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Operational maps of monthly mean temperature for WMO Region VI (Europe and Middle East)

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Abstract—A spatial interpolation method for the construction of operational climate maps for the WMO RA VI Region (Europe and Middle East) is presented on the example of monthly mean temperature. The method is suitable for an in situ data base with relatively low data coverage in a relatively large and climatically heterogeneous area, and considers the classical geographical parameters latitude, longitude, and altitude by multi-dimensional linear regression, but improved by continentality, using a new continentality index. A comparison of several interpolation methods reveals that radial basis functions (subtype multiquadratic) seems to be the most appropriate approach. Separate regressions for land and sea areas further improve the results.

Key-words: spatial interpolation, multi-dimensional linear regression, climate maps, RA VI, Europe

1. Introduction

Climate monitoring requires an operational analysis of the variability of climatic quantities in space and time. For this purpose, operational maps, generated for regular time intervals (days, months, seasons, years) are very useful to see at a glance the spatial variability of climate elements and its change with time. Such maps are often used by national meteorological and hydrological services as a basis for climate reviews and interpretation of outstanding features of climate variability. Maps are available for various spatial areas from the catchment scale to the whole globe.

For some recent years, the German Meteorological Service (Deutscher Wetterdienst, DWD) develops methods for generating such operational maps. These methods are not exactly the same for all climate elements due to various databases, their special nature of variability, and the data availability. Some are based on satellite data (e.g., cloud and radiation parameters), others are based only on in situ data, because in that cases the in situ data have a relatively good quality compared to satellite data (e.g., temperature, precipitation, sunshine duration, snow depth). Examples of these maps can be seen on the DWD website (www.dwd.de/rcc-cm, www.dwd.de/snowclim, www.dwd.de/satklim).

On the other hand, it is desirable to use consistently the same method for each climate element to achieve consistent maps, at least the same basic principle of a method. Our present strategy is to develop a basic approach which is at least applicable for most of the in situ data. The process of map generation is still under further development.

Usually, maps are a result of gridding or spatial interpolation of point data into the area. Nowadays, a large variety of mathematical and geostatistical methods for spatial interpolation is available. However, in practice, it has turned out that pure mathematics and geostatistics are necessary, but not sufficient for construction of climate monitoring maps; instead it has been found that the consideration of geographical conditions and climate processes can much improve the results. Nevertheless, the impact of such additional parameters and processes depends highly on the extent and topography of the area of interest, and also on data density. Therefore, the choice of the gridding method depends on the selected area, and the selected climate element as well.

This paper refers specifically to spatial interpolation of monthly mean temperature and its anomalies from the reference period 1961–1990 in a relatively large area, the WMO (World Meteorological Organization) Region VI (covering nearly the whole Europe and the Middle East). The next chapter describes this area and the motivation for the choice of this area. After a short review of previous literature, the data and the succeeding steps of the method applied in this paper are described and compared with a number of alternatives. Results of the comparison and the mapping are presented in Section 6, followed by some conclusions in Section 7.

The main goal of this paper is to propose a method of spatial interpolation of monthly temperature data in WMO Region VI which is suitable for an operational generation of monthly climate monitoring maps. However, it is intended that this approach is applicable to other climate elements as well to receive maps of various elements which are consistent to each other as far as possible, at least for in situ data. Other data sources, like satellite data which already have a large spatial coverage certainly require a different approach.

2. *The WMO Region VI and the Regional Climate Centre (RCC) network*

Recently, a new network of so-called Regional Climate Centres (RCCs) has been established under the auspices of the World Meteorological Organization (WMO) (http://www.wmo.int/pages/prog/dra/eur/RAVI_RCC_Network.php). The term "regional" refers to the six WMO Regions which cover roughly (but not exactly) the various continents and the surrounding sea areas on the globe.

Nearly the whole of Europe (except the easternmost parts of European Russia from 50°E to the Ural) belongs to the WMO Region VI (often referenced as "RA VI", indicating the Regional Association of the WMO in Region VI). Beside Europe, this region also covers parts of the Middle East which belong geographically to Asia, and also large sea areas, namely large parts of the northern and central North Atlantic, the Norwegian Sea, the European part of the Arctic, and the whole Mediterranean. The RA VI area is displayed in *Fig. 1*.

The border of the Region VI (Europe and Middle East) is not rectangular, because it is defined by the borders of single countries, which means largely by political conditions. Over European Russia, the eastern border runs along the 50°E meridian. In the south and west, the border crosses the Mediterranean Sea and the Atlantic Ocean to the Davis Strait and the Baffin Bay between Greenland and Canada.

Thus, that Region covers quite a large and climatically very heterogeneous area, spanning a wide range of latitude, longitude, and altitude and strong contrasts between land and sea climates.

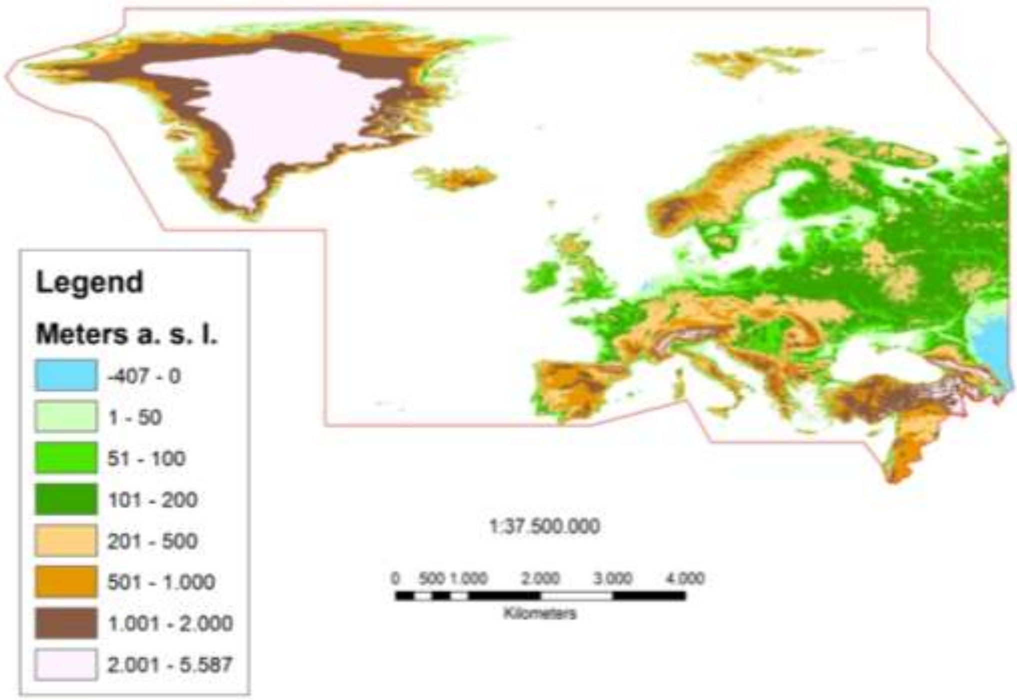

Fig. 1. Map of the Region VI with the height above sea level. The kilometer bar refers to Central Europe.

In RA VI, presently three RCCs (so-called nodes of the RCC network) are already preliminarily established and are operating in a pilot phase since June 2009: one RCC node on climate data, one on climate monitoring, and one on long-range forecasting. The DWD has taken over the lead function of the RCC node on climate monitoring in RA VI, within a consortium consisting of some more members (national meteorological and hydrological services) of RA VI. To fulfill this function, the generation of climate maps for various climate elements in RA VI is a very important task.

3. Previous approaches

A large number of papers dealing with spatial interpolation of climate data have already been published. Basic information about spatial interpolation methods can be found in various books, especially for the widely used kriging technique, which was very popular already in the 1990s (e.g., *Lang*, 1995; *Stein*, 1999). In the 2000s, geographical information systems (GIS) came more and more into operation for climate mapping. Commercial GIS software has made it technically very easy to apply spatial interpolation methods on any geographically defined data points. In 2001, the COST Action 719 was launched (COST= European Cooperation on Science and Technology, an intergovernmental framework for research coordination in Europe, supported by the European Union). The goal of COST 719 was to review and assess the use of GIS for spatial interpolation in meteorology and climatology. The Action had been finished in 2006, resulting in an overview of spatial interpolation methods and their application in climatology by GIS software (*Thornes*, 2005; *Tveito et al*., 2008) and many related papers (e.g., *Ustrnul* and *Czekierda*, 2005; *Dobesch et al.*, 2007).

Until now, there are several more recent papers. Various methods are applied to national data, some also to larger areas, e.g., the Alps, some to global data, but in coarse resolutions. Many investigators used ordinary or residual kriging techniques for monthly, seasonal, or annual data, e.g., *Bjornsson et al.* (2007) for temperature in Iceland, *Ustrnul* and *Czekierda* (2005) for temperature in Poland, *Dolinar* (2006) for sunshine duration in Slovenia, *Perčec Tadić* (2010) for climate normal values of various elements (including temperature) for Croatia, *Alsamamra et al.* (2009) for solar radiation in southern Spain. Others just used multiple regression techniques, but in a dense station network and with many geographical predictors, e.g., *Hiebl et al.* (2009) for monthly temperature in the Alps or *Claps et al.* (2008) for monthly temperature in Italy. Non-linear instead of linear statistical relationships between terrain variables as predictors and climate variables lead to an improvement at least for special variables like, e.g., fog frequency as shown by *Vicente-Serrano et al.* (2010) for northeast Spain. In some cases, circulation types were used as predictor, e.g., the well-known “Grosswetterlagen” catalogue from *Hess* and *Brezowsky* (1952) for the temperature in Poland (*Ustrnul*, 2006). Other authors included remote sensing data for statistical temperature modeling (e.g., *Cristóbal et al.*, 2008 for northeast Spain).

In contrast, there have been very few attempts to look for a method which is specifically appropriate for an area like RA VI. Recently, *Haylock et al.* (2008) presented a new European high-resolution gridded data set of daily precipitation and surface temperature for the period 1950 –2006 on four spatial resolutions (the so-called E-OBS data set). Although this data set is widely known and used, the authors themselves pointed to limitations of their gridded data due to inhomogeneities and interpolation uncertainties (*Hofstra et al.*, 2009). *Hofstra et al.* (2008) also compared several interpolation methods for various variables in some parts of Europe and found that the main controlling factor on the skill of interpolation is rather the density of the station network than the interpolation method. Only recently, another investigation used the spatial variability from past observations of a denser network to improve the interpolation skill, in this case applied to precipitation in the complex terrain of Switzerland (*Schiemann et al*., 2010).

Monthly, seasonal, and annual maps are frequently used for operational climate monitoring activities. The monitoring of the WMO RA VI Regional Climate Centre on Climate Monitoring (WMO RAVI RCC-CM) can be found on the web: http://www.dwd.de/rcc-cm, including links to national maps of many national meteorological and hydrological services. For global climate monitoring, monthly temperature maps are displayed, e.g., on the website of the National Oceanic and Atmospheric Administration (NOAA) in the USA:
http://www.ncdc.noaa.gov/climate-monitoring/index.php#global-icon .

4. Data and data quality

Since the goal is to generate monthly maps for RA VI in the operational environment of DWD, it is essential to use monthly in situ data which are available at DWD soon after the end of month, but, nevertheless, of good quality. National data sets exist for each country in RA VI. Mainly they are under the responsibility of the public national and hydrological services. Due to this national responsibility of the data, each country has its own data policy, and in most cases there are restrictions in data distribution beyond the national services. For this reason, only a limited number of all existing data can be used in the DWD environment. However, there are some data which are distributed internationally and regularly via the Global Telecommunication System (GTS) of the WMO. Two important data sets in this case are the SYNOP and CLIMAT data. SYNOP data are data from synoptical stations, distributed several times a day (often hourly), containing also the air temperature at two meters height over ground. They are mainly intended for usage in weather forecasting. CLIMAT data are distributed only monthly and the number of stations is much smaller than for SYNOP, but the selection of CLIMAT stations was done for usage of climate analyses. Monthly mean temperature is one of the climate elements which are reported in the CLIMAT bulletin. DWD has taken over the task to check the quality of the CLIMAT data each month in various steps. The quality check consists of two steps: a quick automatical check soon after data arrival and a more thoroughly manual check later. More details about the CLIMAT data archive and quality control method can be found on the DWD website (www.dwd.de – click on Climate and Environment – Climate Data Centers – ACD). The first step of quality check is normally done within 10 days after the end of each month. The check of SYNOP data would be more time consuming, and a complete routine quality control for SYNOP temperature data at DWD is only performed for German data, but not for the whole of the RA VI area. For this reason it was decided to use the CLIMAT data of monthly mean temperature for spatial interpolation, which means a data basis which is timely available in good data quality, but relatively poor data coverage (*Fig. 2a*). Around 800 CLIMAT stations are currently available for RA VI each month, and the area has an extension of several 1000 km in both zonal and meridional directions. This decision means to invest into an appropriate and reasonable interpolation procedure, which also takes the diverse topography of RA VI into account.

CLIMAT stations are available only for the land areas, but not for the sea. However, there exist weather reports from ships which are summarized into a $2.5° \times 2.5°$ latitude-longitude grid and are archived at DWD. Altogether, around 130 sea grid points are used for each month. Although the grid points are uniformly distributed over the area, the underlying ship reports are not equally distributed. The best data coverage can be found along the main shipping routes such as between Europe and the eastern coast of the USA or Brasilia, and the main route to the Mediterranean Sea, but in other areas ship data are quite rare (*Fig. 2b*). Thus, the quality of ship data is strongly dependent on ship observation coverage. They are most reliable along the main shipping routes where a large number of ship observations during the whole month are considered for gridding, but quite poor in those regions where only very few ship observations are available, e.g., over the Arctic Sea. Long-term averages for the 1961–1990 reference data (CLIMAT and ship data, as far as data available) are also quality controlled and included in the DWD archive, and anomalies (monthly means minus long-term averages) are computed each month as well.

For using the topography in the interpolation procedure, grid data for altitude are needed. Data for the height above sea level are taken from the GTOPO30 altitude raster from the U.S. Geological Survey (www.usgs.gov). The data are available in a spatial resolution of 30 seconds of degree in latitude and longitude (it means about 1 km for middle latitudes). For the operational maps, a spatial resolution of 0.1° was taken; thus, the GTOPO30 data were averaged into a 0.1° grid.

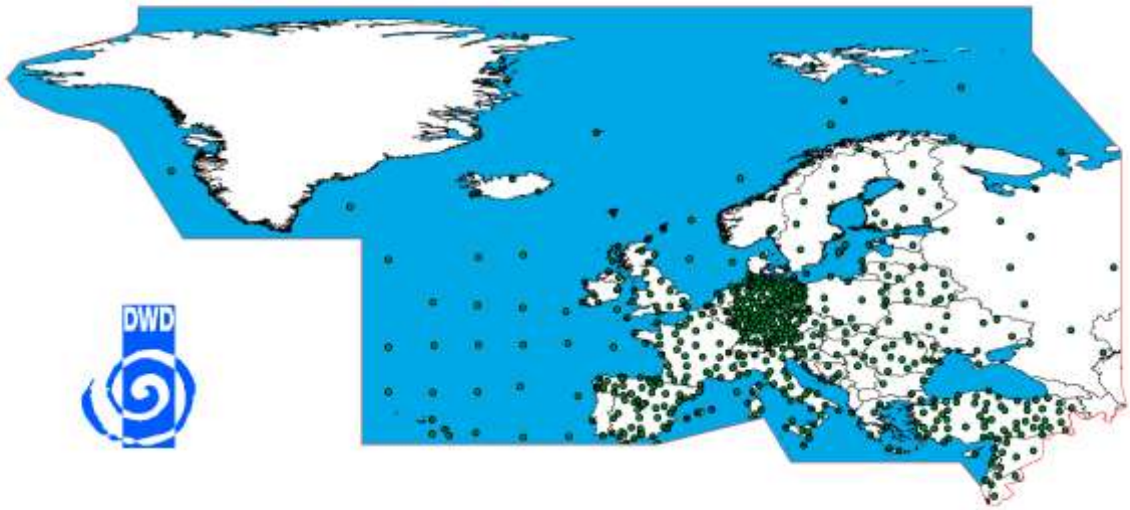

Fig. 2a. Spatial distribution of CLIMAT stations and ship data points available at DWD for September 2010 as an example. Ship data of the whole month are arithmetically averaged into a $2.5° \times 2.5°$ grid.

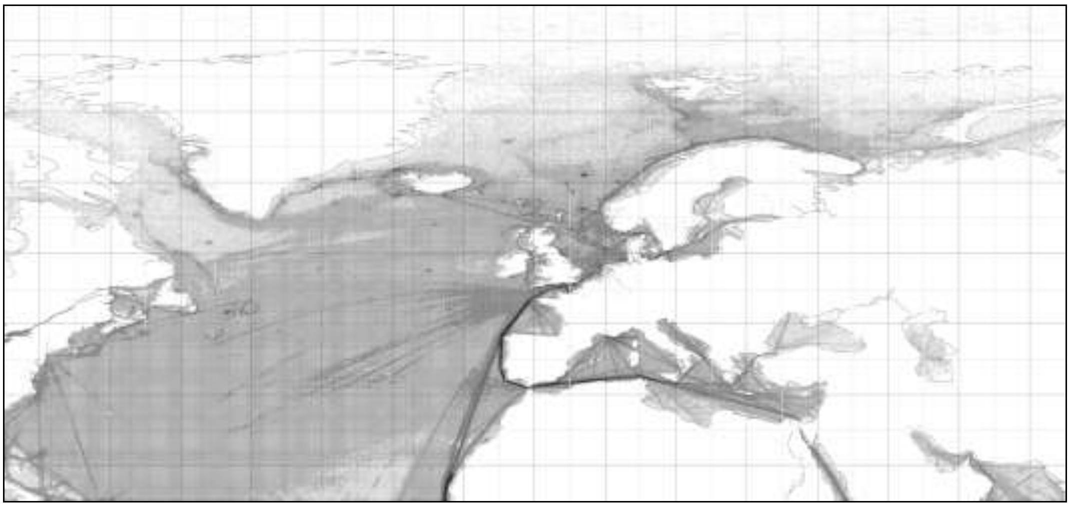

Fig. 2b. Ship data coverage, data from DWD (white = land area, light grey to dark grey = more travel on sea, if the color is darker, more ships travel on this route).

5. Methods

In principle, the spatial interpolation method for monthly averages used here consists of three steps. The first step is a multi-dimensional linear reduction of the station data, which means a multiple linear regression of latitude, longitude, altitude, and other parameters to zero level. The linear regression model is subtracted from the original data; the results of the subtraction are often called "residuals".

The second step is the interpolation of residuals with the method radial basis functions, using the version of the software ESRI Arc GIS 9.2 within the tool geostatistical analyst. The last step is recomputing the interpolated residuals to the original values of latitude, longitude, altitude, and other parameters. This computing is achieved by using the raster calculator of Arc GIS 9.2 within the tool spatial analyst. The three steps are described in more detail in Sections 5.1–5.6.

For the anomalies there is no reduction, just a spatial interpolation is necessary, assuming that they do not depend very strongly on geographical parameters. Spatial resolution is 0.1°; this corresponds to about 10 km over Central Europe. The number of grid points in the RA VI area roughly amounts to nearly one million.

At the borders of Region VI, the problem of extrapolation appears. For this reason, the interpolation is computed for an extended area (from 85°W to 70°E and from 20°N to 90°N), but only the Region VI itself is displayed. For this purpose, some more climate stations beyond Region VI are added to the data pool. The additional climate stations are located in the east part of the USA and Canada, the North African states, and in the part of the Middle East, which belongs to the Region II Asia.

5.1. General approach of multiple regression in latitude, longitude, altitude

The assumption of the multi-dimensional reduction is that the spatial variability of monthly averaged climate is dominated by a very limited number of impact factors.

The general approach is

$$Y = a\, f_1(x_1, x_2, \ldots, x_n) + b\, f_2(x_1, x_2, \ldots, x_n) + \ldots + k, \tag{1}$$

where Y is a climate state variable like temperature, x_1, x_2, … are impact factors like latitude etc., $f_1()$, $f_2()$, … are functions of impact factors, which are not necessarily linear, and a,b, …, k are constant values.

This approach is used to find the dominating impacts, x_1, x_2, and the functions of impacts, $f_1()$, $f_2()$, for each Y. The functions of the impact factors must be linearly independent from each other. Then, a linear regression can be computed.

5.2. Multiple linear regression in latitude, longitude, altitude

We start with latitude, longitude, and altitude as predictors. These factors are reasonable because of the following reasons: latitude characterizes the climate due to the solar angle, which is, by far, the most dominating factor for Region

VI. The longitude is the alternative for land-sea contrasts or continentality, which explains much of the seasonal variations. Finally, the altitude is included, because all climate state variables increase or decrease more or less with height above sea level. For monthly mean temperature, this factor is generally weak within Region VI compared to latitude and longitude but not negligible, especially in mountainous areas. The amount of variation of temperature as function of altitude varies largely from month to month, depending on season and the prevailing weather type during the month. In most cases, monthly mean temperature decreases with altitude, but in winter months, when inversion weather types are prevailing, a slight increase with altitude can also happen. For this reason, the regression model is fitted for each month separately.

The linear approach in this special case yields:

$$Y = a \cdot latitude + b \cdot longitude + c \cdot altitude + k \,. \tag{2}$$

This is a specialization of the general approach Eq. (1). The three predictors (latitude, longitude, and altitude) represent the three spatial dimensions which are obviously orthogonal and, therefore, independent from each other. The coordinates are mostly well known for each station, thus, these predictors are mostly easily available. The fitting of the multi-linear regression has been done using the method of least squares (see, e.g., *Mosteller* and *Tukey*, 1977).

5.3. Continentality impact

For improving the approach, the longitude is replaced by a suitable continentality index. The continentality is a function of latitude and the annual temperature amplitude, which is calculated by the difference of the long-term means (1961–1990) of the maximum temperature in summer (June to August) and that of the minimum temperature in winter (from December to February). That calculation of the annual temperature amplitude is only an approximation for simplifying the computation, but does not reflect exactly the real annual amplitude. For example, March, which belongs to spring, is sometimes the coldest month in the year because of the drifting ice in bays near Finland in the Baltic Sea. In the literature, there are various versions of continentality indices (see, e.g., *Blüthgen*, 1980). Many equations show that the continentality for Europe can be described by a function of latitude and the annual temperature amplitude. One example is the approach by *Iwanow* (1959). Hogewind (*Hogewind*, 2010) modified this index to obtain a better suitability for the Region VI:

$$k = 260 \cdot \frac{annual \;\; amplitude}{latitude \varphi}, \qquad \textit{Iwanow}\text{ (1959) and}$$

$$k = \frac{110 \cdot annual \;\; amplitude}{(latitude \; \varphi + 6)}, \qquad \textit{Hogewind} \; (2010).$$

This modification results in four classes in the range of the index: between 0 and 25 (highly maritime), from 26 to 50 (maritime), from 51 to 75 (continental), and from 76 to 100 (highly continental) over Region VI and its surroundings, and a threshold of around 50 between prevailing maritime and prevailing continental areas (*Fig. 3*).

Taking the continentality into account, the modified regression approach reads:

$$Y = a \cdot latitude + b \cdot altitude + c \cdot annual \;\; amplitude + d \cdot continentality + k \,. \qquad (3)$$

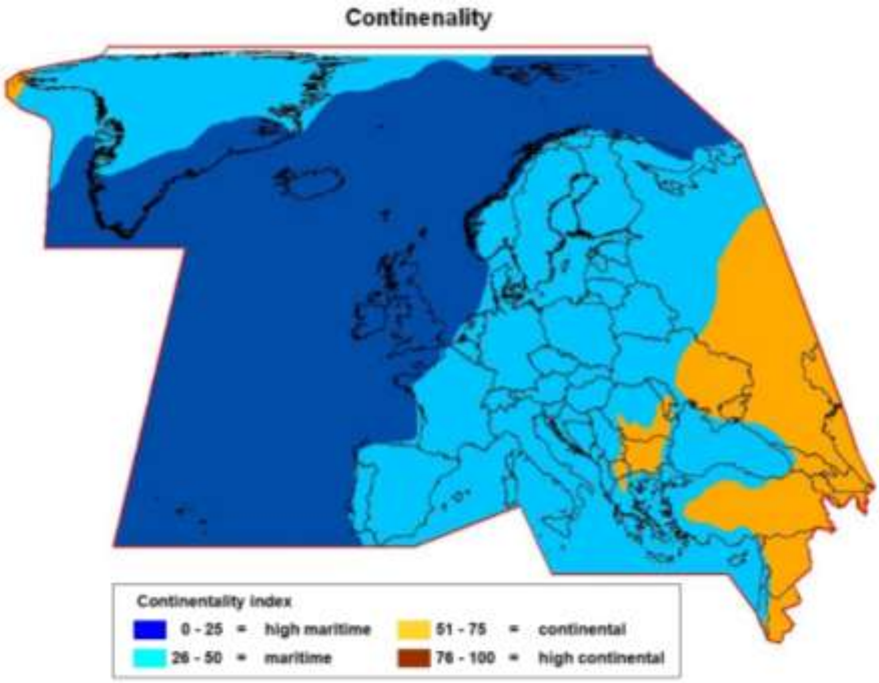

Fig. 3. Continentality (*Hogewind*, 2010).

This is now a non-linear approach in the explanatory variables, because continentality is a non-linear function of latitude, but the multiple regression is still linear, because a non-linear data transformation has been done (*Wilks*, 2006).

To get the residuals (T_{red}, the part of variability which is not explained by the regression model), the linear regression is subtracted from the original monthly mean temperature value for each station:

$$T_{red} = T_m - (a \cdot latitude) - (b \cdot altitude) - (c \cdot annual \, amplitude) \\ - (d \cdot continentality) - k \,. \qquad (4)$$

The considered parameters are now latitude, altitude, annual amplitude, and the newly created continentality index.

5.4. Interpolation of residuals

The reduced climate state variable, also known as residual (here T_{red}) is given for each measurement station and has to be interpolated into the area. The main question is now: which is the best suitable interpolation method?

The used software ArcGIS 9.2 Geostatistical Analyst offers a number of methods: inverse distance weighted, global polynomial interpolation, local polynomial interpolation, radial basis function, kriging, cokriging, and subtypes for each. From these methods a number of alternative approaches, which seem reasonable, are taken and applied to the computed residuals.

All these methods are described in the literature. An overview can be found in *Tveito et al.* (2008) including the mathematical background, the implementation in GIS software, and further references. The method "radial basis functions", which has been used for the final construction of maps in this paper, is described in the next section.

5.5. Radial basis functions

A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin, so that $\Phi(x) = \Phi(||x||)$, or, alternatively, on the distance from some other point c, called a center, so that $\Phi(x,c) = \Phi(||x-c||)$. Any function φ that satisfies the property $\Phi(x) = \Phi(||x||)$ is a radial function. The norm is usually the Euclidean distance, although other distance functions are also possible. For example, by using the Lukaszyk-Karmowski metric, for some radial functions it is possible to avoid problems with ill conditioning of the matrix solved to determine coefficients ω_i (see below), since the $||x||$ is always greater than zero.

Sums of radial basis functions are typically used to approximate given functions. This approximation process can also be interpreted as a simple kind of neural network.

The radial basis functions type used in this paper is multiquadratic ($r = || x - c_i ||$):

$$\varphi(r) = \sqrt{r^2 + \beta^2} \qquad \text{for some } \beta > 0. \tag{5}$$

Radial basis functions are typically used to build up function approximations of the form:

$$y(x) = \sum_{i=1}^{N} \omega_i \ \Phi(||x - c_i||), \tag{6}$$

where the approximating function $y(x)$ is represented as a sum of N radial basis functions, each associated with a different center c_i, and weighted by an appropriate coefficient ω_i. The weights ω_i can be estimated using the matrix methods of linear least squares, because the approximating function is linear in the weights.

Approximation schemes of this kind have been particularly used in time series prediction and control of non-linear systems exhibiting sufficiently simple chaotic behavior, and 3D reconstruction in computer graphics (*Lukaszyk*, 2004; *Buhmann*, 2003).

Eq. (6) can also be interpreted as a rather simple single-layer type of an artificial neural network, called a radial basis function network, with the radial basis functions taking the role of the activation functions of the network. It can be shown that any continuous functions on a compact interval can in principle be interpolated with arbitrary accuracy by a sum of this form, if a sufficiently large number of radial basis functions is used.

The approximant $y(x)$ is differentiable with respect to the weights ω_i. The weights could thus be learned using any of the standard iterative methods for neural networks.

There is a lot of literature about radial basis functions for further reading (e.g., *Baxter*, 1992; *Beatson et al.*, 2000; *Bors*, 2001; *Buhmann*, 2003; *Wei*, 1998).

5.6. Recomputing interpolated residuals

For recomputing the interpolated residuals to original data, the same regression equation, Eq. (4), as for reduction is used (Section 5.3). The difference is that this time the computing is not carried out for stations, but for the interpolated grid for the Region VI

$$\begin{aligned} T = T_{red} &+ (a \cdot latitude) + (b \cdot altitude) + (c \cdot annual\,amplitude) \\ &+ (d \cdot continentality) + k. \end{aligned} \tag{7}$$

Therefore, gridded data for latitude, altitude, annual temperature amplitude, and continentality are needed. Latitude is just a linear interpolation in meridional direction. For altitude, the grid GTOPO30 from U.S. Geological Survey is used with a recalculated resolution in 0.1°. The annual amplitude is interpolated by the interpolation method radial basis functions from station data, and finally, the continentality is computed from latitude and annual amplitude for each grid point (see Section 5.3).

5.7. Cross validation and root mean square error (RMSE)

To assess the quality of the spatial interpolation, a cross validation of the residuals has been carried out. This means that the spatial interpolation has been repeated after omitting one of the residual station values, and this has been done for each station value. Then, for all station points the difference between the residual station value and the corresponding interpolated value at this point has been computed. Finally, the root mean square error (RMSE) has been computed over the differences for all points, and then for each month and each of various interpolation methods, among them radial basis functions, several kriging approaches, and inverse distance weighted interpolation. Therefore, the RMSE is a quantity for estimating the mean interpolation error. However, it has to be kept in mind that the RMSE only can represent the information at the station points, but not for the whole area, and therefore, it does not exactly give the real mean interpolation error. Nevertheless, the estimate should be near to reality if the stations are representative for the area. As most stations are located in Central Europe, where the interpolation error is expected to be lower than in other more data sparse regions, the real mean interpolation error should be greater than the RMSE, which means that the RMSE can only give a minimum estimation. However, as the data base is the same for each method and each month (except for a few stations missing from month to month), the RMSE is a comparable measure of skill for each interpolation method.

6. Results

6.1. Results of the multiple regression

For the first approach (Eq. (2)), the three predictors (latitude, longitude, and altitude) explain a large part of the variance, generally over 70% for monthly mean temperature in Region VI for all months (*Table 1*).

Table 1. Explained variance in % for each of the predictors in Eqs. (2) and (3), for all months of the 1991–2000 average. Other periods have similar results

Month	**Latitude**	**Longitude**	**Altitude**	**Annual amplitude**	**Continen-tality**	**Lat+lon+alt (Eq. (2))**	**Lat+alt+amp+ cont (Eq. (3))**
Jan	60.98	5.36	3.90	50.78	10.30	70.29	93.83
Feb	66.21	4.85	2.52	43.93	6.13	73.74	93.44
Mar	74.32	2.60	1.17	30.75	1.42	80.07	91.33
Apr	83.92	0.68	0.23	13.73	0.76	89.08	90.72
May	85.02	0.00	0.09	3.36	7.50	90.12	89.02
Jun	80.85	0.54	0.42	0.00	18.63	88.04	88.93
Jul	79.83	0.31	0.86	0.25	23.21	85.74	90.03
Aug	83.78	0.01	0.55	0.12	17.56	88.56	91.33
Sep	88.20	0.84	0.04	5.96	5.17	92.54	93.82
Oct	86.28	2.39	0.64	16.47	0.33	91.73	94.94
Nov	75.07	5.86	2.91	35.66	2.74	83.81	95.89
Dec	65.77	6.95	3.98	47.29	8.08	75.72	95.07

The largest part is explained by latitude, especially in the warmer half year, due to the large variability of temperature as function of the solar angle. The explained part of variance in Eq. (3), using the predictors latitude, altitude, annual amplitude, and continentality, is considerably larger, especially during the colder months (from November to March) compared to Eq. (2), over 90%, due to the high impact of the annual amplitude particularly in winter, which has a high spatial variability within Europe. In the warmer half year, there is practically no or only a slight improvement concerning the explained variance by Eq. (3) compared to Eq. (2). However, the explained variance by Eq. (3) is within a range between 89 and 96% (rounded) for each month.

6.2. Results of the spatial interpolation

Results of the comparison between the various interpolation methods are shown in *Fig. 4*. For some of the interpolation methods and subtypes, unwanted interpolation islands appear (so-called bulls eyes), in particular for inverse distance weighting, global and local polynomial interpolation. Some kriging and cokriging subtypes are not exact at the station points and smooth too much. The interpolation method cokriging needs a second variable with the same resolution as the climate variable. This cannot be an impact variable, because this has already been removed by reduction. Some methods, especially cokriging, need quite a high computing time depending on spatial resolution, and thus, they are not convenient for operational use.

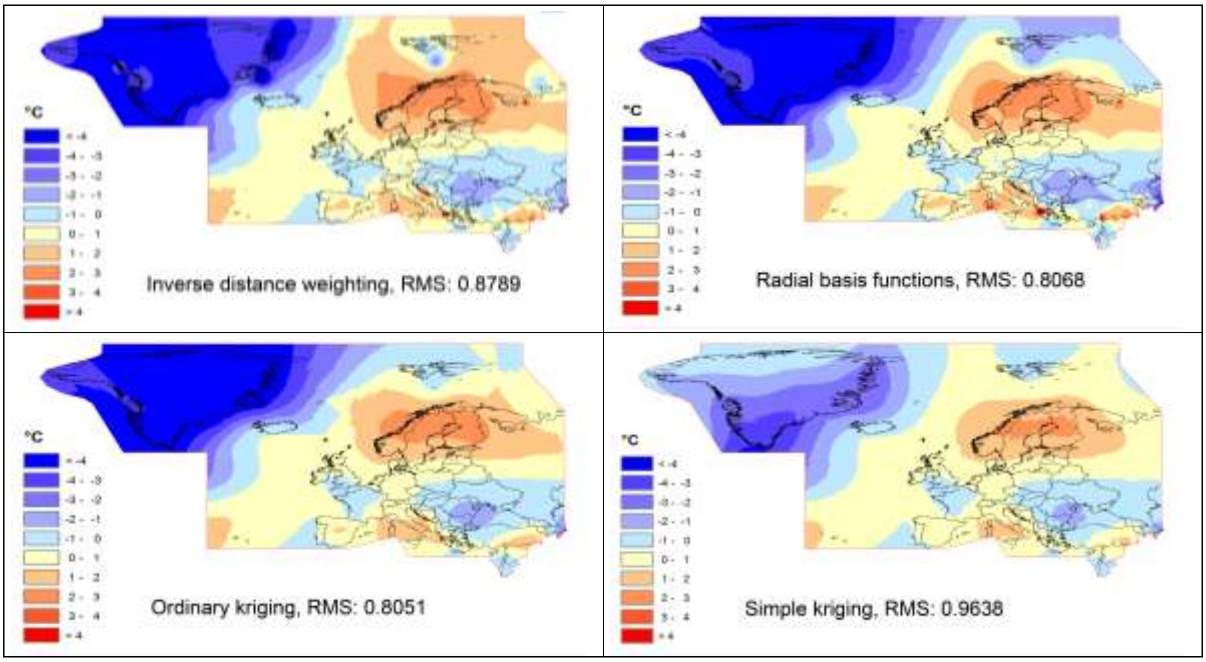

Fig. 4. Interpolated residuals (after subtracting the linear regression model) of annual temperature normal values of the period 1961–1990 using the following interpolation methods: inverse distance weighted (upper left), radial basis functions (upper right), ordinary kriging (lower left), simple kriging (lower right). RMS errors given for each method in K refer to the residuals.

Fig. 4 also shows the root mean square errors (RMSE) for various interpolation methods. The highest RMS errors of these show the interpolation methods simple kriging (*Fig. 4,* lower right) and inverse distance weighted (upper left). For inverse distance weighted, obvious interpolation islands can be clearly seen. Simple kriging amplifies point-to-point differences too much. The other two methods (ordinary kriging, *Fig. 4,* lower left, and radial basis functions, upper right), although basically different from each other, produce more or less the same results. The difference between these two interpolation methods is the longer computing time and the more difficult calibration of ordinary kriging because of every individual interpolation for the climate variable and period. As a result of this comparison of the different methods, the radial basis functions method with the subtype multiquadratic appears as the most suitable method for meeting our demands on operational map generation. The main advantages are exactness at data points (values at the data points are not changed after interpolation, except due to different altitudes and locations of the stations compared to the grid points), no smoothing, but no unrealistic interpolation islands either. The exactness at data points is also good to detect suspicious data on the map. The RMS error for the selected method is one of the lowest, the results are similar to ordinary kriging, but the computing is faster than kriging. Kriging, on the other hand, offers more possibilities of error assessment, but they are more difficult to interpret as they are not comparable with error assessments of other methods. Generally, the choice of the interpolation method matters only in data sparse areas. Otherwise, it is more important, when the regression error is higher or the data quality is worse.

The results of the described process need a further development which is described by *Hogewind* (2010). The different thermal conditions between land and sea require a separate regression over land and sea with separate regression coefficients for land and sea, but each applied to the whole RA VI area (*Fig. 5*). To consider coastal effects, the climate stations near the coast are used for both computing processes for overlapping land-sea areas. Furthermore, the data pool is increased by including the stations from the European Climate Assessment Dataset (ECA&D, www.knmi.nl). To study the space-time variability, the procedure has also been carried out for 10-year subperiods of the period 1951–2000. Examples of recomputed temperature fields for land and sea are shown in *Figs. 6a* and *6b* (for recomputation, a land-sea mask was used). These fields are overlaid to one complete map for the whole Region VI like a puzzle (*Fig. 7*). The effect of the thermal contrast between land and sea can be seen in various places, e.g., for Turkey.

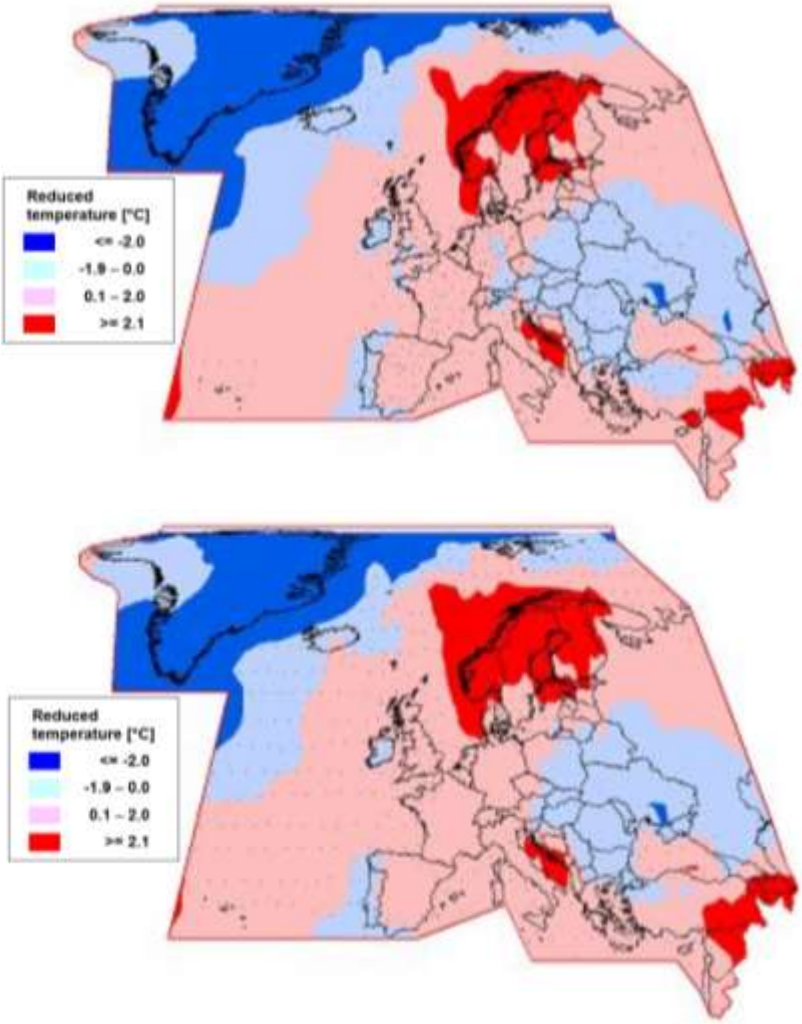

Fig. 5. Reduced temperature (residuals) over land (upper) and sea (lower) in September for the period of 1991–2000. Separate regression coefficients for land and sea are used, but applied to the whole RA VI area.

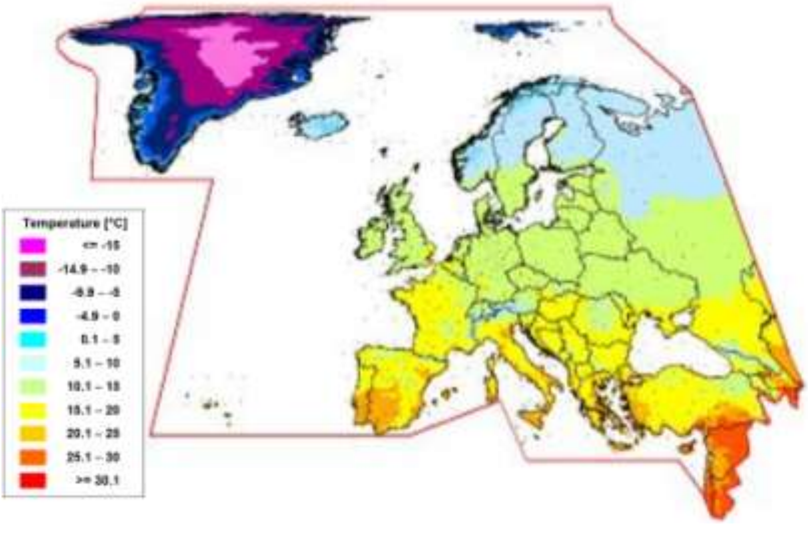

Fig. 6a. Recomputed temperature over land in September for the period of 1991–2000 White areas are excluded by using a land-sea mask.

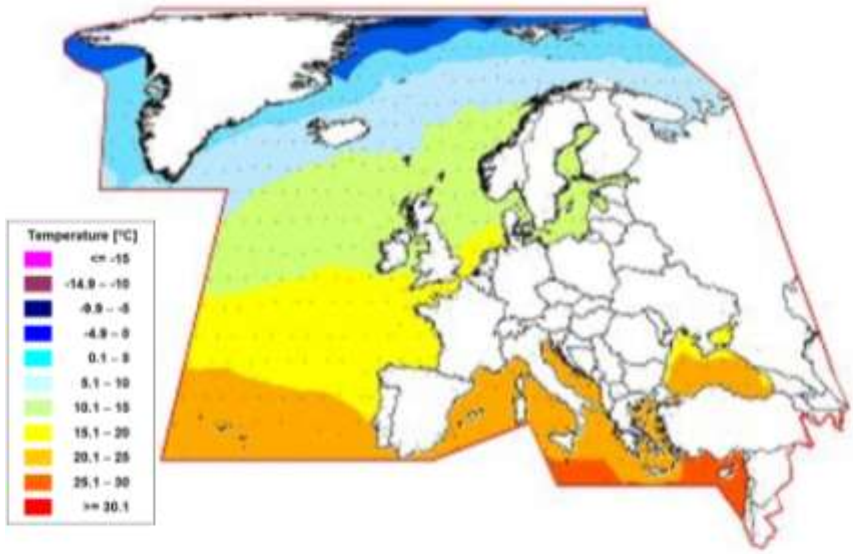

Fig. 6b. Recomputed temperature over sea in September for the period of 1991–2000 White areas are excluded by using a land-sea mask.

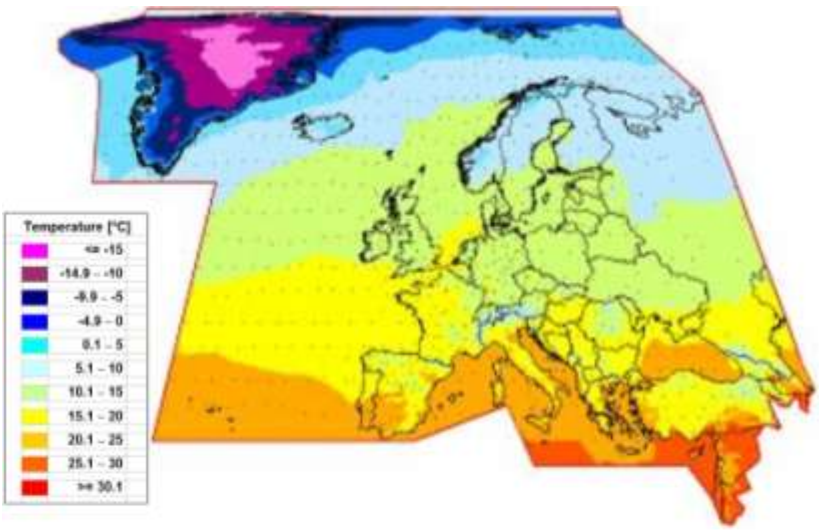

Fig. 7. Recomputed temperature in September for the period of 1991–2000 for the whole RA VI Region (consisting of separate calculations over land and sea as in Fig. 6).

7. Conclusions

The newly created continentality index (*Hogewind*, 2010) improves the regression model in comparison to longitude. The separate land-sea regressions improve the regression model, too. Nevertheless, the most important parameter for Region VI is still the latitude because of the strong influence of the angle of solar radiation. Residuals up to 2 K (RMSE 0.9 K) do not change, due to small scale effects. Radial basis functions turned out to be the most suitable interpolation method at the moment, at least for operational map production of monthly mean temperature in WMO Region VI. The method is exact, has a relatively low RMSE, can be realized very easily by using GIS software, and the interpolation can be computed in reasonable time. Probably the most promising effort to improve the results further is to enlarge and improve the data base and the regression model. Another challenge will be the application of this method to daily instead of monthly data.

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References

Alsamamra, H., Ruiz-Arias, J.A., Pozo-Vázquez, D., Tovar-Pescador, J., 2009: A comparative study of ordinary and residual Kriging techniques for mapping global solar radiation over southern Spain. *Agr. Forest. Meteorol. 149*, 1343-1357.

Baxter, B.J.C., 1992: The interpolation theory of radial basis functions. Cambridge University.

Beatson, R.K., Light, W.A., Billings, S., 2000: Fast solution of the radial basis function interpolation equations: Domain decomposition methods. *Society for Industrial and Applied Mathematics 22*, 1717-1740.

Bjornsson, H., Jonsson, T., Gylfadottir, S.S., Olason, E.O., 2007: Mapping the annual cycle of temperature in Iceland. *Meteorol. Z. 16,* 45-56.

Blüthgen, J., 1980: *Allgemeine Klimageographie*. 3. new revised edition. De Gruyter, Berlin (in German).

Bors, A.G., 2001: Introduction of the Radial Basis Function (RBF) Network. Online Symposium for Electronics Engineers.

Buhmann, M.D., 2003: *Radial Basis Functions: Theory and Implementations*. Cambridge University Press.

Claps, P., Giordano, P., Laguardia, G., 2008: Spatial distribution of the average air temperatures in Italy: quantitative analysis. *J. Hydrolog. Eng. 13*, 242-249.

Cristóbal, J., Ninyerola, M., Pons, X., 2008: Modelling air temperature through a combination of remote sensing and GIS data. *J. Geophys. Res. 113*, D13106.

Dobesch, H., Dumolard, P., Dyras, I., 2007: Spatial interpolation for climate data. The use of GIS in climatology and meteorology. *Geographical Information Systems Series*. ISTE, London.

Dolinar, M., 2006: Spatial interpolation of sunshine duration in Slovenia. *Meteorol. Appl. 13*, 375-384.

Haylock, M.R., Hofstra, N., Klein Tank, A.M.G., Klok, E.J., Jones, P.D., New, M., 2008: A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. *J. Geophys. Res. 113*, D20119.

Hess, P., Brezowsky, H., 1952: Katalog der Grosswetterlagen Europas. *Ber. Deutscher Wetterdienst in US Zone*, Nr. 33.

Hiebl, J., Auer, I., Böhm, R., Schöner, W., Maugeri, M., Lentini, G., Spinoni, J., Brunetti, M., Nanni, T., Perčec Tadić, M., Bihari, Z., Dolinar, M., Müller-Westermeier, G., 2009: A high-resolution 1961-1990 monthly temperature climatology for the greater Alpine region. *Meteorol. Z. 18*, 507-530.

Hofstra, N., Haylock, M., New, M., Jones, P.D., 2009: Testing E-OBS European high-resolution gridded data set of daily precipitation and surface temperature. *J. Geophys. Res. 114*, D21101.

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. 113*, D21110.

Hogewind, F., 2010: Raum-zeitliche Analyse der Klimavariabilität anhand von hochaufgelösten interpolierten Klimakarten am Beispiel von Europa und dem Nahen Osten (Region VI der Weltorganisation für Meteorologie). Preliminary results (in German, to be published in PhD thesis, University of Mainz, Germany).

Iwanow, N.N., 1959: Belts of continentality on the globe. (Izwest. Wsejoj. Geogr. Obschtsch. 91, 410-423 (in Russian). Cited in *Blüthgen* (1980), p. 590 (in German).

Lang, C., 1995: *Kriging Interpolation*. Department of Computer Science, Cornell University.

Lukaszyk, S., 2004: A new concept of probability metric and its applications in approximation of scattered data sets. *Computational Mechanics 33*, 299-304.

Mosteller, F., Tukey, J.W., 1977: *Data Analysis and Regression* – a second course in statistics. Addison-Wesley, Reading MA, ISBN 020104854X.

Perčec Tadić, M., 2010: Gridded Croatian climatology for 1961-1990. *Theor. Appl. Climatol. 102*, 87-103.

Schiemann, R., Liniger, M.A., Frei, C., 2010: Reduced space optimal interpolation of daily rain gauge precipitation in Switzerland. *J. Geophys. Res. 115*, D14109.

Stein, M. L., 1999: Interpolation of spatial data: Some theory for kriging. In *Springer Series in Statistics*. New York, Berlin; Springer.

Thornes, J.E., 2005: Special Issue on the use of GIS in Climatology and Meteorology. *Meteorol. Appl. 12*, i-iii.

Tveito, O.E., Wegenhenke, M., van der Wel, F., Dobesch, H., 2008: The use of geographic information systems in climatology and meteorology. *Office for Official Publications of the European Communities*, 245 pp.

Ustrnul, Z., 2006: Spatial differentiation of air temperature in Poland using circulation types and GIS. *Int. J. Climatol. 26*, 1529-1546.

Ustrnul, Z. and *Czekierda, D.*, 2005: Application of GIS for the development of climatological air temperature maps: an example from Poland. *Meteorol. Appl. 12*, 43-50.

Vicente-Serrano, S.M., López-Moreno, J.I., Vega-Rodríguez, M.I., Begueria, S., Cuadrat, J.M., 2010: Comparison of regression techniques for mapping fog frequency: application to the Aragón region (northeast Spain). *Int. J. Climatol. 30*, 935-945.

Wei, G.-Q., 1998: Three-dimensional reconstruction by radial basis function networks: Shape from shading and stereo vision. Munich, Dissertation.

Wilks, D.S., 2006: *Statistical Methods in the Atmospheric Sciences.* 2. Ed. Elsevier, Academic Press.