INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. (2015)
Published online in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.4436

RMetS
Royal Meteorological Society

Spatial downscaling of European climate data

Adam Moreno* and Hubert Hasenauer

Institute of Silviculture, University of Natural Resources and Life Sciences, Vienna, Austria

ABSTRACT: E-OBS(European Observations) is a gridded climate data set which contains maximum temperature, minimum temperature, and precipitation on a daily time step. The data can be as fine as 0.25° in resolution and extends over the entire European continent and parts of Africa and Asia. However, for studying regional or local climatic effects, a finer resolution would be more appropriate. A continental data set with resolution would allow research that is large in scale and still locally relevant. Until now, a climate data set with high spatial and temporal resolution has not existed for Europe. To fulfil this need, we produced a downscaled version of E-OBS, applying the delta method, which uses WorldClim climate surfaces to obtain a $0.008\overline{3}°$ (about 1 × 1 km) resolution climate data set on a daily time step covering the European Union. The new downscaled data set includes minimum and maximum temperature and precipitation for the years 1951–2012. It is analysed against weather station data from six countries: Norway, Germany, France, Italy, Austria, and Spain. Our analysis of the downscaled data set shows a reduction in the mean bias error of 3 °C for mean daily minimum temperature and of 4 °C for mean daily maximum temperature. Daily precipitation improved by 0.15 mm on average for all weather stations in the validation. The entire data set is freely and publically available at ftp://palantir.boku.ac.at/Public/ClimateData.

KEY WORDS temperature; precipitation; climate; Europe; downscaling; E-OBS; elevation; WorldClim

Received 17 March 2015; Revised 5 June 2015; Accepted 8 June 2015

1. Introduction

Climate data are essential for understanding and modelling many ecological processes (VEMAP Members, 1995; Haylock *et al.*, 2008; Waring and Running, 2010). Gridded climate data provide information for every point across a landscape. These gridded data sets are essential for performing climate analyses, understanding biogeochemical processes, and for use in conjunction with satellite data and models.

Nearly 20 years ago, the first daily large-scale, fine-resolution climate data sets of the entire United States became available with the development of PRISM and Daymet with 1 × 10 km and 500 × 500 m resolutions respectively; both were limited by the digital elevation model resolution (Daly *et al.*, 1994; Thornton *et al.*, 1997). The availability of high-resolution, large-scale climate data sets has enabled more detailed studies of the climate's impact on epidemiology, ecology, agriculture, and genetics across United States (Guo *et al.*, 2006; Wimberly *et al.*, 2008; Luedeling *et al.*, 2009; Jay *et al.*, 2012). Large-scale, fine-resolution climate data sets in the United States are possible because of the easy accessibility policies to weather station data. Researchers studying Europe have been limited by the current state of climate data policy.

The absence of a comprehensive European weather network, a result of the continents administrative and cultural heterogeneity, makes obtaining weather station data very difficult and costly. European weather stations lack the density needed for daily interpolations to be made at high resolution and at regional-scales (Wijngaard *et al.*, 2003; Daly, 2006). Compounding the problem of data accessibility for climate interpolation throughout Europe, the quantity, quality, accessibility, and format of weather data varies from country to country (Wijngaard *et al.*, 2003). Many countries or geographic regions in Europe have their own locally produced interpolated gridded climate data sets that were possible because of access to the local weather station data network (Hofstra *et al.*, 2009; Isotta *et al.*, 2014; Masson and Frei, 2015). These data sets however use different methods and assumptions making harmonization difficult to obtain a single continental data set.

The ENSEMBLES group runs the European Climate Assessment & Data set (ECA&D) project which has gathered 7852 weather stations. Using this weather station network, they developed an interpolated gridded climate data set. This data set, referred to as European Observations (E-OBS), covers Europe on a daily time step (Haylock *et al.*, 2008). The resolution of the E-OBS data set is on a 0.25° regular grid (approximately 30 × 30 km). The coarseness of the gridded data is a result of station density limitations but is sufficient for studies performed at continental scale.

For studying orographic effects on climate, performing regional climate change analysis, and providing knowledge of spatial and temporal climate dynamics to users, it is essential to have high-resolution information (Frei and Schaer, 1998). Climate data at continental scales in high

* Correspondence to: A. Moreno, Institute of Silviculture, University of Natural Resources and Life Sciences, Vienna, Peter Jordan Straße 82, A-1190 Vienna, Austria. E-mail: adam.moreno@boku.ac.at

resolution allow large-scale research efforts to provide insights which are locally relevant. A 1×1 km resolution data set permits more accurate simulations of carbon and water fluxes than the currently available 50×50 km or 10×10 km resolutions climate data sets (Turner *et al.*, 1996). Researchers with the ability to address fine scale issues while maintaining a large spatial outlook may better assist managers in decision making by providing information about processes on both local and landscape scales (Turner *et al.*, 1996; Seidl *et al.*, 2013). Furthermore, climate data at a resolution of 1×1 km ($0.008\overline{3}°$ or 30 arc seconds) can be used in conjunction with remote sensing products such as Moderate Resolution Imaging Spectroradiometer (MODIS) gross primary production and net primary production products that require such data for their processing algorithms (Zhao *et al.*, 2005). Therefore having a climate data set at a 1×1 km resolution combined with other data sets or algorithms provides a better understanding of the spatio–temporal complexities of European landscapes at various scales.

In Europe, scientists are forced to focus either on individual countries or regions using national data sets (Hasenauer *et al.*, 2003; Venäläinen *et al.*, 2005; Maselli *et al.*, 2012). Another common way to study climate on larger scales in Europe is to use point data, from weather stations or flux towers, as representive of larger areas (Janssens *et al.*, 2001; Ciais *et al.*, 2005). In addition, research performed at larger scales with low-resolution data lack the ability to analyse local level climate effects (Lorenz *et al.*, 2012; Hawkins *et al.*, 2013). However, to compare climate data from multiple regions of Europe, some sort of harmonization is required. The aformentioned data can prevent discrepancies between country boundries that result from different methodologies and weather station networks. A unified data set, covering the entirety of Europe, while maintaining fine-resolution information would reduce errors, uncertainty, and inconsistencies.

The aim of this study is to advance the current scientific understanding of both local level processeses and landscape level dynamics by developing a Pan-European high-resolution climate data set. A lack of accessibility to primary data collected from weather stations prevents direct interpolation of a gridded data set with a resolution of 1×1 km on a European scale. This limitation makes downscaling previously interpolated climate data the only option to create high-resolution data for all of Europe. The objective of this study is to downscale the E-OBS data set using WorldClim data (Hijmans *et al.*, 2005). We produced a new downscaled climate data set which covers the European continent. It includes daily minimum and maximum temperature and precipitation at a $0.008\overline{3}°$ (approximately 1×1 km) resolution for the years 1950–2012. To reach our objective we

1. Create an algorithm to downscale E-OBS data using WorldClim data.
2. Evaluate random variation and/or error resulting from the downscaling algorithm.
3. Validate the downscaled results against weather station data not used in the original E-OBS interpolation.

2. Data

Two data sets were used in the downscaling process: E-OBS version 8.0 at 0.25° resolution (approximately 30 km) obtained on 25 April 2013 and WorldClim version 1.4 release 3 at a $0.008\overline{3}°$ resolution (approximately 1 km) obtained on 22 February 2013.

2.1. European Observations

E-OBS is an interpolated gridded daily climate data set that covers all of Europe, including portions of Russia, Asia, and Africa from 1950 to the present (Haylock *et al.*, 2008). Several parameters are included in this data set: daily mean temperature, maximum temperature, minimum temperature, precipitation, and sea level pressure. These data are available on various resolutions including on a regular grid with 0.25° and 0.5° resolutions

The E-OBS data set was created using a hybrid approach of Kriging and a thin-plate spline (Journal and Huijbregts, 1978; Haylock *et al.*, 2008). The authors of E-OBS first generated monthly means using the spline technique. Kriging was used to interpolate daily differences from the monthly mean. This difference was then applied to the monthly mean to obtain a daily value. E-OBS used 7852 weather stations throughout Europe for the release used in this study. Only 61% of which were publicly available to others outside the ENSEMBLE group. E-OBS has an uneven underlying weather station density across Europe which creates areas of high and low uncertainty (Haylock *et al.*, 2008).

2.2. WorldClim

WorldClim is a set of climate surfaces designed to provide long-term monthly averages of several climate variables (Hijmans *et al.,* 2005). Every cell has 12 values for each parameter, one value for each month. These values are the monthly means over the entire time period that was available for interpolation. WorldClim monthly mean variables include minimum and maximum temperature, precipitation, and 19 derived bioclimatic variables, which were not used in our study. WorldClim data are available at a $0.008\overline{3}°$ resolution globally.

WorldClim is developed using ANUSPLIN (Hutchinson, 2004), a thin-plate smoothing spline procedure as described in Hutchinson (Hutchinson, 1995). Hijmans *et al.* (2005), the developers of WorldClim, obtained input data from various sources globally consisting of 47 554 weather stations. In addition to climate data, they use two different digital elevation models (DEM) for interpolation. The two DEMs used were the Shuttle Radar Topography Mission (SRTM) (Farr *et al.*, 2007) and the GTOPO30 from the United States Geological Survey (USGS). Several problems exist associated with the input data sets. First, the authors of WorldClim note that there were problems matching weather station elevation with

DEM elevation; many times they simply did not match. Second – and relevant to our study – the authors explicitly note that obtaining weather station data in Europe was difficult. Finally, precipitation uncertainty is higher in mountainous regions. Many studies use WorldClim data to study ecosystems in areas with a lack of climate data (Nekola and Brown, 2007; Peterson and Nakazawa, 2007; Peterson *et al.*, 2007; Hawkins, 2010). Studies have found the accuracy of WorldClim data varies seasonally (Ezzine *et al.*, 2014).

3. Methods

3.1. Downscaling procedure

The conceptual framework is to use the fine-resolution WorldClim data to adjust the course resolution E-OBS cells to obtain our desired 1 × 1 km resolution daily. We applied a spatial delta method with a monotone cubic interpolation of anomalies (Mote and Salathe, 2010; Mosier *et al.*, 2014).

Columns 118–298 and rows 16–163 of the original E-OBS gridded data were downscaled due to data storage and computation limitations. The latitude and longitude of the upper left corner are 71.33°N, 10.833°W and the lower right hand corner are 34.583°N, 34.2499°E.

We used the delta method for downscaling, similar to the Piecewise Cubic Hermite Interpolating Polynomials (PCHIP) method described in Mosier *et al.* (Mosier *et al.*, 2014). This method uses climate data sets at different spatio–temporal resolutions to derive a new data set with a desired spatio–temporal resolution. This specific method is essentially a monotone cubic interpolation that varies the calculation of anomalies based on whether we are calculating temperature or precipitation.

To begin downscaling, in step 1, we upscaled the WorldClim data to the E-OBS resolution of 30 × 30 km (Figure 1). We averaged the WorldClim cells within each 30 × 30 km area for upscaling.

In step 2, we calculated the difference between the upscaled WorldClim cell and the E-OBS cell (Figure 1). The calculations in our algorithm for temperature are different than those for precipitation (Equations (1) and (2)). The difference in calculations was to prevent negative precipitation values which can occur with a simple subtraction:

$$\mathrm{d}T = \mathrm{WC} - E \tag{1}$$

$$\mathrm{d}P = E/\mathrm{WC} \tag{2}$$

where dT is the difference for temperature, dP is the difference for precipitation, WC is the upscaled WorldClim value, and E is the E-OBS value.

In step 3, we step through each cell of the WorldClim gridded data, one at a time, retrieving the value of the cell which was then be used in step 5 (Figure 1). This location was also found on the 30 × 30 km difference cells. Note that WorldClim data are given on monthly time steps and all calculations used the appropriate month's data.

During step 4, we calculated the weighted difference of the selected 30 × 30 km cell and that of the three adjacent 30 × 30 km cells (Figure 1). These four differences were weighted by the distance from the downscaling point to each 30 × 30 km cell. We then summed the weighted differences for the final difference value. If the downscaling point was in the centre of an E-OBS cell, then it is influenced only by that cell. If the downscaling point was located in a cell corner, then it was influenced almost equally by all four different cells. This avoided artificial delineations when moving from one E-OBS cell to another.

In step 5, we calculated the final downscaled value using the original WorldClim value and the summed inverse distance-weighted difference value from step 4 (Figure 1). The formulas for final downscaled cell values are

$$\mathrm{v}T = \mathrm{wc} - \mathrm{d}F \tag{3}$$

$$\mathrm{v}P = \mathrm{wc} \times \mathrm{d}F \tag{4}$$

where vT is the final downscaled cell value for daily temperature, vP is the final cell value for daily precipitation, dF is the sum of the weighted differences, and wc is the original 1 × 1 km WorldClim value.

3.2. Evaluation method

Evaluation of the downscaled and E-OBS data was performed to ensure that no added random variation or increased error occurred from the downscaling procedure. The evaluation compared weather station data used to create the original E-OBS with the corresponding grid point in our downscaled data and E-OBS data with (Table 1).

All statistics from Willmott and Matsuura (Willmott and Matsuura, 2006) were calculated for both E-OBS and the downscaled data sets (derived data) *versus* the corresponding weather station data. We calculate the mean ($\bar{x}$), the minimum, and maximum values of all three data sets. For E-OBS and the downscaled data, we calculate the mean biased error (MBE) which equals the mean difference between the derived data sets and the weather stations; this value represents the overall bias in the data set. The mean absolute error (MAE) is the mean absolute residual between the derived and weather station data; this value represents the mean residual – whether above or below – between the derived and the weather station data. The root mean square error (RMSE) is the square root of the mean squared residual between the weather station values and the derived values; this value is similar to the MAE except that it is more sensitive to outliers in the residuals. The squared Pearson's correlation coefficient (R^2) is the measure of the linear relationship between two data sets. In addition to the Willmott and Matsuura (2006) statistics, we calculated the linear error in probability space (LEPS) and the critical success index (CSI) as calculated in Hofstra *et al.* (Hofstra *et al.*, 2008). The LEPS is calculated as such:

$$\mathrm{LEPS} = \frac{\left|P_{\mathrm{v}} - 0.5\right| - \left|P_{\mathrm{f}} - P_{\mathrm{v}}\right|}{0.25} \tag{5}$$

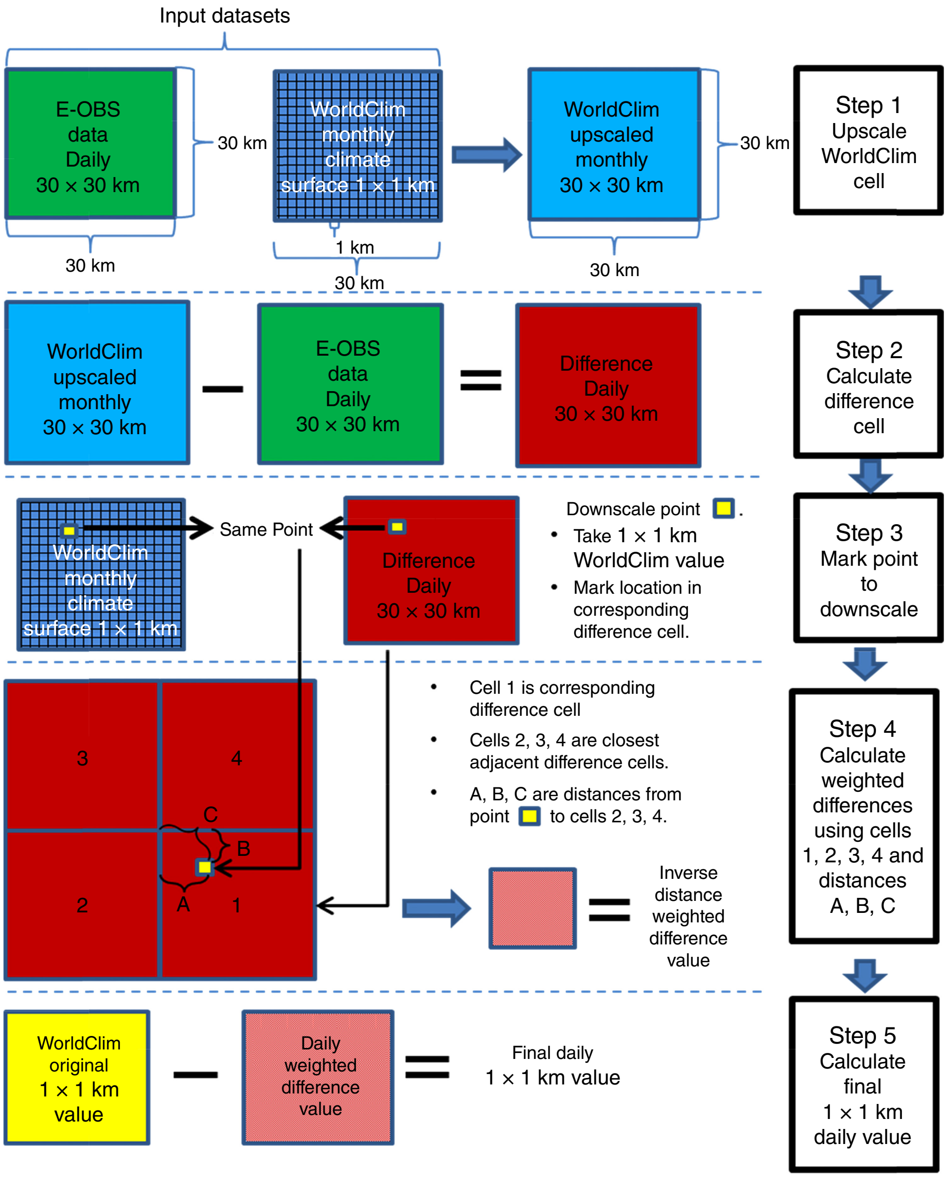

Figure 1. Methodology flow diagram for the delta downscaling algorithm.

where P_v is the probability of occurrence of the weather station value in the weather station data's cumulative distribution function (CDF). P_f is the probability of occurrence of the derived data value in the weather station data's CDF. This particular LEPS equation gives values from −1 (no skill) to 1 (prefect skill). A 0 value is given if the median value (probability = 0.5) of the weather station data is given as a derived value on every data point. The benefit of using LEPS is that calculating error in probability space gives better scores to derived values that come close to extreme observed values and worse scores to derived value that do not accurately predict median values. LEPS requires a normal distribution – because in the precipitation (Prcp) CDF 0 is both an extreme value and close to the median value – which is not present in the precipitation data set, therefore we did not provide an LEPS value for precipitation. For precipitation, we calculated the CSI which measures the success of the derived data sets in capturing rain days. CSI is calculated as such:

$$\mathrm{CSI} = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}} \quad (6)$$

where hits represent the number of days when rain was observed in the weather station data and predicted in the derived data. Misses are the number of days when rain was observed but not predicted, and false alarms are the number of days when rain was predicted but not observed. For all variables, we also calculated the CSI for extreme high and extreme low values. Where extreme high values are defined as those values above the 95th percentile of the weather station CDF and extreme low values are those values below the 5th percentile of the weather station data. A value of 1 means perfect skill and 0 means no skill.

We used weather station data from Norway, Italy, Germany, France, and Spain. The weather station data were obtained from the E-OBS website and cover the

Table 1. Evaluation/validation results of original E-OBS and the downscaled data *versus* weather station data.

			Weather station	E-OBS						Downscaled						
			$\bar{x}$(min, max)	$\bar{x}$(min, max)	MBE (MAE)	RMSE	R^2	LEPS	CSI (low, high)	$\bar{x}$(min, max)	MBE (MAE)	RMSE	R^2	LEPS	CSI (low, high)	# Stations
Validation	Austria	T_{min} (°C)	3.8 (−30.8, 26.1)	3.1 (−25.9, 23.2)	−0.6 (2.5)	3.2	0.72	0.65	NA (0.46, 0.31)	3.98 (−25.2, 23.4)	0.2 (2.2)	2.8	0.89	0.7	NA (0.47, 0.41)	434
		T_{max} (°C)	13.1 (−26.1, 39.5)	11.7 (−20.7, 38.4)	−1.4 (3.4)	4.5	0.82	0.61	NA (0.39, 0.29)	12.92 (−20.9, 38.7)	−0.2 (2.4)	3.2	0.99	0.74	NA (0.51, 0.46)	434
		Prcp (mm)	2.9 (0, 1099.8)	3.1 (0.0, 166)	0.3 (3.4)	7.9	0.75	NA	0.54 (0.61, 0.12)	2.95 (0.0, 159.4)	0.1 (3.3)	7.7	0.77	NA	0.51 (0.6, 0.16)	449
Evaluation	Norway	T_{min} (°C)	−1.3 (−84, 31)	−2.2 (−50.9, 19.3)	−1.0(1.7)	2.1	0.95	0.80	NA (0.74, 0.36)	−1.5 (−50, 20.8)	−0.2 (1.5)	2.0	0.90	0.83	NA (0.71, 0.54)	17
		T_{max} (°C)	9.3 (−21, 34.2)	8.4 (−23.7, 32.5)	−0.9 (2.0)	2.2	0.99	0.75	NA (0.59, 0.48)	8.2 (−23.8, 31.7)	−1.1 (1.6)	1.8	0.93	0.81	NA (0.66, 0.58)	4
		Prcp (mm)	3.2 (0, 99.6)	3.3 (0.0, 104.3)	0.1 (1.1)	2.7	0.91	NA	0.80 (0.80, 0.53)	3.3 (0.0, 113.1)	0.1 (1.1)	2.5	0.92	NA	0.80 (0.79, 0.64)	55
	Germany	T_{min} (°C)	4.4 (−32.8, 85.8)	4.6 (−29.7, 23.3)	0.2 (1.1)	1.9	0.70	0.84	NA (0.65, 0.61)	4.6 (−30.2, 22.7)	0.2 (1.1)	2.0	0.84	0.84	NA (0.65, 0.68)	47
		T_{max} (°C)	12.4 (−28.9, 74.8)	13.0 (−21.0, 39.3)	0.6 (1.2)	2.4	0.66	0.86	NA (0.57, 0.73)	12.9 (−22.0, 39.3)	0.5 (1.2)	2.6	0.64	0.85	NA (0.56, 0.79)	47
		Prcp (mm)	2.3 (0, 99.4)	2.1 (0.0, 97.2)	−0.2 (0.9)	2.4	0.81	NA	0.80 (0.82, 0.48)	2.1 (0.0, 95.0)	−0.2 (0.8)	2.3	0.88	NA	0.82 (0.82, 0.56)	46
	France	T_{min} (°C)	7.7 (−39.8, 27.6)	7.2 (−22.0, 25)	−0.5 (1.1)	1.8	0.65	0.80	NA (0.64, 0.62)	7.2 (−21.6, 25.6)	−0.5 (1.1)	1.7	0.74	0.81	NA (0.68, 0.68)	23
		T_{max} (°C)	16.1 (−22.8, 41.9)	16.0 (−14.9, 40.6)	−0.1 (1.1)	1.9	0.71	0.86	NA (0.67, 0.68)	16.0 (−15.7, 40.9)	−0.1 (0.9)	1.9	0.91	0.88	NA (0.72, 0.76)	24
		Prcp (mm)	2.1 (0, 99.0)	1.9 (0.0, 119.5)	−0.2 (1.0)	3.1	0.62	NA	0.74 (0.82, 0.47)	1.9 (0.0, 117.1)	−0.2 (1.0)	3.1	0.80	NA	0.73 (0.81, 0.54)	18
	Spain	T_{min} (°C)	9.5 (−21.0, 30.5)	8.8 (−19.6, 26.7)	−0.7 (2.7)	3.6	0.09	0.51	NA (0.29, 0.26)	8.6 (−22.5, 25.6)	−0.9 (3.1)	4.1	0.03	0.45	NA (0.24, 0.31)	16
		T_{max} (°C)	19.6 (−8.2, 47.2)	18.9 (−13.7, 47.3)	−0.7 (3.1)	4.1	0.87	0.54	NA (0.36, 0.19)	18.8 (−17.2, 47.0)	−0.8 (3.2)	4.4	0.78	0.53	NA (0.33, 0.27)	38
		Prcp (mm)	2.1 (0, 99.8)	1.6 (0.0, 133.6)	−0.4 (2.4)	6.5	0.12	NA	0.40 (0.70, 0.11)	1.7 (0.0, 164.4)	−0.4 (2.4)	6.6	0.06	NA	0.42 (0.70, 0.14)	18
	Italy	T_{min} (°C)	6.3 (−24.3, 45.1)	8.2 (−18.0, 27.8)	1.9 (2.4)	3.5	0.96	0.69	NA (0.20, 0.74)	7.6 (−20.1, 28.1)	1.3 (1.9)	3.0	0.89	0.76	NA (0.34, 0.79)	5
		T_{max} (°C)	13.8 (−20.6, 44.4)	17.1 (−10.6, 41.2)	3.3 (3.7)	5.7	0.93	0.60	NA (0.05, 0.79)	16.2 (−14.0, 40.9)	2.5 (2.8)	5.0	0.74	0.69	NA (0.19, 0.79)	5
		Prcp (mm)	1.7 (0, 99.8)	2.4 (0.0, 178.0)	0.7 (1.8)	6.2	0.01	NA	0.62 (0.82, 0.26)	2.2 (0.0, 143.6)	0.5 (1.7)	5.4	0.00	NA	0.62 (0.81, 0.39)	8
All evaluation stations		T_{min} (°C)	5.0 (−84.0, 85.8)	4.9 (−50.9, 27.8)	−0.2 (1.5)	2.2	0.91	0.77	NA (0.56, 0.50)	4.9 (−50.0, 28.1)	−0.1 (1.5)	2.3	0.90	0.77	NA (0.55, 0.59)	108
		T_{max} (°C)	15.4 (−28.9, 74.8)	15.5 (−23.7, 47.3)	0.1 (1.9)	3.0	0.87	0.76	NA (0.49, 0.53)	15.4 (−23.8, 47.0)	0.0 (1.9)	3.1	0.85	0.76	NA (0.49, 0.61)	118
		Prcp (mm)	2.6 (0.0, 99.8)	2.5 (0.0, 178.0)	−0.1 (1.2)	3.3	0.88	NA	0.75 (0.80, 0.42)	2.5 (0.0, 164.4)	−0.1 (1.2)	3.2	0.90	NA	0.75 (0.79, 0.52)	145

$\bar{x}$(min, max) provide the mean and the minimum and maximum values of the data set. The mean bias error (MBE) is the weather station data minus the modelled data averaged over the number of stations, and the mean absolute error (MAE) is the average absolute value of MBE. The root mean squared error (RMSE) provides the root mean squared error. Number of stations gives us the number of weather stations that were used in this evaluation and validation.

time period 1951–2012, the same period of time the gridded data covers. We downloaded minimum temperature (T_{min}), maximum temperature (T_{max}), and Prcp data for every available station for each country. We chose these countries because they cover a large portion of Europe and span the continental latitudinal gradient. E-OBS current data portal made obtaining weather station data time consuming not allowing us to use the entire ENSEMBLE weather station data set.

Every station was analysed individually using the mean of each variable over the entire time period. This analysis was spatially explicit but temporally averaged. We also analysed every individual day averaged over all of the stations and years. This method is daily explicit but averaged over space and years. Finally, we also evaluated all available stations and days averaged together (Table 1).

3.3. Validation method

We validated our downscaled data and E-OBS data with the corresponding grid cell of weather stations in an independent data set, from Austria, not used to create the original E-OBS, as opposed to the evaluation that used data that were used to create E-OBS. We performed a validation to assess improvement in accuracy and precision as a result of downscaling using the same statistics we described in the evaluation method section. Austrian weather station data were obtained from the Austrian Central Institute for Meteorology and Geodynamics (ZAMG) and contain all of Austria's weather stations (Hasenauer *et al.*, 2003). Twenty-four stations that were used to create E-OBS were removed (ECA&D provide a list with the location of stations included in their interpolation). There were over 430 weather stations used to validate each variable for the time period 2000–2012. Some of these stations are replacements and so have identical locations as their antecedents giving 250 independent locations. The time period is due to data availability (Table 1). Austria is a representative country for a European climate validation. Austria has a heterogeneous landscape caused by the Alps mountain range, an abundance of large water bodies, and a location within Europe where it is influenced by Nordic, Mediterranean, and inner-continental weather patterns. All of these factors give Austria a very dynamic area on which to analyse climate. We also chose Austria because of data availability.

We analysed every weather station individually averaged daily throughout the entire time period. We also analysed the daily average over all stations throughout the entire time period (Figure 6). We used a downscaling algorithm and not an interpolation of weather stations making a cross-validation impossible.

4. Analysis and results

Our analysis performs three steps to meet the objectives of the study. (1) We first visually assess the spatial pattern of the downscaled data compared to the original E-OBS – to ensure overall continuity between the two data sets (downscaled gridded data). (2) We evaluate the downscaled and original E-OBS data *versus* weather station data – which were used in the original E-OBS interpolation – for any change due to downscaling (evaluation). (3) We validate the downscaled and original E-OBS data *versus* weather stations that were not used in the original E-OBS interpolation. The validation analyses accuracy and error by quantifying any change that arose from the downscaling process (validation).

4.1. Downscaled gridded data

We produced gridded data of minimum temperature, maximum temperature, and precipitation of Europe at a 1×1 km resolution on a daily time step from year 1950 until 2012. The downscaling procedure should enhance local level climate features, such as those created by topography, while maintaining the continental scale pattern of E-OBS. We ensure continental scale continuity between our downscaled data and the original E-OBS by visually assessing gridded data examples for differences and plotting the CDF of both gridded data.

As the data set contains over 54 000 daily gridded data, we assessed a yearly average gridded data set to test the visual differences between the original and downscaled gridded data. No visual differences are apparent in spatial pattern between the original and downscaled versions (Figure 2(a) and (b)). Further, the value ranges of both gridded data are similar (−9 min, 29 max). The CDFs of both data sets indicate that the downscaling did not affect the overall values (Figure 2(c)). The overlay of the CDFs demonstrates that at the continental scale both gridded data have the same distribution of values.

Next, we were interested in how our procedure affected local scale climate features; thus we focused on the Iberian Peninsula centred on Madrid, because of its local scale climatic differences caused by elevation variation, to enhance the visible effect of the downscaling (Figure 3). Figure 3 shows that there are much finer scale temperature features, caused by the incorporation of elevation effects, in the downscaled version than in the original. Figures 2 and 3, therefore, indicate that we have increased local level features while maintaining the overall continental scale pattern.

As explained in the methods section, downscaling precipitation uses different equations than downscaling temperature. Thus, we sought to ensure that downscaling precipitation had also maintained the continental scale pattern. Visually, both the E-OBS, the downscaled map and value ranges of precipitation are the same (Figure 4(a) and (b)). When viewed at this continental scale, the local level effects of downscaling are already apparent as Figure 4(b) appears sharper than Figure 4(a). The CDF's of both data sets are almost identical at this scale as they overlay one another (Figure 4(c)).

4.2. Evaluation

The evaluation examines change that occurred during the downscaling procedure at the points used to create E-OBS.

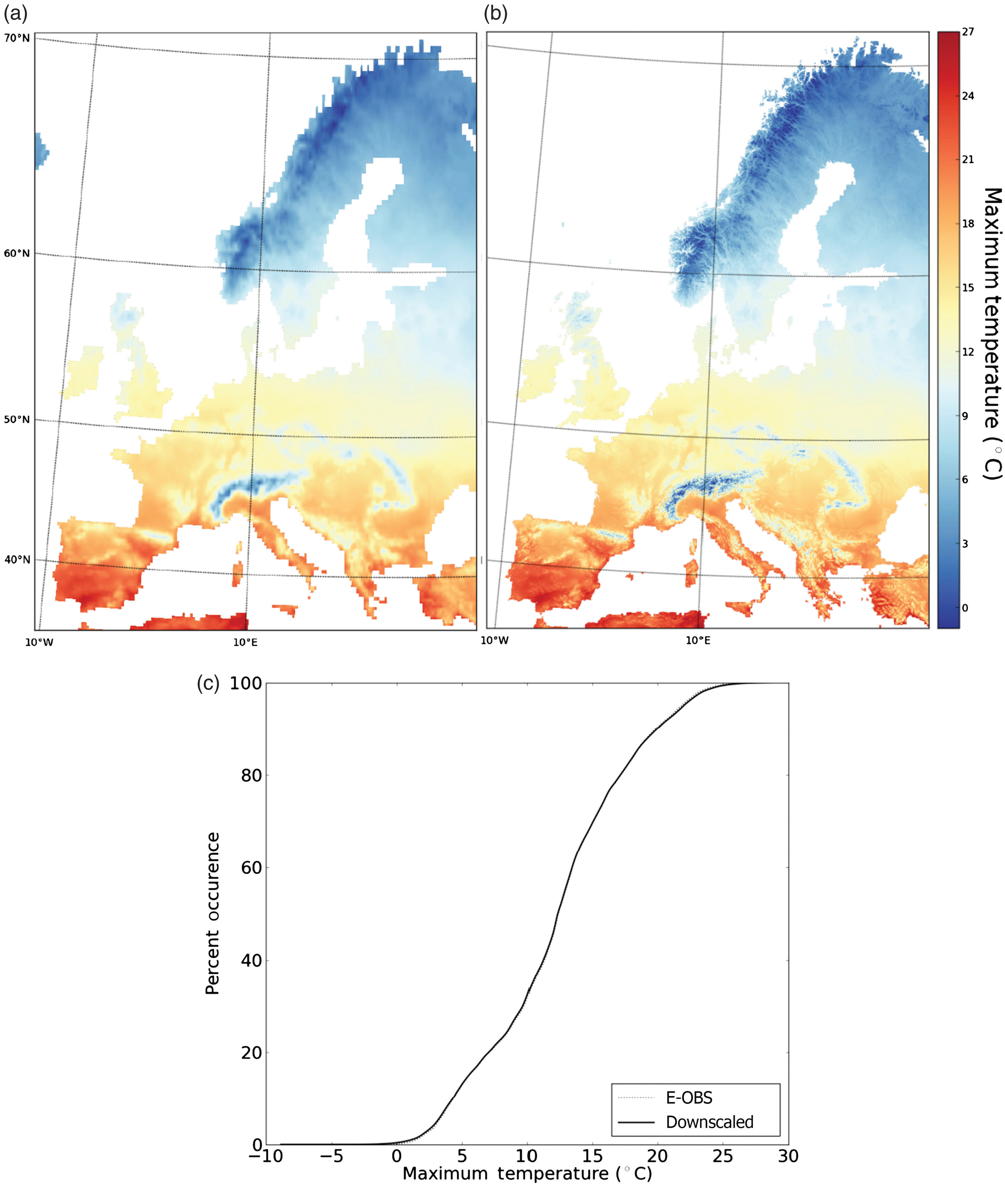

Figure 2. (a) Original E-OBS average daily T_{max} for year 2001. (b) Downscaled average daily T_{max} for year 2001. (c) Cumulative distribution function of average daily T_{max} for year 2001 (downscaled climate data, solid; original E-OBS, dotted). The lines overlay one another.

E-OBS' spline-based spatial interpolation and weather station density indicate that E-OBS should accurately represent the station points. The downscaling algorithm may modify every point on the gridded data not knowing which points were used for the E-OBS interpolation. The sparse density of the weather station network used to interpolate the original E-OBS means that the cells will have values close to that of the weather station data; therefore, we assume high confidence in E-OBS data at locations of weather stations used for the original E-OBS interpolation. There is a chance that we can reduce accuracy through downscaling at those points because our algorithm has no knowledge of the location of weather stations.

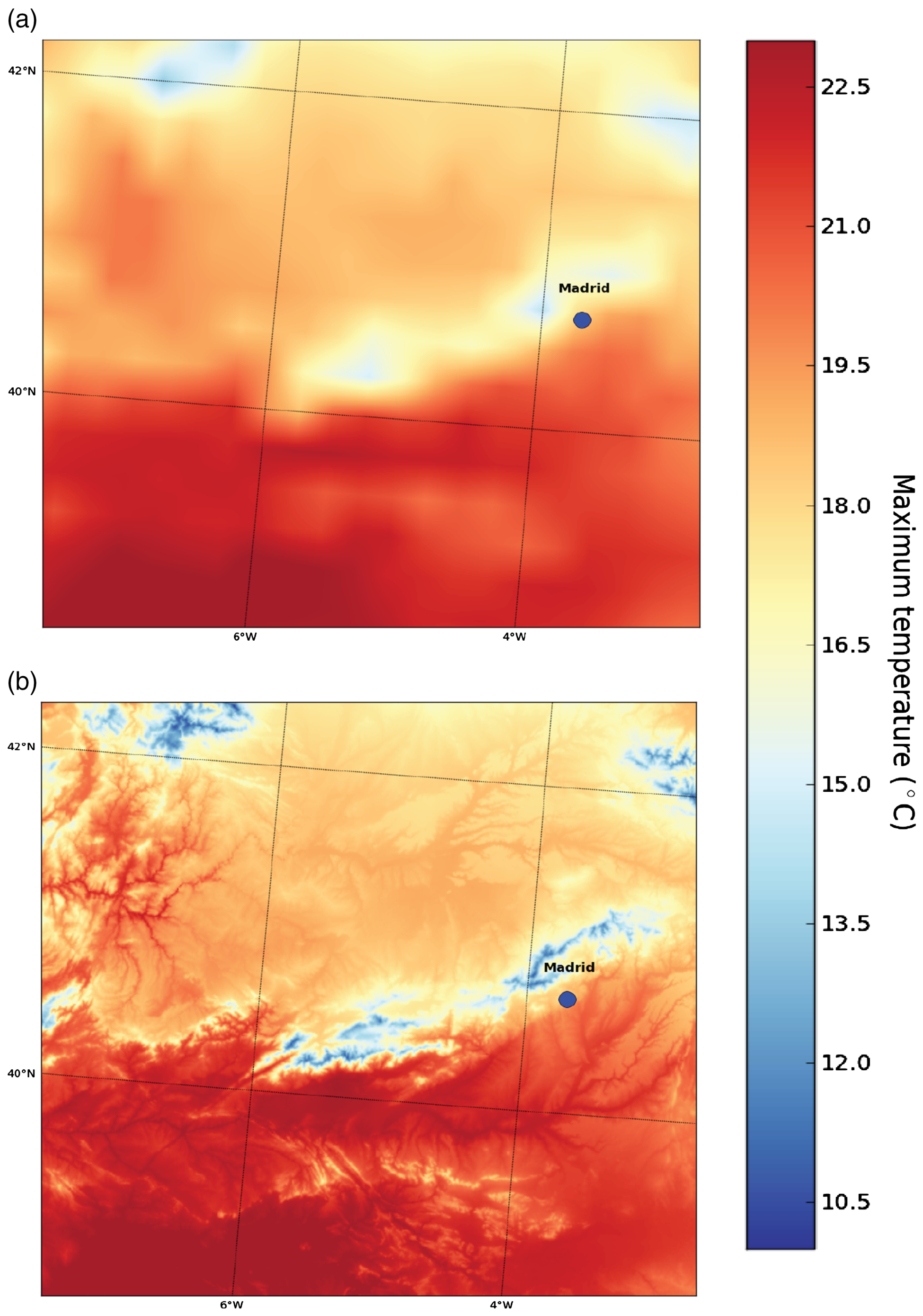

Figure 3. Original E-OBS average daily T_{max} and downscaled average daily T_{max} for year 2001.

The results show that accuracy consistently remained equal between the two data sets. For all countries, the results show similar variation and error between the original and downscaled data (Table 1, Figure 5). The greatest overall difference in MBE is 0.1 °C in both minimum and maximum temperature. Precipitation is underestimated in both the original E-OBS and the downscaled version by 0.1 mm per weather station per year. However, the similarities between the two data sets are different for individual countries. Northern countries have more similarities than southern countries between the original and the downscaled data sets. RMSE and bias (MBE) for Germany and France improve or remain the same for all measures across all variables, with the exception of T_{max} in Germany which has a higher root mean RMSE and lower R^2 value. Downscaled data set for Norway has an increase in bias and a decrease in R^2 values but a decrease in RMSE for temperature. Although the R^2 values drop, they still remain over 0.9. Precipitation for Norway improves with downscaling (Table 1, Figure 5).

The LEPS values for all evaluation stations remain the same after downscaling at 0.77 and 0.76 for T_{min} and T_{max}, respectively. The LEPS values of the individual countries all increase or remain the same after downscaling with the

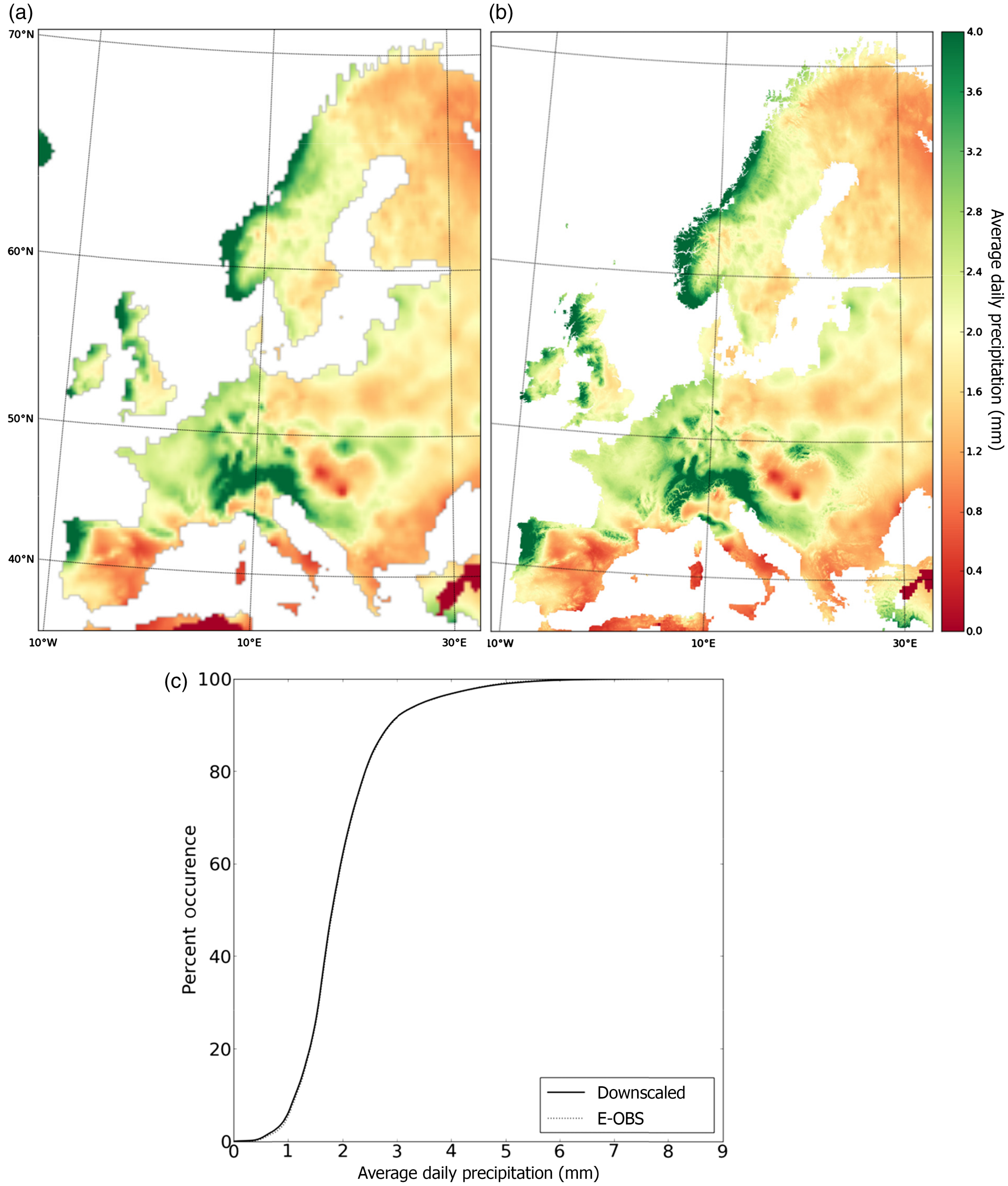

Figure 4. (a) Original E-OBS average daily precipitation for year 2001. (b) Downscaled average daily precipitation for year 2001. (c) Cumulative distribution function of average daily precipitation for year 2001 (downscaled climate data, solid; original E-OBS, dotted). The lines overlay one another.

exception of T_{min} of Spain which decreases from 0.51 to 0.45. The Prcp CSI values for of all evaluation stations remain the same after downscaling at 0.75. The CSI low values of all evaluation stations for all variables remain the same after downscaling. The CSI high values increase for all variables with the largest increase in Prcp from 0.42 in the original E-OBS to 0.52 in the downscaled version.

Spain and Italy have high bias and error and low R^2 values for precipitation in the original and downscaled data sets. Minimum temperature in Spain has high RMSE and low R^2 values in both the original and downscaled data sets. In Spain and Italy, for every variable downscaling created higher bias and RMSE and lower R^2 values than the original data.

Seasonally E-OBS underestimates temperature in the winters and overestimates in the summer. The temperature seasonality difference for both the original and downscaled data sets never exceeds 0.01 °C. The modelled

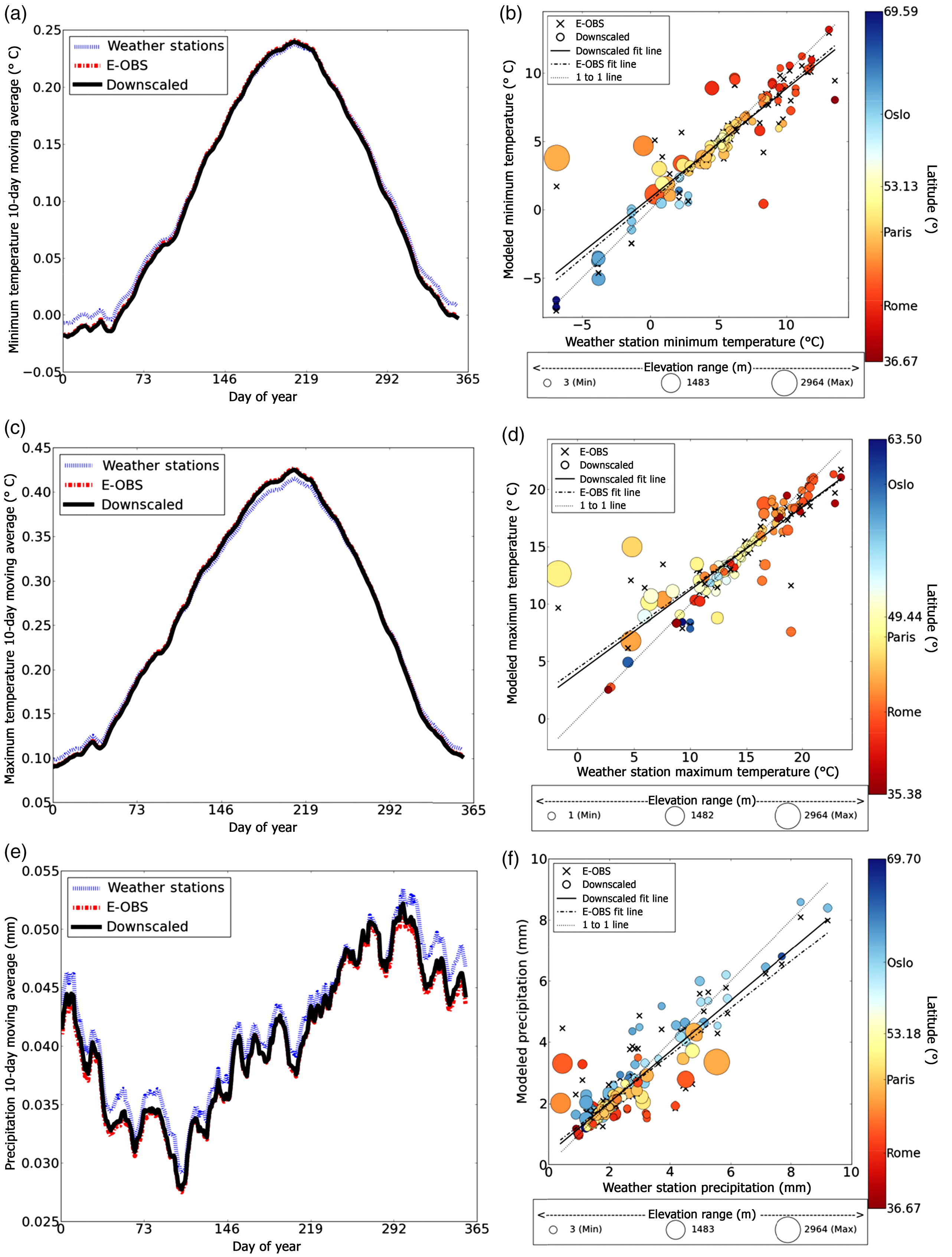

Figure 5. Evaluation of E-OBS and downscaled data against weather station data from Norway, Germany, France, Spain, and Italy. All of these stations were used to create E-OBS. Minimum temperature, maximum temperature, and precipitation are shown. Left column gives daily averages for years 1950–2012 of all stations. Right column shows weather station data (x-axis) *versus* E-OBS and downscaled data (y-axis). Size of downscaled points indicates the elevation of the station at that point. The colour of the downscaled points (circles) indicates latitude of the corresponding weather station.

data sets consistently underestimate precipitation seasonally but never more that by 0.0025 mm per day. Downscaled daily precipitation is consistently more accurate than E-OBS (Figure 5).

The scatter plot in Figure 5 shows that both the original E-OBS and the downscaled version (interpolated data) minimum temperature values best fit weather station data between 1 and 7 °C. Interpolated data minimum temperature becomes more accurate towards lower elevations and towards higher latitudes (Figure 5). Maximum temperature is accurate for all temperatures and latitudes however elevation greatly affects accuracy – with lower accuracies occurring at high elevations. Precipitation data have higher accuracy at lower values of precipitation. Interpolated data precipitation is more accurate at higher latitudes and underestimates at lower latitudes. Precipitation accuracy is higher at lower elevations. For all variables, the fit lines for both data sets are similar and close to the 1 to 1 line (Figure 5).

At grid points with weather stations used to produce E-OBS, the downscaling maintains or improves upon the error already incorporated in the original E-OBS data set (Table 1). This evaluation confirms that our downscaling algorithm does not increase error at grid points with which we have high confidence in the original E-OBS.

4.3. Validation

We validated the new data set against an independent data set of over 400 Austrian weather stations that were not used in the original E-OBS interpolation. Downscaled variables have R^2 values of 0.77 or better, a bias of 5% or lower, and an RMSE of 5% or less (Table 1). We improve the bias for T_{max}, T_{min}, and Prcp by 89, 65, and 60% and the RMSE by 29, 11, and 2%, respectively. R^2 values increase for T_{max}, T_{min}, and Prcp by 24, 20, and 3% respectively. All downscaled variables improve compared to the original E-OBS (Table 1, Figure 6).

The LEPS values of T_{min} and T_{max} both increased with downscaling by 9 and 21%, respectively. The CSI low score for T_{min} did not improve much with downscaling with a score of 0.47. The T_{min} CSI high score did improve from 0.31 to 0.41. Both CSI scores for T_{max} improved from 0.39 to 0.51 for the CSI low and from 0.29 to 0.46 for the CSI high. The CSI score for Prcp decreased from 0.54 to 0.51. The Prcp CSI low score remained constant at 0.6. The Prcp CSI high score improved from 0.12 to 0.16.

The seasonal pattern of precipitation matches the weather station data (Figure 6). The absolute values yield the greatest improvement through downscaling in the winter (Figure 6). The downscaled daily values of both T_{min} and T_{max} improved over the original E-OBS values (line graphs Figure 6). Individual station precipitation has higher accuracy at lower absolute values. Precipitation accuracy appears to be independent of elevation and latitude (scatter plots Figure 6). For individual stations, the downscaled precipitation values only slightly changed from the E-OBS values. Although the fit line of the downscaled data is further from the 1 to 1 line than the E-OBS fit line, all other metrics show a slight improvement in precipitation values due to the increase in temporal accuracy (Table 1, Figure 6).

Both T_{min} and T_{max} have a visible temporal improvement with the downscaled curve overlaying that of the weather stations (Figure 6). This pattern is consistent across seasons with no seasonally dependent error (line graphs Figure 6). When viewing individual stations (scatter plots Figure 6), minimum temperature has increased accuracy through downscaling, primarily, by increasing values that were underestimated by E-OBS. Elevation and latitude do not affect the accuracy of downscaled T_{min} (scatter plot Figure 6). The original E-OBS data set tends to underestimates T_{min} to a greater extent relative to the downscaled data (Table 1, Figure 6). The greatest improvement from downscaling can be seen in T_{max}. The downscaled fit line overlays the 1 to 1 line. The downscaled T_{max} values have almost no error as compared to E-OBS values. The magnitude temperature values, elevation, and latitude do not affect the accuracy of the downscaled values, whereas the E-OBS values have more error towards higher temperatures. The original E-OBS had a consistent bias towards underestimating both T_{min} and T_{max} which is removed through downscaling (Table 1, Figure 6).

5. Discussion

A lack of access empirical data from weather stations makes downscaling the original E-OBS data set only option to create a higher resolution gridded data that spans Europe. It is only possible to download 77% of all the weather stations' data sets used to create E-OBS. We were only able to obtain weather station data not used in E-OBS from one country, Austria, which we used for validation. The method we used for downscaling, the delta method, is designed to integrate various data sets with different temporal/spatial scales (Mote and Salathe, 2010; Mosier *et al.*, 2014; Reeves *et al.*, 2014). Although the delta method has been used in numerous studies, its application must be customized to cater to each study's unique parameters which inevitably have slightly different temporal and spatial resolutions.

We produced a downscaled climate data set that increases local scale accuracy while maintaining the continental scale patterns of the E-OBS data set (Figures 2 and 4). Averaged over five countries that span Europe's latitudinal gradient, the new data set maintains the bias and error at points used to create the original E-OBS (Table 1, Figure 5). In Austria, at grid points that contain weather stations not used in the original E-OBS derivation, the downscaling improves all climate variables as shown in our validation (Table 1, Figure 6).

Our downscaling algorithm utilizes the strengths of both input data sets. E-OBS was derived by a Kriging/spline method accounting for distance relationships and expert knowledge. E-OBS provides daily values that are designed for the continental scale. WorldClim's monthly climate surfaces use an interpolation technique with DEMs (SRTM, GTOPO30) incorporating elevation effects on

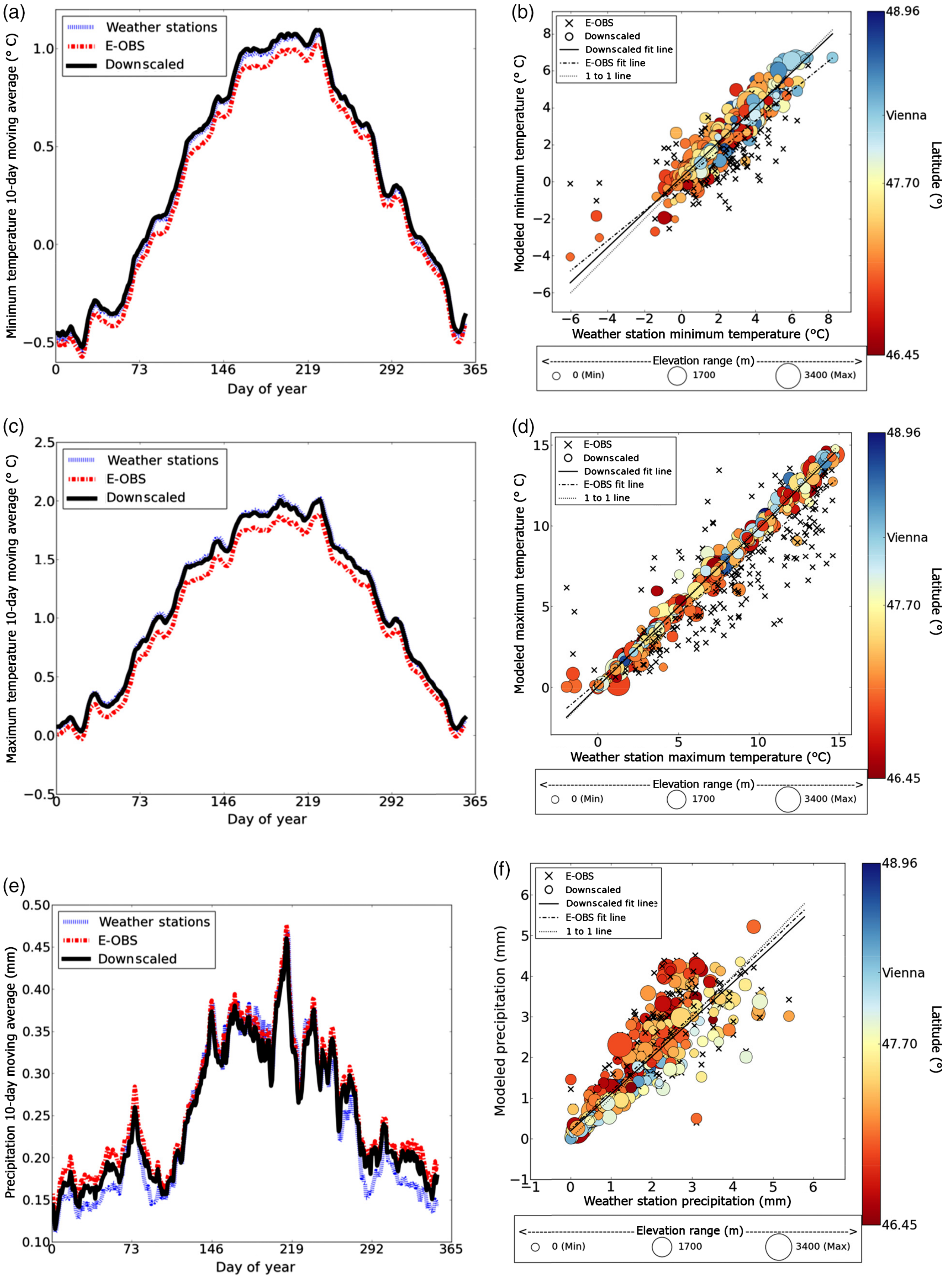

Figure 6. Validation of E-OBS and downscaled data against weather station data from Austria. None of these stations were used to create E-OBS. Minimum temperature, maximum temperature, and precipitation are shown. Left column gives daily averages for years 2000–2012 of all stations. Right column shows weather station data (x-axis) *versus* E-OBS and downscaled data (y-axis). Size of downscaled points (circles) indicates the elevation of the station at that point. The colour of the downscaled points indicates latitude of the corresponding weather station.

climate. The primary benefit of the downscaling method we used is the incorporation of elevation, through WorldClim, into the E-OBS daily climate data. Temperature is strongly influenced by elevation (through its lapse rate) more so than precipitation. However, one cannot apply a single lapse rate in every location for every day of the year. Lapse rates vary by elevation, latitude, weather type, and season (Stone and Carlson, 1979; Blandford *et al.*, 2008). Lapse rates for precipitation, in particular, are not constant through seasons, regions, or across scales (Daly *et al.*, 1994). Therefore, it is beneficial to incorporate WorldClim into E-OBS because it is based on real world observations (which capture mean local lapse rates), has monthly values, is spatially explicit, and represents the average weather conditions over an extended time period. Because of the nature of the delta method, however, the base ratios between downscaled cells – lapse rates – only change by month and not from year to year.

Table 1 shows that the MBE, for the majority of variables and countries in the evaluation, improved or retained its previous value through downscaling. This result was also found by Mosier *et al.* (Mosier *et al.*, 2014) when comparing downscaled data against stations that were used within the WorldClim interpolation. The R^2 values are all above 0.64 except for $T_{\min}$ and Prcp in Spain and Prcp in Italy. E-OBS had weather stations in these countries that are not publicly available and thus not available for our evaluation. During interpolation, these station values, to which we have access, may have been smoothed by incorporating stations to which we do not have access. It is also important to note that across all statistical measures aggregating all countries together improves both data sets. This again indicates that E-OBS was designed for continental scale studies.

The temperature LEPS values indicate that the downscaled version did not affect the accuracy of E-OBS in probability space meaning that it has the same ability to predict both median values as well as more extreme values as the original E-OBS. The CSI high values increase for all evaluation stations for all variables. This indicates that downscaling has a positive effect on the data set's ability to match extreme high values. CSI values for all variables for all evaluation stations indicate that the downscaled version captures extreme values more than half of the time. Prcp CSI values show that the downscaled version captures rain days 75% of the time. Prcp CSI low values are slightly higher than the Prcp CSI values, indicating that when the downscaled data have a false alarm for a rain-day, it is at least only a low amount of Prcp.

At weather station points not used to create E-OBS, in Austria, the greatest improvement from downscaling is in temperature. This is most likely because of the large effect incorporating elevation into the climate data has on temperature as compared to precipitation. Of all variables, downscaled precipitation has the least improvement. The original WorldClim authors' (Hijmans *et al.*, 2005) explicitly state that they had difficulty in modelling precipitation in mountainous regions. This weakness in WorldClim can explain the lack of improvement in precipitation from our downscaling algorithm when compared against data from a mountainous country such as Austria. Also, we do not perform any new climatological calculations, such as convective precipitation, so we will not capture small precipitation events that were not captured by E-OBS.

The LEPS scores for minimum and maximum temperature of Austria show a positive response to downscaling increasing by 0.05 and 0.13, respectively. This increase in LEPS values along with the decrease in MAE values due to downscaling lead to the conclusion that the downscaled version not only more accurately captures mean temperature values but also extreme values than does the original E-OBS. The CSI score for extreme lows and highs of temperature all improved with downscaling as well. This is to be expected as our method increase/decreases temperature from the E-OBS values which can be interpreted as a mean of the larger area. However, the CSI values for high and low extremes of minimum and maximum temperatures indicate that we still only capture extreme values from 41 to 51% of the time.

The CSI values for precipitation in Austria, on the other hand, have a weaker response to downscaling than temperature. This lack of response is again a demonstration that our method of integrating elevation into the E-OBS data set has more influence on temperature than precipitation.

Considering the daily graphs and the stations scatter plots of Austria together, we show that those errors which occur at individual stations get cancelled out when viewed over time (Figure 6). Thus, the original E-OBS data represent data on the country scale but have much higher error when viewed on a local level. It also shows that at both the local and country scales the downscaled data perform better.

Many studies have used E-OBS to examine various aspects of European ecosystems, making it a widely used and recognized data set (Ziello *et al.*, 2009; Hirschi *et al.*, 2010; Gottfried *et al.*, 2012). Other studies have also examined the validity of E-OBS data itself (Hofstra *et al.*, 2009; Kysely and Plavcova, 2010). These studies compare E-OBS with national gridded climatology or selected weather stations. They found various biases and errors in both temperature and precipitation. Examples of such findings include low levels of precipitation, higher error of precipitation in mountainous regions, and incorrect temperature. Hofstra *et al.* (2009) reports RMSE of temperature of 0.7–0.9 °C and RMSE of 0.85–0.92 mm for Prcp in the United Kingdom and RMSE of 5.77 mm for Prcp in the Alps. Hofstra *et al.* (2009) also reports that over the Alps both absolute error and error as a percent of absolute Prcp are both higher than Prcp error in the United Kingdom. This finding from Hofstra *et al.* (2009) along with the assertion of Hijmans *et al.* (2005) that WordClim does not capture all variation in mountainous precipitation shows that our data will our downscaled precipitation data will also have higher area in mountainous areas. One other source of error in the precipitation data that was not addressed in our study was that of precipitation frequency. We only changed the magnitude of an existing rain event. We did not create rain events not included in E-OBS.

Maselli *et al.* (2012) created a locally downscaled E-OBS data set for Italy, by applying a regression function for downscaling calibrated for their area of study. They validated their data against ten Italian weather stations for the time period 2000–2009. The authors do not state whether the stations used for analysis were used to create E-OBS or are an independent data set. Our validation against Austrian weather stations and our evaluation of Italian data show reduced bias (MBE) and RMSE for all variables. The Italian downscaled data improve the bias of only the maximum temperature values. As a comparison, the Italian data have an MBE over all stations for minimum temperature of 3.0 while our MBE is 0.2 for Austria and 1.3 for Italy. However, compared to the Italian data, our RMSE values tend to be higher for precipitation and maximum temperature but lower for minimum temperature.

Compounding errors from both of our input data sets, E-OBS and WorldClim, exist and are difficult to quantify. We only downscale grid points that have both WorldClim and E-OBS values. This creates data limitations, mostly from E-OBS, primarily around the coastline making them artificially square. Additionally, a lack of stations in mountainous regions used in our input data sets makes our knowledge of the accuracy in Alpine regions weaker than in other regions. Also, assumptions were made reading ambiguous weather station data in E-OBS, such as inconsistencies in the data collection date and time (Haylock *et al.*, 2008), which could result in fallacious local scale E-OBS outputs and gives less confidence in the weather station data. Also, contradictory elevation data between stations and DEM's used to create WorldClim further weakens confidence in Alpine areas (Hijmans *et al.*, 2005). The extremes of the downscaled data are most likely too conservative as this is also true in E-OBS (Haylock *et al.*, 2008). Incorporating WorldClim will most likely not increase the likelihood of capturing extreme values – which is an increasingly more important aspect of climate data to capture – as WorldClim is itself only a mean value over a long timeframe (Schär *et al.*, 2004). This downscaling method still suffers from the lack of weather station density inherited from both input data sets.

6. Conclusion

We have used the delta method to incorporate E-OBS data ($0.25^\circ \times 0.25^\circ$ resolution, daily) and WorldClim data ($0.008\overline{3}^\circ \times 0.008\overline{3}^\circ$ resolution, monthly climate surface) to produce a new downscaled climate data set, which covers Europe and includes maximum temperature, minimum temperature, and precipitation on a daily time step at a $0.008\overline{3}^\circ \times 0.008\overline{3}^{\circ\circ}$ resolution (approximately 1×1 km) from 1950 to 2013. This data set will be updated as new E-OBS versions are released. Scientists can use one data set to do research in various areas of Europe at a local level and have results be directly comparable allowing studies of important environmental and economic issues at a local level over a larger landscape than previously possible. We did not increase random variation or error at points used to make the original E-OBS as a result of the downscaling process. The downscaled data also have a higher accuracy and precision than the original E-OBS data at weather stations not used in the original E-OBS interpolation. One major benefit of the method we used for downscaling is that because WorldClim is a global data set, this method can be applied anywhere in the world that already has a low-resolution gridded climate data set.

The most accurate climate data sets with fine resolutions are most likely the national climate data sets; however, those are often difficult, costly, or impossible to obtain and inherently only cover the spatial extent of their particular country. We created these data for those researchers who desire a continental scale data set with a fine resolution and for policy makers or land managers who need locally relevant information on large scales that cross countries and regions in Europe. A better solution would be a European wide interpolation at this resolution such as those that have been done in the United States for over 20 years. However, current infrastructure, policy obstacles, and data sharing culture make such an interpolation with a reasonable level of accuracy unattainable. Until a more coherent, consistent, and open access weather station network is available, downscaling is the only option to create gridded data at this resolution for Europe. This entire data set can be obtained at ftp://palantir.boku.ac.at/Public/ClimateData.

Acknowledgements

We thank Dr Rupert Seidl, Dr Christopher Thurner, Mrs Loretta Moreno, and Dr Phillip Mohebalian for their help in reviewing and revising the article. Data that were downscaled in this article can be obtained at http://www.ecad.eu/download/ensembles/download.php and http://www.worldclim.org/download, and we thank all of the researchers and technicians who make all of these data easily accesible and free. The research leading to these results has received funding from the European Union Seventh Framework Programme under grant agreement n° 311970.

References

Blandford TR, Humes KS, Harshburger BJ, Moore BC, Walden VP, Ye H. 2008. Seasonal and synoptic variations in near-surface air temperature lapse rates in a mountainous basin. *J. Appl. Meteorol. Climatol.* **47**: 249–261, doi: 10.1175/2007JAMC1565.1.

Ciais Ph., Reichstein M, Viovy N, Granier A, Ogée J, Allard V, Aubinet M, Buchmann N, Bernhofer Chr., Carrara A, Chevallier F, De Noblet N, Friend AD, Friedlingstein P, Grünwald T, Heinesch B, Keronen P, Knohl A, Krinner G, Loustau D, Manca G, Matteucci G, Miglietta F, Ourcival JM, Papale D, Pilegaard K, Rambal S, Seufert G, Soussana JF, Sanz MJ, Schulze ED, Vesala T, Valentini R. 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature* **437**(7058): 529–533. DOI: 10.1038/nature03972.

Daly C. 2006. Guidelines for assessing the suitability of spatial climate data sets. *Int. J. Climatol.* **26**(6): 707–721, doi: 10.1002/joc.1322.

Daly C, Neilson RP, Phillips DL. 1994. A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *J. Appl. Meteorol.* **33**(2): 140–158, doi: 10.1175/1520-0450(1994)033<0140:ASTMFM>2.0.CO;2.

Ezzine H, Bouziane A, Ouazar D. 2014. Seasonal comparisons of meteorological and agricultural drought indices in Morocco using open short time-series data. *Int. J. Appl. Earth Obs. Geoinf.* **26**: 36–48, doi: 10.1016/j.jag.2013.05.005.

Farr TG, Rosen PA, Caro E, Crippen R, Duren R, Hensley S, Kobrick M, Paller M, Rodriguez E, Roth L, Seal D, Shaffer S, Shimada J, Umland J, Werner M, Oskin M, Burbank D, Alsdorf D. 2007. The Shuttle Radar Topography Mission. *Rev. Geophys.* **45**(2): 1944–9208, doi: 10.1029/2005RG000183.

Frei C, Schaer C. 1998. A precipitation climatology of the Alps from high-resolution rain-gauge observations. *Int. J. Climatol.* **18**(8): 873–900.

Gottfried M, Pauli H, Futschik A, Akhalkatsi M, Barančok P, Benito Alonso JL, Coldea G, Dick J, Erschbamer B, Fernández Calzado MR, Kazakis G, Krajči J, Larsson P, Mallaun M, Michelsen O, Moiseev D, Moiseev P, Molau U, Merzouki A, Nagy L, Nakhutsrishvili G, Pedersen B, Pelino G, Puscas M, Rossi G, Stanisci A, Theurillat J-P, Tomaselli M, Villar L, Vittoz P, Vogiatzakis I, Grabherr G. 2012. Continent-wide response of mountain vegetation to climate change. *Nat. Clim. Change* **2**(2): 111–115, doi: 10.1038/nclimate1329.

Guo Y, Gong P, Amundson R, Yu Q. 2006. Analysis of factors controlling soil carbon in the conterminous United States. *Soil Sci. Soc. Am. J.* **70**(2): 601, doi: 10.2136/sssaj2005.0163.

Hasenauer H, Merganicova K, Petritsch R, Pietsch S, Thornton PE. 2003. Validating daily climate interpolations over complex terrain in Austria. *Agric. For. Meteorol.* **119**(1-2): 87–107, doi: 10.1016/S0168-1923(03)00114-X.

Hawkins BA. 2010. Multiregional comparison of the ecological and phylogenetic structure of butterfly species richness gradients. *J. Biogeogr.* **37**(4): 647–656, doi: 10.1111/j.1365-2699.2009.02250.x.

Hawkins E, Fricker TE, Challinor AJ, Ferro CAT, Ho CK, Osborne TM. 2013. Increasing influence of heat stress on French maize yields from the 1960s to the 2030s. *Glob. Change Biol.* **19**(3): 937–47, doi: 10.1111/gcb.12069.

Haylock M, Hofstra N, Tank AK. 2008. A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *J. Geophys. Res.* **113**: D20119, doi: 10.1029/2008 JD010201.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* **25**(15): 1965–1978, doi: 10.1002/joc.1276.

Hirschi M, Seneviratne SI, Alexandrov V, Boberg F, Boroneant C, Christensen OB, Formayer H, Orlowsky B, Stepanek P. 2010. Observational evidence for soil-moisture impact on hot extremes in southeastern Europe. *Nat. Geosci.* **4**(1): 17–21, doi: 10.1038/ngeo1032.

Hofstra N, Haylock M, New M, Jones P, Frei C. 2008. Comparison of six methods for the interpolation of daily, European climate data. *J. Geophys. Res. Atmos.* **113**(21): D21, doi: 10.1029/2008JD010100.

Hofstra N, Haylock M, New M, Jones PD. 2009. Testing E-OBS European high-resolution gridded data set of daily precipitation and surface temperature. *J. Geophys. Res.* **114**(D21): D21101, doi: 10.1029/2009JD011799.

Hutchinson MF. 1995. Interpolating mean rainfall using thin plate smoothing splines. *Int. J. Geogr. Inf. Syst.* **9**(4): 385–403, doi: 10.1080/02693799508902045.

Hutchinson MF. 2004. *Anusplin Version 4.3. Centre for Resource and Environmental Studies*. The Australian National University: Canberra.

Isotta FA, Frei C, Weilguni V, Perčec Tadić M, Lassègues P, Rudolf B, Pavan V, Cacciamani C, Antolini G, Ratto SM, Munari M, Micheletti S, Bonati V, Lussana C, Ronchi C, Panettieri E, Marigo G, Vertačnik G. 2014. The climate of daily precipitation in the Alps: development and analysis of a high-resolution grid dataset from pan-Alpine rain-gauge data. *Int. J. Climatol.* **34**(5): 1657–1675, doi: 10.1002/joc.3794.

Janssens IA, Lankreijer H, Matteucci G, Kowalski AS, Buchmann N, Epron D, Pilegaard K, Kutsch W, Longdoz B, Grunwald T, Montagnani L, Dore S, Rebmann C, Moors EJ, Grelle A, Rannik U, Morgenstern K, Oltchev S, Clement R, Gudmundsson J, Minerbi S, Berbigier P, Ibrom A, Moncrieff J, Aubinet M, Bernhofer C, Jensen NO, Vesala T, Granier A, Schulze E-D, Lindroth A, Dolman AJ, Jarvis PG, Ceulemans R, Valentini R. 2001. Productivity overshadows temperature in determining soil and ecosystem respiration across European forests. *Glob. Change Biol.* **7**(3): 269–278, doi: 10.1046/j.1365-2486.2001.00412.x.

Jay F, Manel S, Alvarez N, Durand EY, Thuiller W, Holderegger R, Taberlet P, François O. 2012. Forecasting changes in population genetic structure of alpine plants in response to global warming. *Mol. Ecol.* **21**(10): 2354–68, doi: 10.1111/j.1365-294X.2012.05541.x.

Journal AG, Huijbregts CJ. 1978. *Mining Geostatistics*. Academic Press: London.

Kysely J, Plavcova E. 2010. A critical remark on the applicability of E-OBS European gridded temperature data set for validating control climate simulations. *J. Geophys. Res.* **115**(D23): D23118.

Lorenz R, Davin EL, Seneviratne SI. 2012. Modeling land-climate coupling in Europe: impact of land surface representation on climate variability and extremes. *J. Geophys. Res. Atmos.* **117**: D20109.

Luedeling E, Zhang M, Girvetz EH. 2009. Climatic changes lead to declining winter chill for fruit and nut trees in California during 1950-2099. *PLoS One* **4**(7): e6166, doi: 10.1371/journal.pone.0006166.

Maselli F, Pasqui M, Chirici G, Chiesi M, Fibbi L, Salvati R, Corona P. 2012. Modeling primary production using a 1 km daily meteorological data set. *Clim. Res.* **54**(3): 271–285, doi: 10.3354/cr01121.

Masson D, Frei C. 2015. Long-term variations and trends of mesoscale precipitation in the Alps: recalculation and update for 1901-2008. *Int. J. Climatol.* , doi: 10.1002/joc.4343.

Mosier TM, Hill DF, Sharp KV. 2014. 30-Arcsecond monthly climate surfaces with global land coverage. *Int. J. Climatol.* **34**: 2175–2188, doi: 10.1002/joc.3829.

Mote PW, Salathe EP Jr. 2010. Future climate in the Pacific Northwest. *Clim. Change* **102**: 29–50, doi: 10.1007/s10584-010-9848-z.

Nekola JC, Brown JH. 2007. The wealth of species: ecological communities, complex systems and the legacy of Frank Preston. *Ecol. Lett.* **10**(3): 188–96, doi: 10.1111/j.1461-0248.2006.01003.x.

Peterson AT, Nakazawa Y. 2007. Environmental data sets matter in ecological niche modelling: an example with Solenopsis invicta and Solenopsis richteri. *Glob. Ecol. Biogeogr.* **17**: 135–144, doi: 10.1111/j.1466-8238.2007.00347.x.

Peterson AT, Papeş M, Eaton M. 2007. Transferability and model evaluation in ecological niche modeling: a comparison of GARP and Maxent. *Ecography* **30**(4): 550–560, doi: 10.1111/j.2007.0906-7590.05102.x.

Reeves MC, Moreno AL, Bagne KE, Running SW. 2014. Estimating climate change effects on net primary production of rangelands in the United States. *Clim. Change* **126**: 429–442, doi: 10.1007/s10584-014-1235-8.

Schär C, Vidale PL, Lüthi D, Frei C, Häberli C, Liniger M, Appenzeller C. 2004. The role of increasing temperature variability in European summer heatwaves. *Nature* **427**(January): 332–336, doi: 10.1038/nature02300.

Seidl R, Eastaugh CS, Kramer K, Maroschek M, Reyer C, Socha J, Vacchiano G, Zlatanov T, Hasenauer H. 2013. Scaling issues in forest ecosystem management and how to address them with models. *Eur. J. For. Res.* **132**(5-6): 653–666, doi: 10.1007/s10342-013-0725-y.

Stone PH, Carlson JH. 1979. Atmospheric lapse rate regimes and their parameterization. *J. Atmos. Sci.* **36**: 415–423.

Thornton PE, Running SW, White MA. 1997. Generating surfaces of daily meteorological variables over large regions of complex terrain. *J. Hydrol.* **190**(3-4): 214–251, doi: 10.1016/S0022-1694(96)03128-9.

Turner DP, Dodson R, Marks D. 1996. Comparison of alternative spatial resolutions in the application of a spatially distributed biogeochemical model over complex terrain. *Ecol. Model.* **90**(68): 53–67.

VEMAP Members. 1995. Vegetation/ecosystem modelling and analysis project: comparing biogeography and biogeochemistry models in a continental-scale study of terrestrial responses to climate change and CO 2 doubling. *Glob. Biogeochem. Cycles* **9**(4): 407–437.

Venäläinen A, Tuomenvirta H, Pirinen P, Drebs A. 2005. A basic finnish climate data set 1961-2000 – description and illustrations. Reports 5, Finnish Meteorological Institute: Helsinki, 1–27.

Waring RH, Running SW. 2010. *Forest Ecosystems: Analysis at Multiple Scales (Google eBook)*. Elsevier.

Wijngaard JB, Klein Tank AMG, Koennen GP. 2003. Homogeneity of 20th century European daily temperature and precipitation series. *Int. J. Climatol.* **23**(6): 679–692, doi: 10.1002/joc.906.

Willmott CJ, Matsuura K. 2006. On the use of dimensioned measures of error to evaluate the performance of spatial interpolators. *Int. J. Geogr. Inf. Sci.* **20**(1): 89–102, doi: 10.1080/13658810500286976.

Wimberly MC, Hildreth MB, Boyte SP, Lindquist E, Kightlinger L. 2008. Ecological niche of the 2003 West Nile virus epidemic in the northern great plains of the United States. *PLoS One* **3**(12): e3744, doi: 10.1371/journal.pone.0003744.

Zhao M, Heinsch FA, Nemani RR, Running SW. 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. *Remote Sens. Environ.* **95**(2): 164–176, doi: 10.1016/j.rse.2004.12.011.

Ziello C, Estrella N, Kostova M, Koch E, Menzel A. 2009. Influence of altitude on phenology of selected plant species in the Alpine region (1971–2000). *Clim. Res.* **39**(1): 227–234, doi: 10.3354/cr00822.

