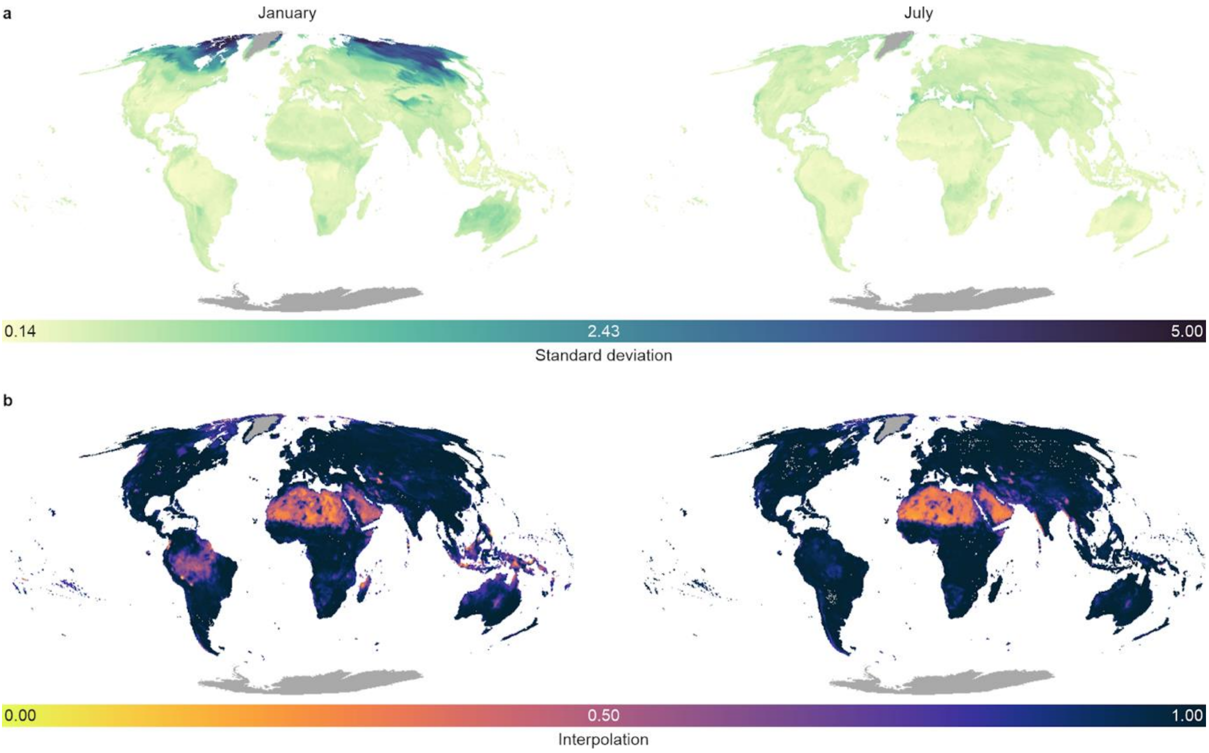

***Figure 5**: **Models of the temperature offset between soil and air temperature have low standard deviations and good global coverage.** Analyses for the temperature offset between in situ measured topsoil (0–5 cm depth) temperature and gridded air temperature. (a) Standard deviation (in °C) over the predictions from a cross-validation analysis that iteratively varied the set of covariates (explanatory data layers) and model hyperparameters across 100 models and evaluated model strength using 10-fold cross-validation, for January (left) and July (right), as examples of the two most contrasting months. (b) The fraction of axes in the multidimensional environmental space for which the pixel lies inside the range of data covered by the sensors in the database. Low values indicate increased extrapolation.*

The importance of explanatory variables in the RF models was largely consistent across months. Macroclimatic variables such as incoming solar radiation as well as long-term averages in air temperature and precipitation were by far the most influential explanatory variables in the spatial models of the monthly temperature offset (Supplementary Material Figs. S12, 13).

We highlight that the current availability of *in-situ* soil temperature measurements is significantly lower in the tropics (Supplementary Material Table S5), where our model had to extrapolate temperatures beyond the range used to calibrate the model (Fig. 5b, Supplementary Material Fig. S6b).

Finally, our comparison with a mean annual soil temperature product derived from the coarse-resolution ERA5L topsoil temperature showed that spatial variability, e.g., driven by topographic heterogeneity, is much better captured here than in the coarser resolution of the ERA5L-based product (Fig. 6c-e). Nevertheless, our predictions at the coarse scale showed to be condensed within a 5°C range of values from the ERA5L-predictions, for more than 95% of pixels globally. Noteworthy, our predictions resulted in consistently cooler soil temperature predictions than topsoil conditions provided by ERA5L across large areas, such as the boreal and tropical forest biomes (Fig. 6a, b). Additionally, our models predicted lower values for SBIO1 than ERA5L in all regions with mean annual soil temperature below 0°C, except for a few locations around Greenland and Svalbard (Fig. 6a, b).

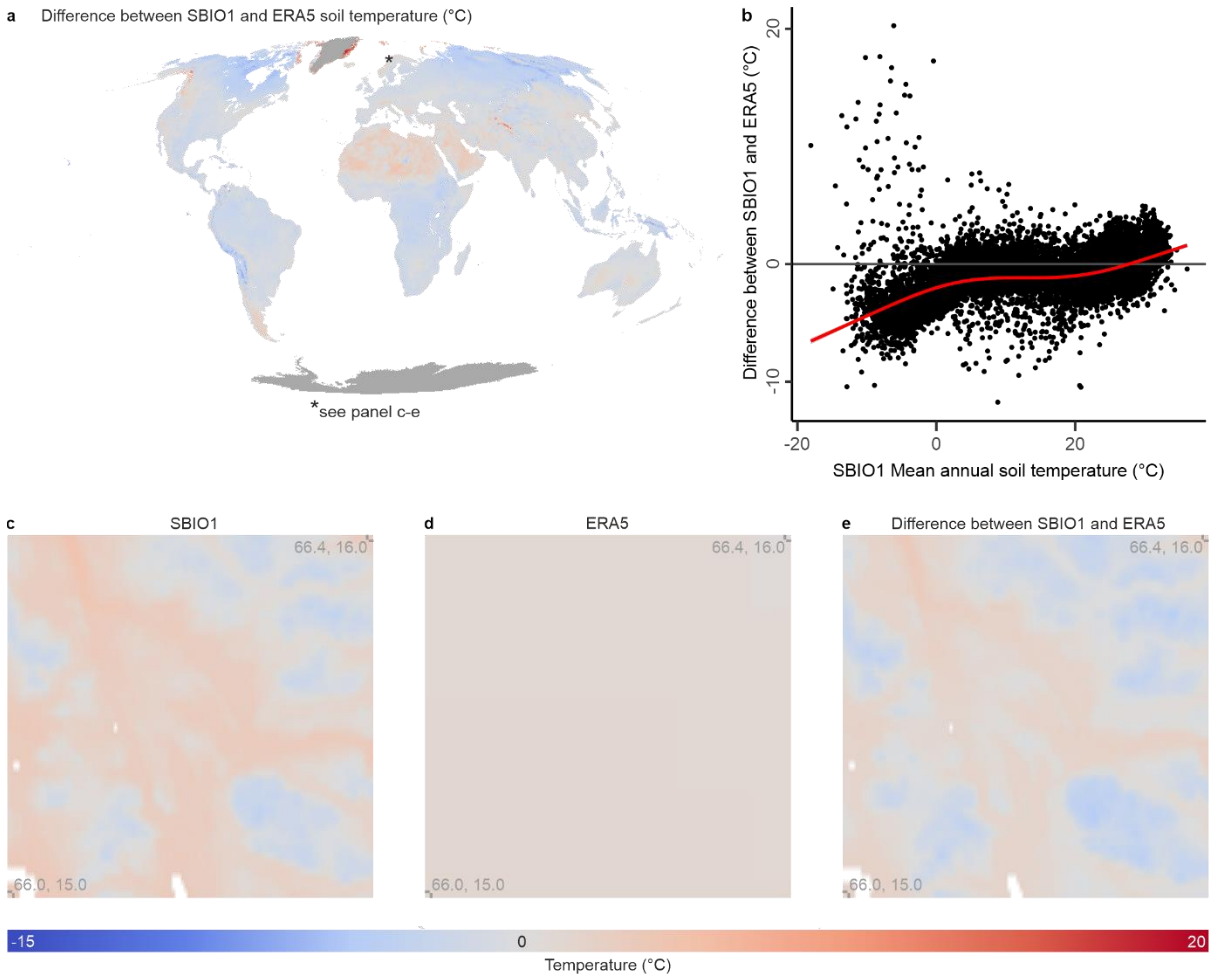

***Figure 6**: The mean annual soil temperature (SBIO1, 1 x 1 km resolution) modelled here is consistently cooler than ERA5L (9 x 9 km) soil temperature in forested areas.* *(a) Spatial representation of the difference between SBIO1 based on our model and based on ERA5L soil temperature data. Negative values (blue colours) indicate areas where our model predicts cooler soil temperature. Dark grey areas (Greenland and Antarctica) are excluded from our models. Asterisk in Scandinavia indicates the highlighted area in panels d to f (see below). (b) Distribution of the difference between SBIO1 and ERA5L along the macroclimatic gradient (represented by SBIO1 itself) based on a random subsample of 50 000 points from the map in a). Red line from a Generalized Additive Model (GAM) with k=4. (c-e) High-resolution zoomed panels of an area of high elevational contrast in Norway (from 66.0-66.4° N, 15.0-16.0° E) visualizing SBIO1 (c), ERA5L (d) and their difference (e), to highlight the higher spatial resolution as obtained with SBIO1.*

Discussion

Global patterns in soil temperature

We observed large spatiotemporal heterogeneity in the global offset between soil and air temperature, often in the order of several degrees annually and up to more than 20°C during winter months at high latitudes. These values are in line with empirical data from regional studies (Zhang *et al.*, 2018, Lembrechts *et al.*, 2019, Obu *et al.*, 2019). Both annual and monthly offsets showed clear discrepancies between cold and dry versus warm and wet biomes. The modelled monthly offsets covaried strongly negatively with both long-term averages in free-air temperature and solar radiation, linking to the well-known decoupling of soil from air temperature due to snow (for cold extremes in cold and cool biomes) (Grundstein *et al.*, 2005). However, the secondary importance of variables related to precipitation and soil structure hints to the additional distinction between wet and dry biomes at the warm end of the temperature gradient, where buffering due to shading, evapotranspiration and the specific heat of water (mostly against warm extremes in warm and wet biomes) results in cooler soil temperature (Geiger, 1950, Grundstein *et al.*, 2005, Hennon *et al.*, 2010, Wang & Dickinson, 2012, De Frenne *et al.*, 2013, Grünberg *et al.*, 2020), a less important process in warm and dry biomes (Wang & Dickinson, 2012, Greiser *et al.*, 2018, Zhou *et al.*, 2021). As such, these results highlight strong macroclimatic impacts on the soil microclimate across the globe (see also De Frenne *et al.*, 2019), yet with soil temperature importantly non-linearly related to air temperature at the global scale. This confirms that the latter is not sufficient as a proxy for temperature conditions near or in the soil. With our soil-specific global bioclimatic products, we have provided the means to correct for these important region-specific, non-linear differences between soil and air temperature at an unprecedented spatial resolution.

Drivers of the temperature offset

Our empirical modelling approach enabled us to accurately map global patterns in soil temperature. In doing so we did not aim to disentangle the mechanisms governing the temperature offset: such an endeavour would require modelling the biophysics of energy exchange at the soil surface across biomes (Kearney *et al.*, 2019, Maclean *et al.*, 2019, Maclean & Klinges, 2021). Importantly, many of the predictor variables used in our study (e.g., long-term averages in macroclimatic conditions or solar radiation) are unlikely to represent direct causal relationships underlying the temperature offset, but may rather indirectly relate to many ensuing factors that affect the functioning of ecosystems at fine spatial scales which, in turn, feedback on local temperature offsets, such as energy and water balances, snow cover, wind intensity and vegetation cover (De Frenne *et al.*, 2021). For example, while increased solar radiation itself would theoretically result in soils warming more than the air, high solar radiation at the global scale often coincides with high vegetation cover blocking radiation input to the soil, thus correlating with relatively cooler soils (De Frenne *et al.*, 2021). Our results highlight, however, that the complex relationship between microclimatic soil temperature and macroclimatic air temperature is predictable across large spatial extents thanks to broad scale patterns, even if this is governed by a multitude of local-scale factors involving fine spatiotemporal resolutions. Nevertheless, the predictive quality of our models was lower in high latitude regions, where high variation in the *in situ* measured offsets – likely driven by the interactions between snow, local topography and vegetation – reduced predictive power of the models at the 1-km² resolution (Greiser *et al.*, 2018, Way & Lewkowicz, 2018, Grünberg *et al.*, 2020, Myers-Smith *et al.*, 2020, Niittynen *et al.*, 2020).

Implications for microclimate warming

Our results highlight clear biome-specific differences in mean annual temperature between air and soil temperatures, as well as a significant reduction in the spatial variation in temperature in the soil or near the soil surface, especially in cold and cool biomes (Fig. 4). These patterns remain even despite the presence of often strongly opposing monthly offset trends (Fig. 2). The observed correlation between long-term averages in macroclimatic conditions and the annual temperature offset illustrates that soil temperature is unlikely to warm at the same rate as air temperature when macroclimate warms. Indeed, one degree of air temperature warming could result in either a bigger or smaller soil temperature change, depending on where along the macroclimatic gradient this is happening. These effects might be seen in cold biome soils most strongly, as they not only experience the largest (positive) temperature offsets and reductions in climate range compared to air temperature (Fig. 4b, c), but they are also expected to experience the strongest magnitude of macroclimate warming (Cooper, 2014, Overland *et al.*, 2014, Chen *et al.*, 2021, GISTEMP Team, 2021). As a result, mean annual temperatures in cold climate soils can be expected to warm slower than the corresponding macroclimate as offsets shrink with increasing macroclimate warming.

Contrastingly, predicted climate warming in hot and dry biomes could be amplified in the topsoil, where we show soils to become increasingly warmer than the air at higher temperatures. Similarly, changes in precipitation regimes – and thus soil moisture – can significantly alter the relationship between air and soil temperature, with critical implications for soil moisture-atmosphere feedbacks, especially in hot biomes (Zhou *et al.*, 2021). Indeed, as precipitation decreases, offsets could turn more positive and soil temperatures might warm even faster than the observed macroclimate warming. Therefore, future research should not only use soil temperature data as provided here to study belowground ecological processes (De Frenne *et al.*, 2013, Lembrechts *et al.*, 2020), it should also urgently investigate future scenarios of soil climate warming in light of changing air temperature and precipitation, at ecologically relevant spatial and temporal resolutions to incorporate the non-linear relationships exposed so far (Lembrechts & Nijs, 2020).

Within-pixel heterogeneity

We chose to use a 1-km² resolution spatial grid to model mismatches between soil and air temperature, aggregating all values from different microhabitats within the same 1-km² grid cell (e.g., sensors in forested versus open patches) as well as all daily and diurnal variation within a month. We are aware that higher spatiotemporal resolutions would likely reveal the importance of locally heterogeneous variables. Finer-scale factors that affect the local radiation balance and wind (e.g., topography, snow and vegetation cover, urbanization) at the landscape to local scales and those that directly affect neighbouring locations (e.g. topographic shading and cold-air drainage, Whiteman, 1982, Ashcroft & Gollan, 2012, Lembrechts *et al.*, 2020) would probably have emerged as more important drivers at regional scales and with higher spatiotemporal resolutions than those used here (Supplementary Material Fig. S12). The latter is illustrated by the multi-degree Celsius difference in mean annual temperature between forested and non-forested locations within the same biome (Supplementary Material Table S7), as well as the lower accuracy obtained during winter months at high latitudes, where and when fine-scale spatial heterogeneity in snow cover and depth probably lowers models' predictability at the 1-km² resolution. *In-situ* measurements were largely from areas with a representative vegetation type, supporting the reliability of our predictions for the dominant habitat type within a pixel. However, improved accuracy at high latitudes will depend on the future development of high-resolution snow depth and/or snow water equivalent estimates (Luojus *et al.*, 2010).

The SoilTemp database (Lembrechts *et al.*, 2020) will facilitate the necessary steps towards mapping soil temperature at higher spatiotemporal resolutions in the future, with its georeferenced time series of *in situ* measured soil and near-surface temperature and associated metadata. Nevertheless, when compared to existing soil temperature products such as those from ERA5L (Copernicus Climate Change Service (C3S), 2019), we emphasize that the increased resolution of our data products already provides a major technical advance, even though substantial finer within-pixel variation is still lost through spatiotemporal aggregation.

Conclusions

The spatial (biome-specific) and temporal (seasonally variable) offsets between air and soil temperature quantified here likely bias predictions of current and future climate impacts on species and ecosystems (Körner & Paulsen, 2004, Kearney *et al.*, 2009, Cooper, 2014, Opedal *et al.*, 2015, Graae *et al.*, 2018, Zellweger *et al.*, 2020, Bergstrom *et al.*, 2021). Temperature in the topsoil rather than in the air ultimately defines the distribution and performance of most terrestrial species, as well as many ecosystem functions at or below the soil surface (Pleim & Gilliam, 2009, Portillo-Estrada *et al.*, 2016, Hursh *et al.*, 2017, Gottschall *et al.*, 2019). As many ecosystem functions are highly correlated with temperature (yet often non-lineary, Johnston *et al.*, 2021), soil temperature rather than air temperature should in those instances be the preferred predictor for estimating their rates and temperature thresholds (Rosenberg *et al.*, 1990, Coûteaux *et al.*, 1995, Schimel *et al.*, 1996). Correcting for the non-linear relationship between air and soil temperature identified here is thus vital for all fields investigating abiotic and biotic processes relating to terrestrial environments (White *et al.*, 2020). Indeed, soil temperature, macroclimate and land-use change will interact to define the future climate as experienced by organisms, and high-resolution soil temperature data is needed to tackle current and future challenges.

By making our global soil temperature maps and the underlying monthly offset data openly available, we offer gridded soil temperature data for climate research, ecology, agronomy and other life and environmental sciences. Future research has the important task of further improving the spatial and temporal resolution of global microclimate products as microclimate operates at much higher temporal resolutions, with temporal variation over hours, days, seasons and years (Potter *et al.*, 2013, Bütikofer *et al.*, 2020), as well as to confirm accuracy of predictions in undersampled regions in the underlying maps (Lembrechts *et al.*, 2021). However, we are convinced that the maps presented here bring us one step closer to having accessible climate data exactly where it matters most for many terrestrial organisms (Ashcroft *et al.*, 2014, Niittynen & Luoto, 2018, Lembrechts & Lenoir, 2019). We nevertheless highlight that there is still a long way to go towards global soil microclimate data with an optimal spatiotemporal resolution. We therefore urge all scientists to submit their microclimate time series to the SoilTemp database to fill data gaps and help to increase the spatial resolution until it matches with the scale at which ecological processes take place (Bütikofer *et al.*, 2020, Lembrechts *et al.*, 2020).

Data availability

All monthly data to train the models and reproduce the figures, sampled covariate data, and models are available at https://doi.org/10.5281/zenodo.4558663. Soil bioclim layers SBIO1-11 are also directly available in Google Earth Engine under projects/crowtherlab/soil_bioclim/soil_bioclim_0_5cm and projects/crowtherlab/soil_bioclim/soil_bioclim_5_15cm.

Code availability

All source code is available at https://doi.org/10.5281/zenodo.4558663.

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Supplementary figures and tables

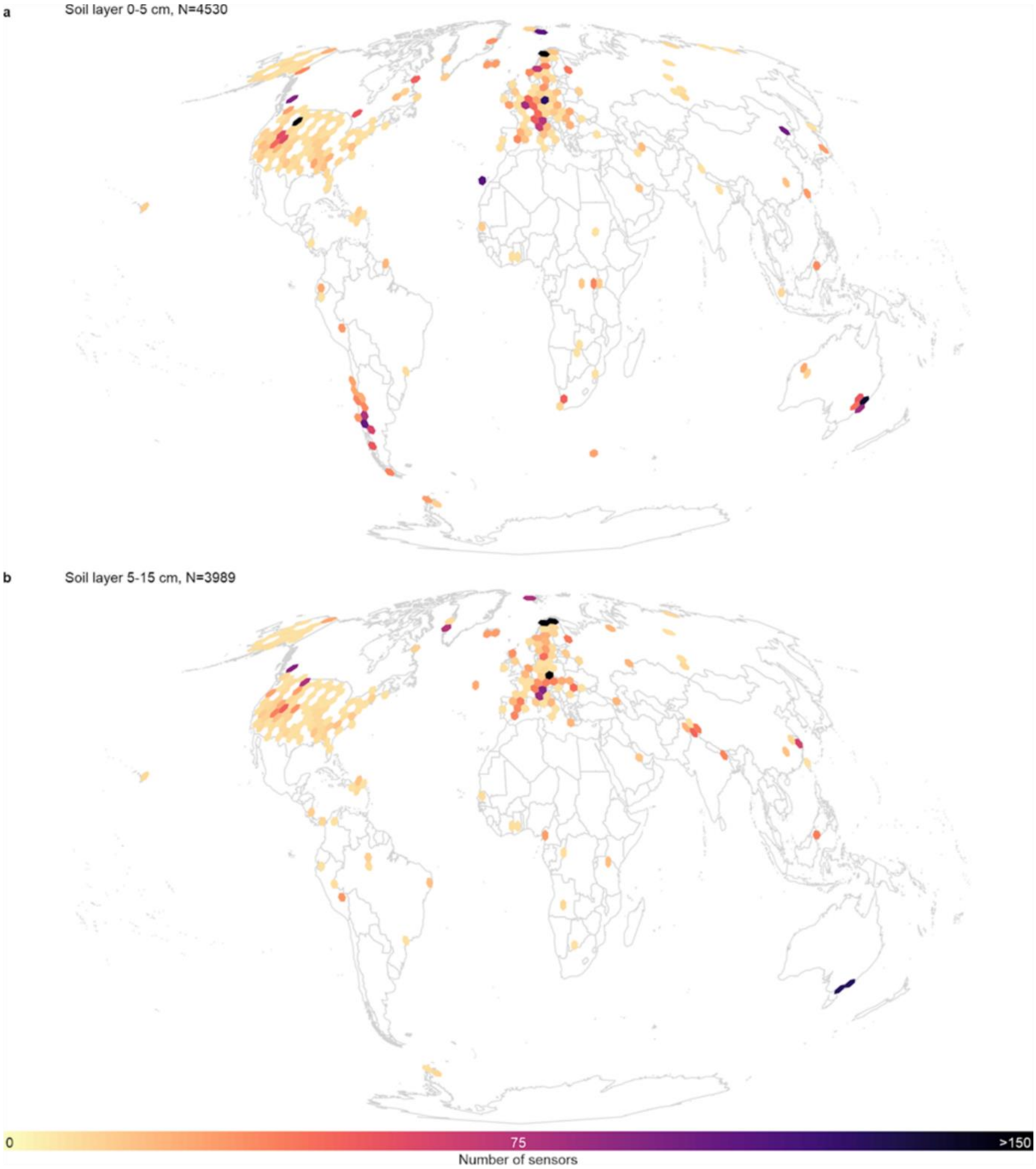

Fig. S1: Global distribution of the in-situ measurements. Distribution of all sensors in the topsoil (0–5 cm depth, (a), N = 4,530) and the second layer (5–15 cm depth, (b), N = 3,989). Background world map in Mollweide projection, hexagons with a resolution of approximately 70,000 km². Note that sensors appearing here and not in Fig. 1a or Fig. S3 covered time series of less than one year, and thus were only used in the monthly models (see methods for details).

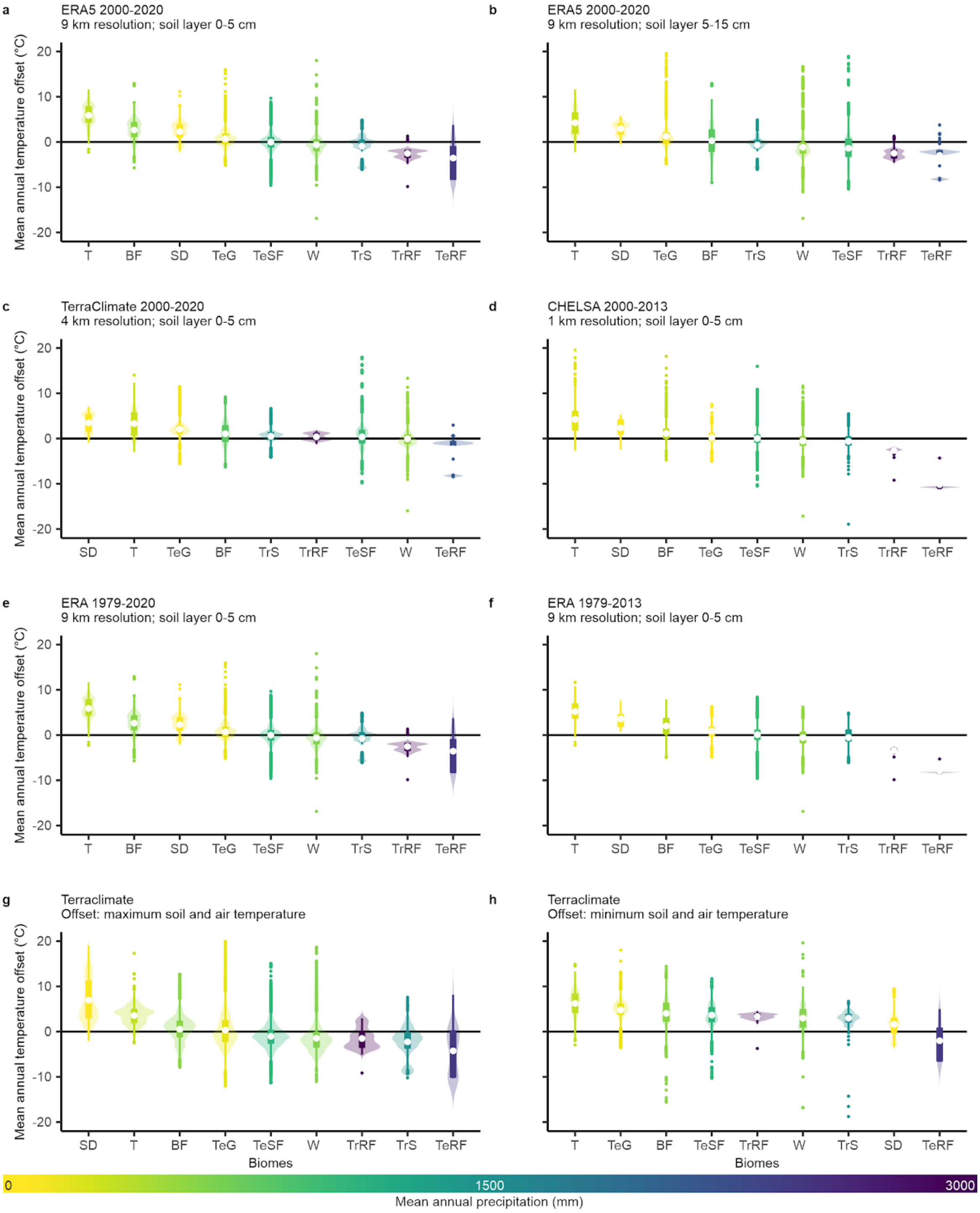

Fig. S2: Annual temperature offsets per biome (as in Fig. 1b), for the first (0–5 cm depth) and second soil layer (5–15 cm depth) and for different air temperature data sources and time periods. Box- and violin plots of the mean annual temperature offsets per Whittaker biome, ordered and coloured by mean annual precipitation. As a standard, we used ERA5L (2000-2020, 9 km resolution) and the topsoil (0–5 cm, (a), see also Fig. 1b). We compare now with the second soil layer (5–15 cm depth, b), with TerraClimate (2000-2020, 4 km resolution, c) and CHELSA (2000-2013, 1 km resolution, d), with ERA5L for the full period (1979-2020, e) and the period matching the bioclimatic variables (1979-2013, f). We also calculate offsets between maximum (95th percentile, g) soil and air temperature, and minimum (5th percentile, h) soil and air temperature, with maximum and minimum air temperature based on TerraClimate. Panels (c) to (h) all use the topsoil data (0–5 cm depth). All panels show relatively consistent results (i.e. strongly positive offsets in tundra, boreal forests, subtropical deserts and temperate grasslands, and weakly negative offsets in tropical savannas and temperate and tropical rainforests). Only annual soil temperature minima were on average higher than corresponding air temperature minima in all but one biomes.

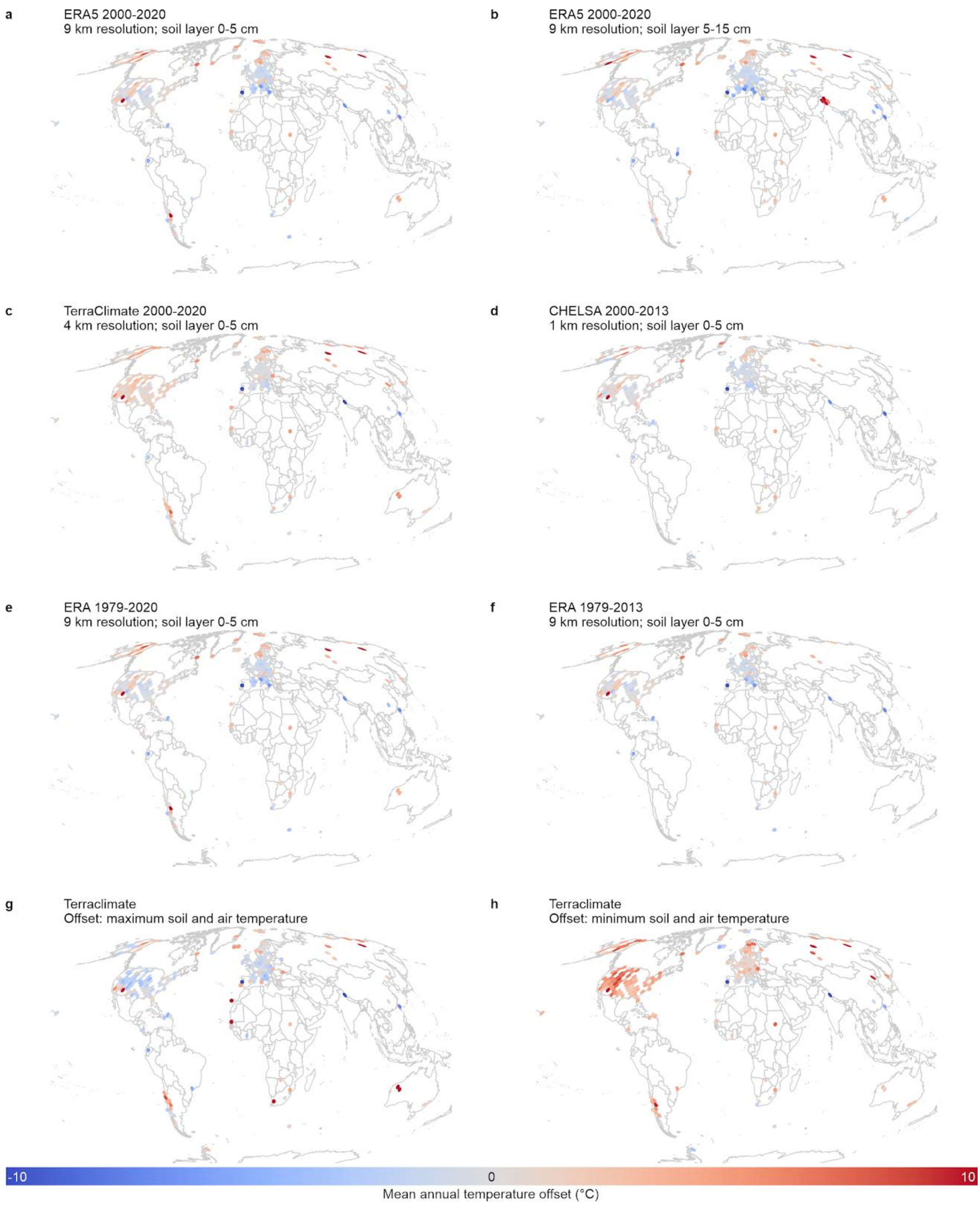

Fig. S3: Annual temperature offset maps (as in Fig. 1a), for the first (0–5 cm depth) and second soil layer (5–15 cm depth), for different air temperature data sources and time periods, and for maximum and minimum temperature. Distribution of sensors across the globe, coloured by the annual offset (in °C) between in-situ measured soil temperature and modelled air temperature. As a standard in Fig. 1a, we used ERA5L (2000-2020, 9 km² resolution) and the topsoil (0–5 cm, also here in a). We compare now with the second soil layer (5–15 cm depth, b), with TerraClimate (2000-2020, 4 km² resolution, c) and CHELSA (2000-2013, 1 km² resolution, d) for the topsoil layer, and with ERA5L for the full period (1979-2020,e) and the period matching the bioclimatic variables (1979-

2013, f). We also calculate offsets between maximum (95^{th} percentile, g) soil and air temperature, and minimum (5^{th} percentile, h) soil and air temperature, with maximum and minimum air temperature based on TerraClimate. Background world map in MollWeide projection, offsets averaged per hexagon with a resolution of approximately 70,000 km^2, made using the dggridR-package in R. Conclusions about consistency between methods similar as in Fig. S2.

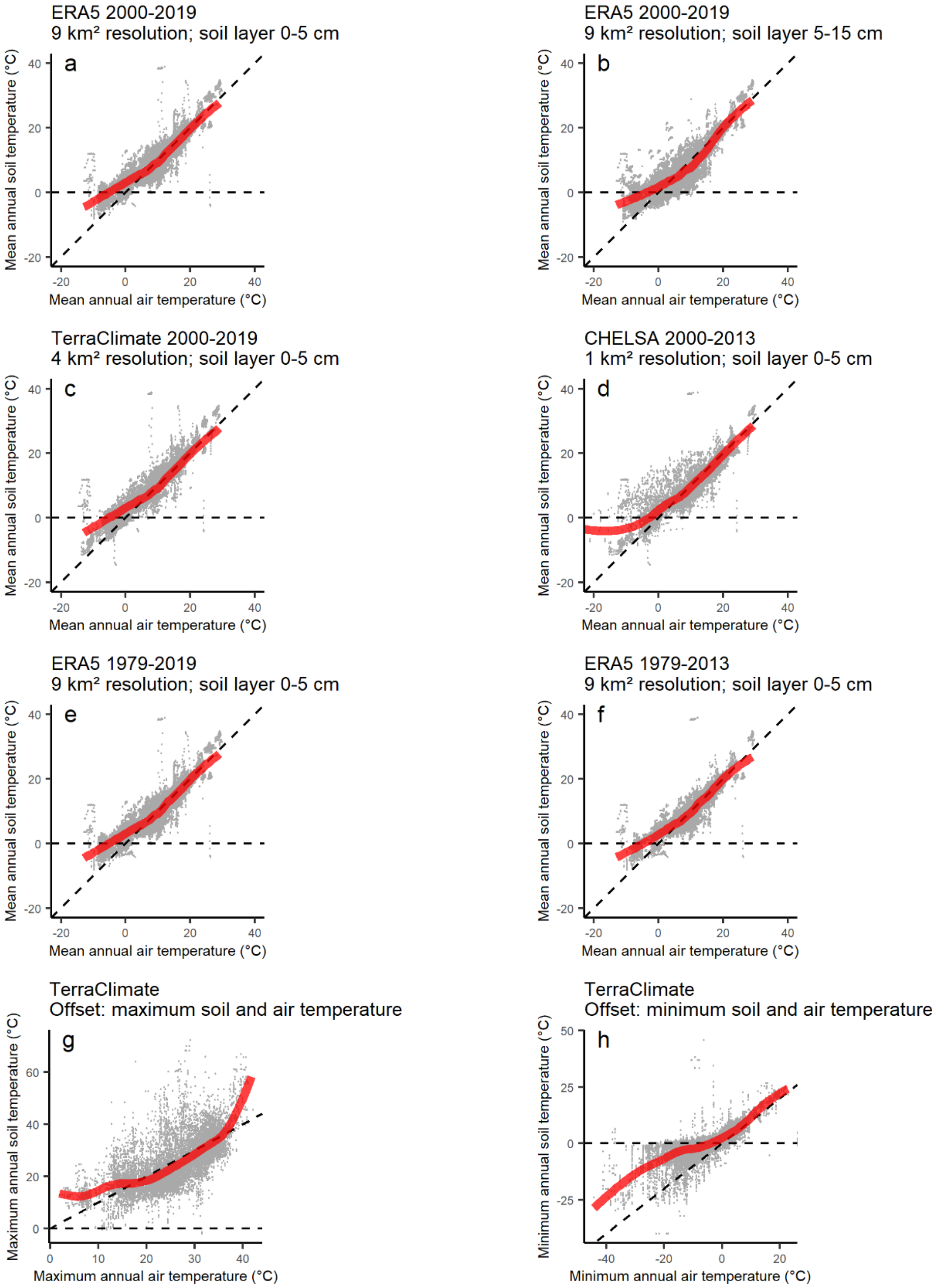

Fig. S4: Relationship between mean annual soil and air temperature at a 1 × 1 km resolution. Point cloud of in-situ mean annual soil temperature (°C) as a function of gridded mean annual air temperature for all in-situ measurements averaged at a 1 × 1 km resolution. As a standard, we used ERA5L (2000-2020, 9 km² resolution) and the topsoil (0–5 cm depth, a). We compare this first with the second soil layer (5–15 cm depth, b). We also compare with analyses for the top soil layer using TerraClimate (2000-2020, 4 km² resolution, c) and CHELSA (2000-2013, 1 km² resolution, d), and with ERA5L for the full period (1979-2020, e) and the period matching the bioclimatic variables (1979-2013, f). We also plot offsets between maximum (95th percentile, g) soil and air temperature, and minimum (5th percentile, h) soil and air temperature, with maximum and minimum air temperature based on

TerraClimate. Straight dashed line indicate a thermal offset of 0°C, and the 1:1-relationship between soil and air temperature, thick red lines the relationship based on generalized additive models, indicating in all cases warmer soil than air temperatures in cold extremes, yet slightly cooler soils at intermediate temperatures (except for h).

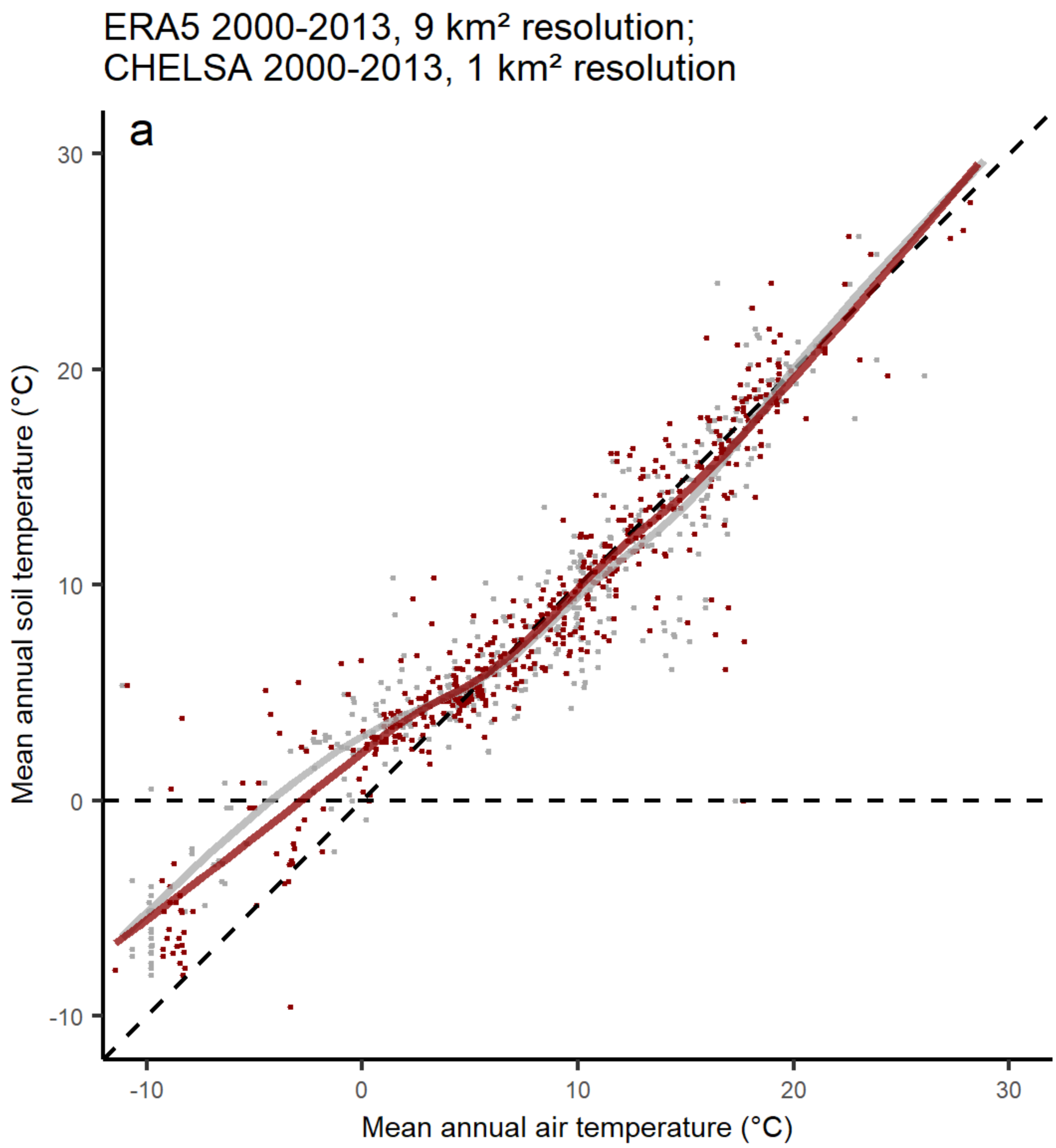

Fig. S5: Relationship between mean annual soil and air temperature for ERA5L (grey) versus CHELSA (red). Point cloud of in-situ mean annual soil temperature (°C) as a function of gridded mean annual air temperature for all in-situ measurements averaged at 1 km², between 2000 and 2013, for ERA5L (grey, 9-km² resolution) and CHELSA (dark red, 1 × 1 km resolution). Straight dashed line indicate a thermal offset of 0°C, and the 1:1-relationship between soil and air temperature, grey and red lines the relationship based on generalized additive models. As in Fig. S4, yet highlighting the strong overlap in pattern when using CHELSA vs ERA5L.

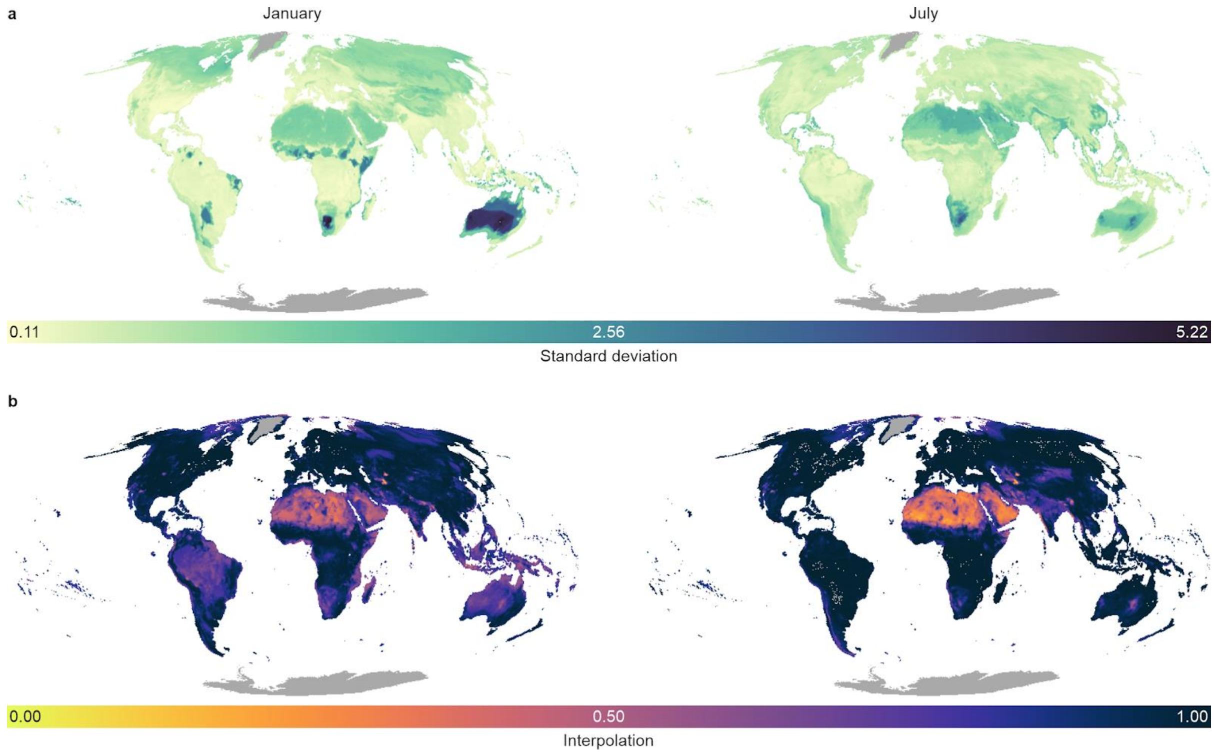

Fig. S6: Predictive performance of the temperature offset models in the second soil layer (5–15 cm depth). Analyses for the temperature offset between in-situ second soil layer (5–15 cm depth) temperature and free-air temperature. (a) Predicted standard deviation from a cross-validation analysis that iteratively varied the set of covariates (explanatory data layers) and model hyperparameters (i.e., number of variables per split; minimum leaf population) across 100 models and evaluated model strength using 10-fold cross-validation, for January (left) and July (right), as examples of the two most contrasting months. (b) The fraction of axes in the multidimensional environmental space for which the pixel lies inside the range of data covered by the sensors in the database. Pixels with low values indicate that the model has to extrapolate for many of the environmental layers for that specific pixel.

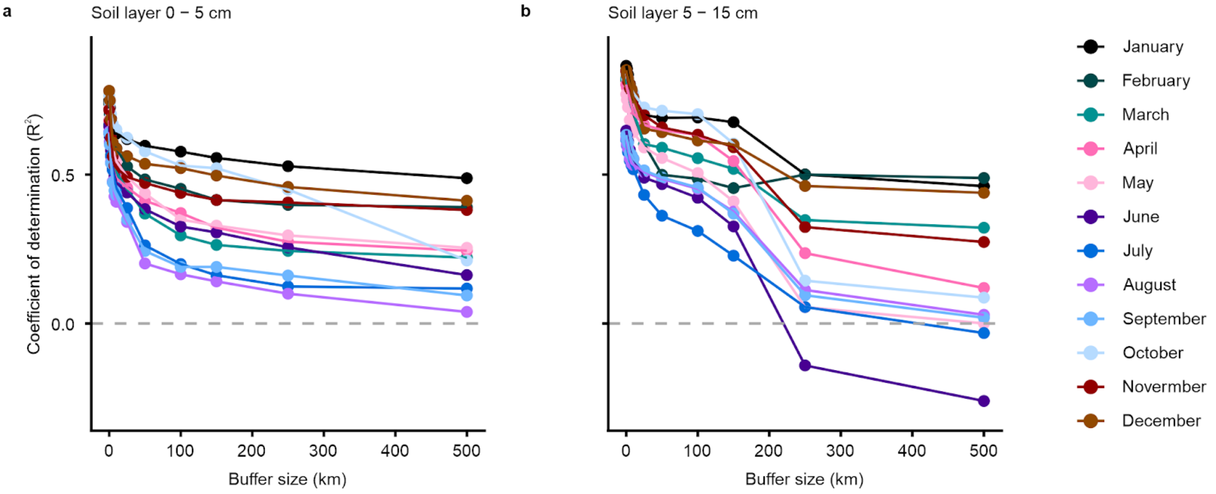

Fig. S7: spatial leave-one-out cross-validation. R^2 of all monthly models at the two soil depths using a spatial leave-one-out cross validation approach. This approach trains a model for each sample in the dataset on all remaining samples, with an increasingly large buffer around that focal sample. Note that a decrease in R^2 should be expected with increasing buffer size due to the removal of parts of the environmental gradient from the training dataset. Nevertheless, results show that spatial autocorrelation differs across the months, with uneven global data coverage likely causing lowest confidence for May to September at 5–15 cm depth, where use of data outside of the environmental gradient as covered by the data is thus particularlydiscouraged (see Fig 5b and Fig. S6b).

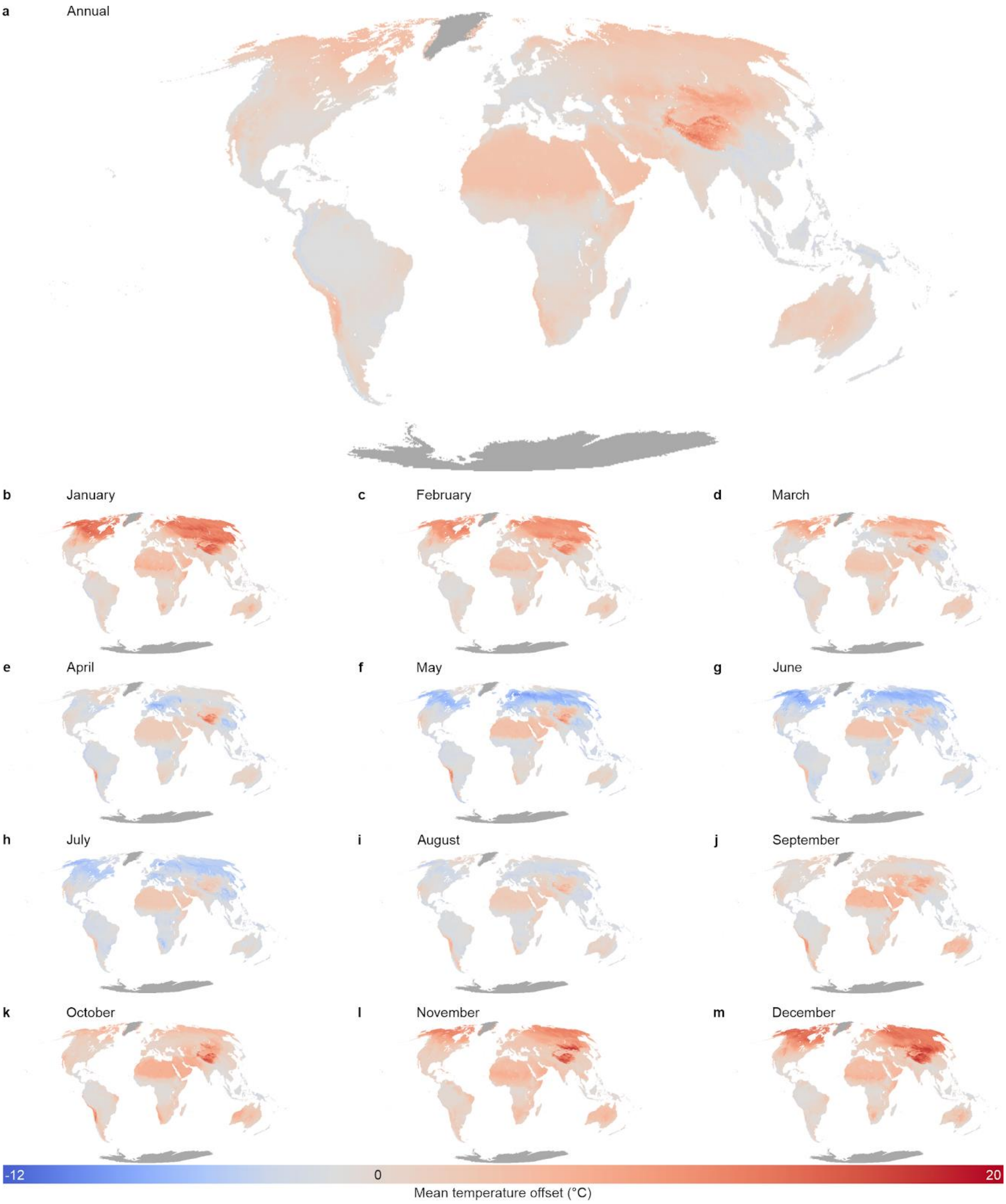

Fig. S8: Modelled mean temperature offset in the second soil layer (5–15 cm depth). Modelled annual (a) and monthly (b-m) temperature offset (in °C) between in-situ measured soil temperature (second soil layer, 5–15 cm depth) and modelled air temperature, in addition to the first soil layer (0–5 cm depth) used in Fig. 2.

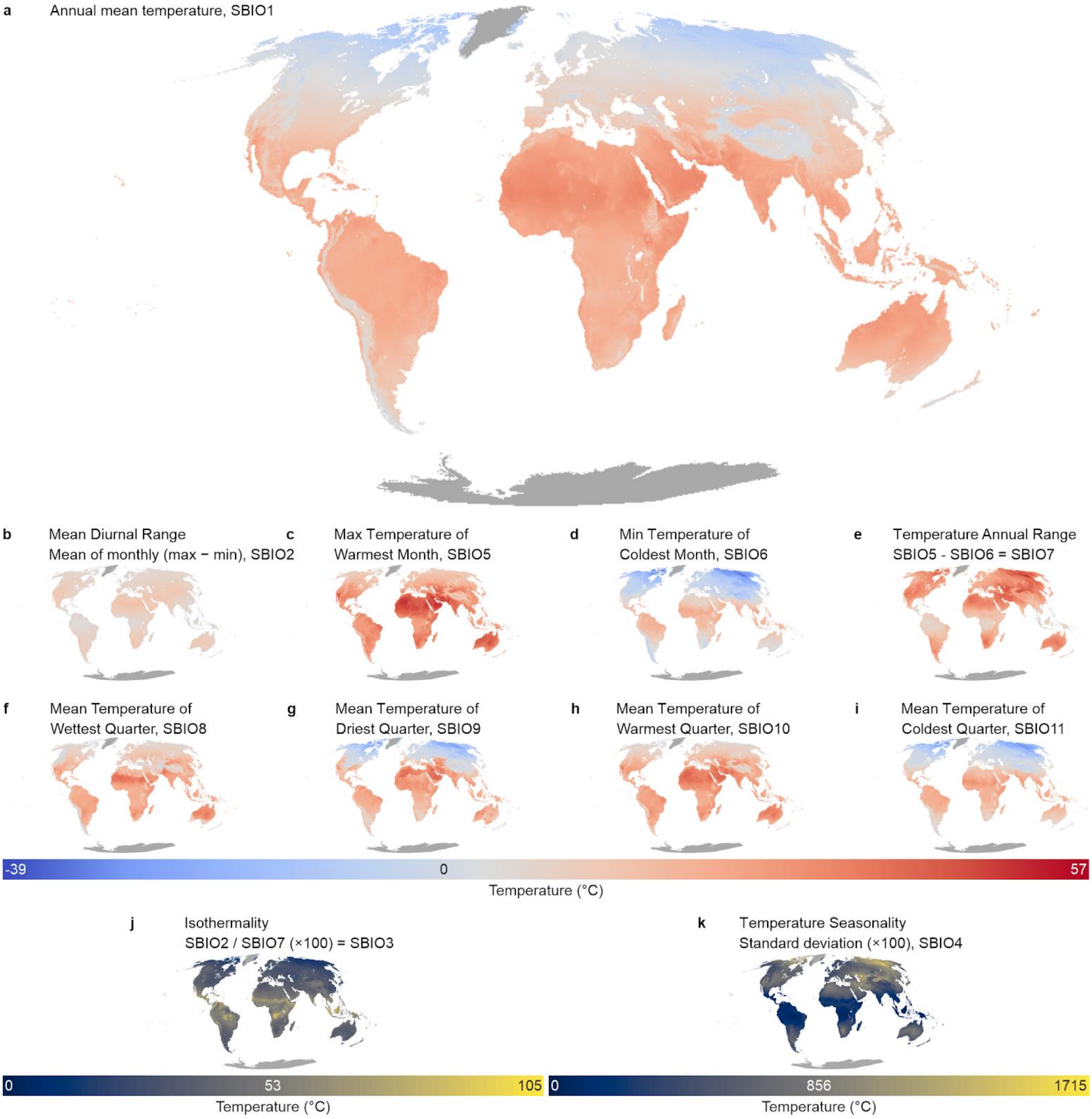

Fig. S9: Bioclimatic variables for the second soil layer. Global maps of bioclimatic variables for the second soil layer (5–15 cm depth) climate, calculated using the maps of monthly temperature offsets (see Fig. 2, Fig. S8) and the bioclimatic variables for air temperature from CHELSA (*4*).

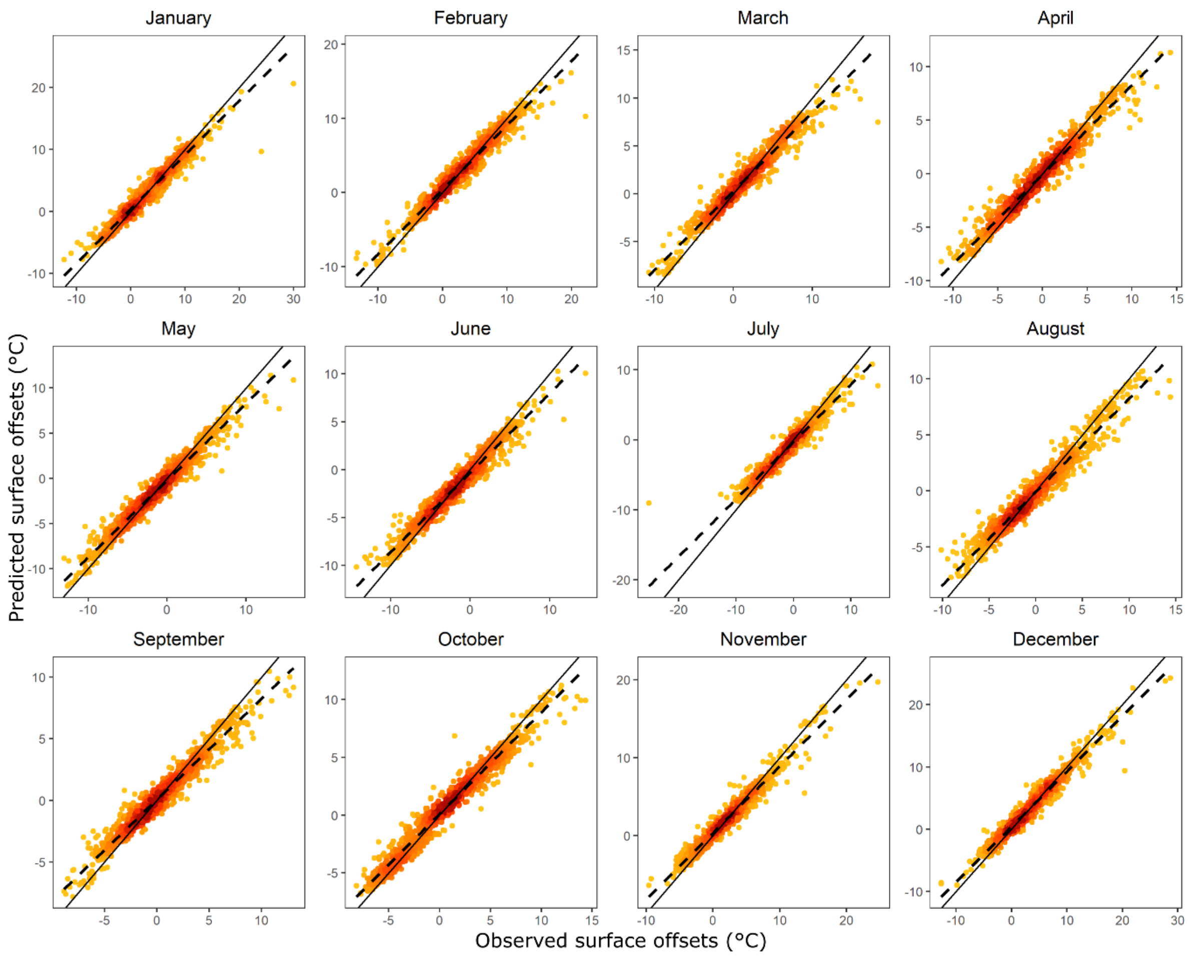

Fig. S10: Observed versus predicted temperature offsets. Correlative plots showing temperature offsets – averaged at a 1 × 1 km resolution – as observed in the field, versus those as predicted by the models, separately for each month. Colours show density of points (darker = higher point density). Dashed lines from linear regressions; solid lines refer to the 1:1-line of perfect correlation between predicted and observed offsets.

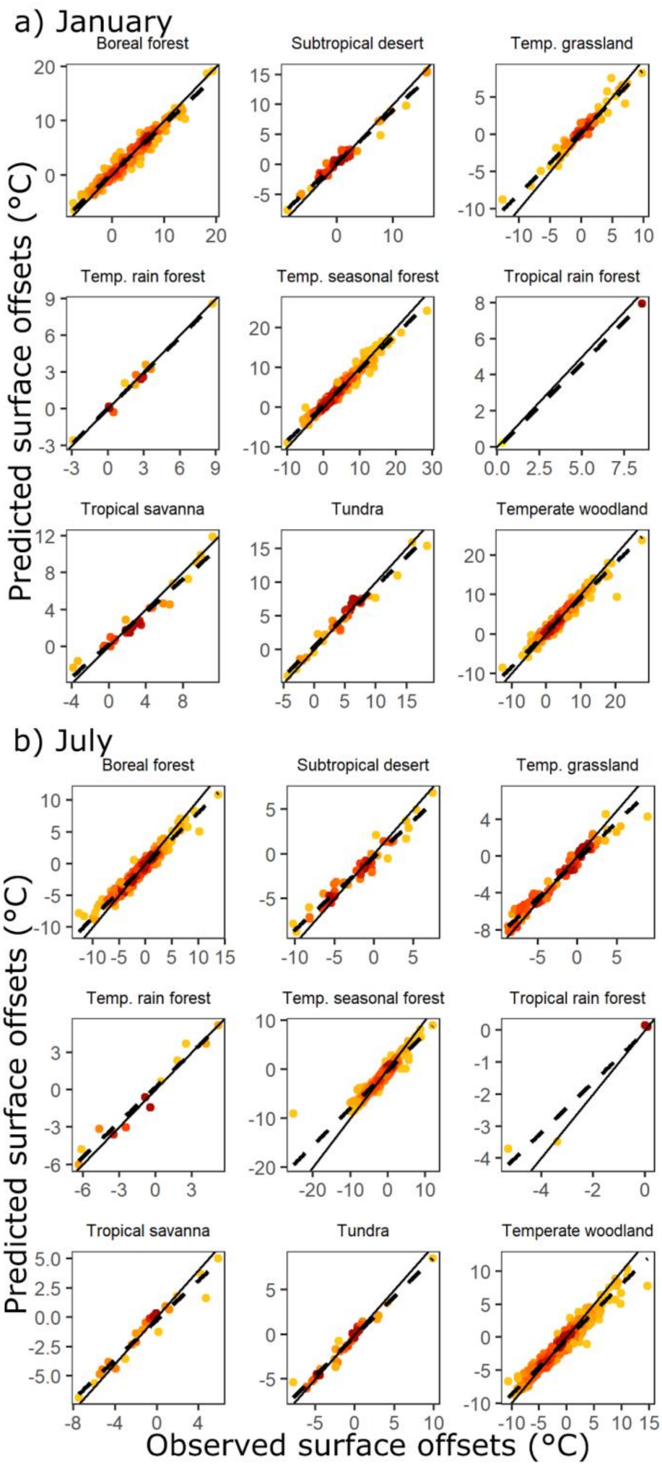

Fig. S11: Observed versus predicted temperature offsets per biome. Correlative plots showing temperature offsets – averaged at a 1 × 1 km resolution – as observed in the field, versus those as predicted by the models, separately for each biome, for January (a) and July (b). Colours show density of points (darker = high point density). Dashed lines from linear regressions; solid lines refer to the 1:1-line of perfect correlation between predicted and observed offsets.

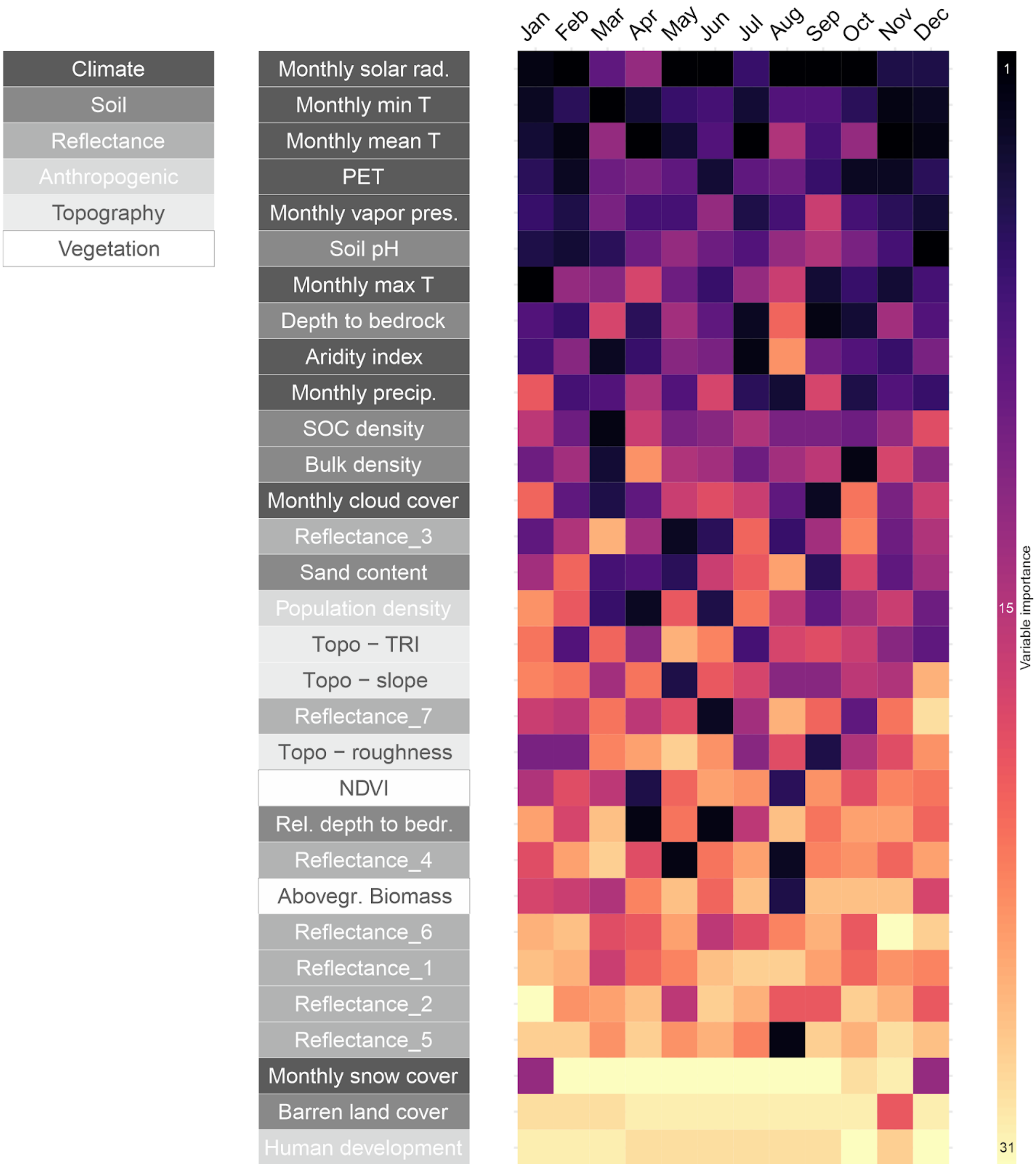

Fig. S12: Relative importance of explanatory variables. Explanatory variables in all twelve monthly analyses sorted by mean Variable Importance (computed based on the summed decrease of impurity over all trees in the forest that results from the variable used at a node; higher for variables with a higher importance) across all models of the first soil layer (0–5 cm depth) (first variable = ranked on average most importantly across all twelve monthly models)**.** Colours represent relative variable importance (ranked from 1 to 31, with 1 the highest importance) within each monthly model for the topsoil (0–5 cm depth). T = temperature, PET = potential evapotranspiration, SOC = soil organic carbon, TRI = topographic roughness index, NDVI = normalized difference vegetation index. For full details on all explanatory variable layers, see Data S1.

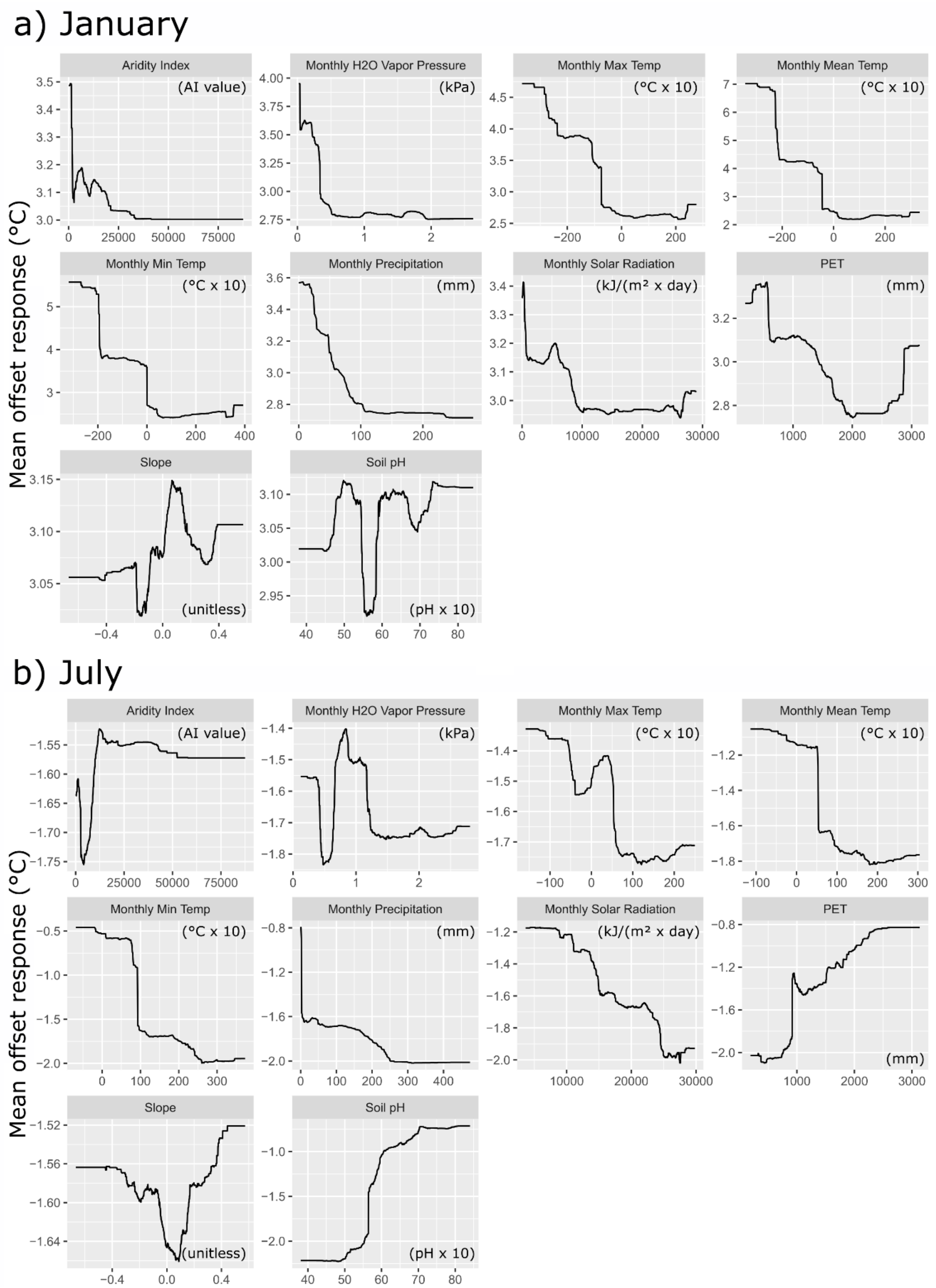

Fig. S13: Partial dependency plots of main effects. Partial dependency plots of the 10 most important variables (selection based on the mean Feature Importance from Fig. S12) for January (a; top) and July (b; bottom), as examples of the two most contrasting months. Results for the first soil layer (0–5 cm depth).

Supplementary Tables

Table S1: Number of sensors from the most common logger brands in the top soil (left, 0–5 cm depth) and the second soil layer (right, 5–15 cm depth). Other sensors include among others Decagon devices, GeoPrecision data loggers, thermocouples and TinyTags.

Logger brand	**Number of sensors**	
	0–5 cm	**5–15 cm**
iButton	1840	1685
TOMST	512	1090
HOBO	689	491
Lascar	247	0
Others	1025	587

Table S2: Number of sensors in each soil layer

Depth of soil layer (cm)	**Number of sensors**
0–5	4530
5–15	3989
15-30	484
30-60	294
60-100	54
100-200	11

Table S3: Number of data points (in brackets the number of unique pixels after averaging at 1 × 1 km pixel resolution) for each month as used in the models.

Month	**N° of data points (0–5 cm)**	**N° of data points (5–15 cm)**
January	6674 (1212)	10130 (977)
February	6649 (1223)	10214 (986)
March	6527 (1184)	10345 (979)
April	6439 (1093)	10266 (989)
May	6611 (1150)	10510 (1003)

June	6537 (1154)	10546 (1011)
July	6874 (1352)	10515 (1141)
August	6960 (1383)	10950 (1098)
September	6690 (1317)	10484 (1019)
October	6991 (1299)	10429 (1018)
November	6995 (1215)	10683 (996)
December	6846 (1193)	10607 (988)

Table S4: Number of unique pixels after averaging the annual data at 1 × 1 km pixel resolution for each biome, as used in Fig. 1. The number of individual annual averages on which this number is based is shown between brackets.

Biome	N° of pixels (0–5 cm)
Boreal forest	240 (10168)
Sub-tropical desert	37 (802)
Temperate grassland	66 (9558)
Temperate rainforest	10 (27)
Temperate seasonal forest	245 (21566)
Tropical rainforest	2 (299)
Tropical savanna	13 (2062)
Tundra	29 (1584)
Temperate woodland	224 (16952)

Table S5: Number of unique pixels after averaging the monthly data at a 1 × 1 km pixel resolution for each biome as used in the models, averaged across all months.

Biome	N° of pixels (0–5 cm)	N° of pixels (5–15 cm)
Boreal forest	284	323
Sub-tropical desert	46	4
Temperate grassland	82	63
Temperate rainforest	12	2
Temperate seasonal forest	349	304
Tropical rainforest	5	9
Tropical savannah	26	31
Tundra	35	34
Temperate woodland	466	353

Table S6: Biome-specific quantile distribution of the estimated aboveground biomass at the 1 x 1 km pixel level (unit: tons/ha i.e., Mg/ha, for the year 2010, Santoro, 2018) for each sensor identified as either measuring in forests (top) or open vegetation (bottom), for all sensors for which the latter information was available (numbers between brackets). Numbers in green indicate sensors under aboveground biomass of 1.00 tons/ha or higher, here identified as forested.

Biome	1%	5%	25%	50%	75%	95%	99%
Forests							
Boreal forest (18)	53.70	60.50	77.50	84.50	106.00	114.15	114.83
Subtropical desert (3)	2.00	2.00	2.00	2.00	38.00	66.80	72.56
Temperate grassland (12)	3.00	3.00	16.00	45.00	86.00	98.00	98.00
Temperate rain forest (7)	53.12	53.60	63.50	76.00	220.00	296.60	322.52
Temperate seasonal for. (227)	17.00	32.50	63.00	101.00	177.00	291.00	431.00
Tropical rain forest (6)	149.50	167.50	245.50	277.50	284.00	313.75	321.15
Tropical savanna (17)	186.00	186.00	186.00	186.00	207.00	224.00	224.00
Tundra (3)	8.04	8.20	9.00	10.00	12.00	13.60	13.92
Temperate woodland (145)	0.00	0.20	8.00	24.00	120.00	218.00	242.36
Open vegetation							
Boreal forest (463)	0.00	0.00	0.00	0.00	53.00	53.00	105.00
Subtropical desert (13)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Temperate grassland (44)	0.00	0.00	0.00	0.00	0.00	32.00	107.00
Temperate rain forest (0)	-	-	-	-	-	-	-
Temperate seasonal for. (89)	0.00	0.00	0.00	0.00	32.00	223.00	248.08
Tropical rain forest (0)	-	-	-	-	-	-	-
Tropical savanna (0)	-	-	-	-	-	-	-
Tundra (75)	0.00	0.00	0.00	0.00	0.00	6.00	10.00
Temperate woodland (93)	0.00	0.00	1.00	19.00	66.00	171.00	172.00

Table S7: Difference in temperature offset between forested and unforested habitats. Mean and standard deviation of offsets per Whittaker biome for all sensors, and for sensors in forested and non-forested habitats separately. All values averaged at a 1 × 1 km resolution (number between brackets = number of unique 1 × 1 km pixels), only biomes with sufficient number of loggers in forested habitats are shown. Habitat assessment at the location of the sensor based on observations by the contributors, whenever available (60% of sensors).

Biome	All	Forested	Non-forested
Boreal forest	2.47 ± 2.01 (240)	3.40 ± 1.64 (41)	3.12 ± 1.77 (105)
Temperate grasslands	0.92 ± 2.13 (66)	1.39 ± 2.79 (4)	1.30 ± 2.79 (27)
Temperate seasonal forests	0.46 ± 2.79 (245)	-0.82 ± 2.21 (53)	1.00 ± 3.95 (20)
Temperate woodland	-0.12 ± 3.38 (224)	-0.71 ± 3.11 (31)	1.22 ± 4.31 (35)

Data S1. (separate file)

Final selection of global covariate layers used for geospatial modelling. A total of 31 global covariate layers was used in our modelling approach.