A Central European precipitation climatology – Part I: Generation and validation of a high-resolution gridded daily data set (HYRAS)

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Abstract
A new precipitation climatology (DWD/BfG-HYRAS-PRE) is presented which covers the river basins in Germany and neighbouring countries. In order to satisfy hydrological requirements, the gridded dataset has a high spatial resolution of 1 km² and a daily temporal resolution that is based on up to 6200 precipitation stations within the spatial domain. The period of coverage extends from 1951 to 2006 for which gridded, daily precipitation fields were calculated from the station data using the REGNIE method. This is a combination between multiple linear regression considering orographical conditions and inverse distance weighting. One of the main attributes of the REGNIE method is the preservation of the station values for their respective grid cells. A detailed validation of the data set using cross-validation and Jackknifing showed both seasonally- and spatially-dependent interpolation errors. These errors, through further applications of the HYRAS data set within the KLIWAS project and other studies, provide an estimate of its certainty and quality. The mean absolute error was found to be less than 2 mm/day, but with both spatial and temporal variability. Additionally, the need for a high station network density was shown. Comparisons with other existing data sets show good agreement, with areas of orographical complexity displaying the largest differences within the domain. These errors are largely due to uncertainties caused by differences in the interpolation method, the station network density available, and the topographical information used. First climatological applications are presented and show the high potential of this new, high-resolution data set. Generally significant increases of up to 40% in winter precipitation and light decreases in summer are shown, whereby the spatial variability of the strength and significance of the trends is clearly illustrated.

Keywords: Precipitation measurement, daily interpolation, climate, KLIWAS.

1 Introduction
Our ecosystem and civilisation strongly depend on water resources. It is therefore important to know not only how precipitation patterns have changed, but also how they are likely to evolve in the future. To project future changes correctly, past regional and global patterns of precipitation have to be analysed and understood. Despite the rapid progress achieved in the last two decades in estimating precipitation from radar and satellite observations, gauge observations still play a critical role in documenting precipitation and their patterns due to their direct measurement method and lengthy time series. However, the stations for precipitation observations are often irregularly spatially and temporally distributed, making climatological analyses more complicated. There are many reasons why interpolation to a regular grid is a prerequisite to such analyses:

• for the bias correction of climate models and their evaluation (e.g. BOE et al., 2007; BERG et al., 2012),
• for impact modelling, e.g. hydrological models e.g. BRONSTERT et al., 2007; LENDERINK et al., 2007; KRAHE et al., 2009),
• for climate analyses in regions without any or with only sparse measurements (e.g. BECKER et al., 2013; SCHNEIDER et al., 2013),
• for regional climate analyses and for pattern analyses on different spatial scales (e.g. JACOBEIT et al., 2009; HUNDECHA and BARDOSY, 2005).

Over the past few decades changes in precipitation patterns have been observed, but it is very difficult to differentiate between natural changes and those due to global warming. Nevertheless, there is clear evidence supporting an anthropogenic influence on precipitation and its distribution due to climate change (SOLOMON et al., 2007). Since the 1990’s there have been numerous studies focused on climatic variation in Central Europe, with much attention directly on Germany. The observation-based studies have concentrated in the last years more and more on developing a set of indices or trends through use of historic meteorological observation databases (e.g. ZOLINA et al., 2008; MOBERG and JONES, 2005; HUNDECHA and BARDOSY, 2005; KLEINTANK et al., 2002; FREI and SCHRÄ, 1998). Changes in precipitation regimes, frequencies and extremes are found and supported by an accumulating amount of evidence that suggests they are the result of global warming (e.g. FREI
et al., 2006). In Germany and Central Europe there has been a marked and significant increase in daily winter precipitation and a small and less significant decrease in the summer (e.g. Zolina et al., 2008; Alexander et al., 2006). Without a doubt, the magnitudes and frequencies of daily precipitation have become more extreme in winter and generally less so in summer (e.g. Zolina et al., 2008; Kleintank et al., 2002), although there is evidence to suggest that extreme events in summer in some places in Central Europe could be becoming more intense. Most studies that have investigated trends in the spring and autumn seasons also show similar but less significant increases to those found in winter (e.g. Hundecha and Bárdossy, 2005). These results are also consistent with other Northern European countries, e.g. for the United Kingdom (Osborn and Hulme, 2002).

As temperature rises, the likelihood of precipitation falling as rain rather than snow also increases. This is especially true in autumn and spring at the beginning and end of the snow season and in areas where temperatures are near freezing. Such changes are observed especially over land in middle and high latitudes of the Northern Hemisphere, leading to increased rains but reduced snow pack and consequently diminished water resources during summer (e.g. Solomon et al., 2007). Nevertheless, the often spotty and intermittent nature of changes in observed patterns for mean precipitation are complex. As climate changes, several influences alter precipitation amount, intensity, frequency and type directly. Warming accelerates land surface drying and increases the potential incidence and severity of droughts. However, a well-established physical law (the Clausius-Clapeyron relation) determines that the water-holding capacity of the atmosphere increases by about 7% for every 1°C rise in temperature. This generally tends to cause increased precipitation intensities and the risk of heavy rain and snow events (Berg et al., 2013; Bengtsson et al., 2009; O’Gorman and Schneider, 2009).

Fundamental theory, climate model simulations and empirical evidence all confirm that warmer climates, owing to increased water vapour, lead to more intense precipitation events even when the total annual precipitation is slightly reduced. When the overall precipitation amounts increase there are prospects for even stronger events. A warmer climate therefore increases risks of both drought and floods but at different times and/or places. The distribution and timing of floods and droughts is most profoundly affected by atmospheric circulation patterns such as El Niño, which triggers the NAO (North Atlantic Oscillation), an important teleconnection pattern for Europe. Some of these observed circulation changes have been associated with climate change (e.g. Jacob et al., 2009; Haylock and Goodess, 2004).

To analyse the potential consequences of climate change on inland and coastal waterways and to formulate appropriate strategies for adaptation to the future environmental conditions, the German government launched the research programme KLIWAS (“Impacts of climate change on waterways and navigation – searching for options of adaptation”, www.kliwas.de). KLIWAS is part of the German Adaptation Strategy (DAS) and a collaborative programme of the German Meteorological Service (DWD), the Federal Institute of Hydrology (BfG), the Federal Maritime and Hydrographic Agency (BSH) and the Federal Waterways Engineering and Research Institute (BAW). Within the context of the KLIWAS research programme and the HYRAS pilot study funded by the BfG, the DWD developed gridded data sets of relevant hydrological parameters on a daily basis for Germany and the neighbouring river basins. This paper focuses on the precipitation data set. The currently existing climatologies provide neither the full spatial coverage of German river basins needed for studies on potential consequences of climate change for navigation on German waterways nor the spatial resolution down to 1 km and/or the daily temporal resolution needed for hydrological modelling (e.g. Schneider et al., 2013; Haylock et al., 2008, Efthymiadis et al., 2006; Schward, 2000, Frei and Schär, 1998; Müller Westermeier, 1995). Regarding hydrological studies the need for high-resolution precipitation data is always in great demand.

In this article we present the DWD/BfG-HYRAS v2.0 precipitation data set (HYRAS-PRE) covering Germany and neighbouring river basins using as many of the available rain-gauge observations as possible between 1951 and 2006. The data set is created using the REGNIE (“REgionalisierte NIEDerschlagshöhe”,engl. regionalised precipitation amount) method, which is comprehensively described for the first time. The REGNIE dataset for Germany is well-known both in the hydrological and meteorological communities. Studies on meteorological forecasting (Schwitalla et al., 2008), on climate simulation (Bellprat et al., 2012; Berg et al., 2012; Kotlarski et al., 2012), hydrological (Graselt et al., 2008; Photiadou et al., 2011) or ecological (Tölle et al., 2012; Samaniego et al., 2013) modelling have all used REGNIE data. One of the research tasks within KLIWAS was to investigate how well this method could be adapted and expanded to bordering river basins as well as to the Alpine region. Another research purpose was to elaborate the uncertainties of such a gridded data set, which is given here by an extensive validation of the data set.

The decision to use the REGNIE method is based on two aspects: As mentioned in the previous paragraph, the REGNIE data for Germany are well-known and accepted, but not yet documented in detail. On the other hand the combination of multiple linear regression (MLR) considering orography and inverse distance weighting (IDW) is very fast and numerically stable for calculating highly resolved, daily precipitation fields and carrying out an extended validation. It is known that an extensive number of interpolation methods exist which can be used with different modulations and with differences in e.g. including neighbouring stations, search radius, sector screening and other calibrations. Often,
geostatistical approaches performs better than IDW, as well as multivariate rather than univariate techniques, although the results differ depending on network density and geographical region. In Ly et al. (2011) external drift kriging with elevation did not improve the interpolation accuracy in comparison to IDW. Also in regions with a sparse network Wagner et al. (2012) found that IDW and Kriging have nearly the same error quantities. In Dirks et al. (1998) no improvements from Kriging instead of IDW were detected. Furthermore, the studies of Hewitson and Crane (2005) and Hofstra et al. (2008) have shown that the station density, the parameter to interpolate, complex topography or a less representative station network leads to more sensitivity in the results than the choice of the interpolation method – especially for highly variable, daily precipitation processes.

This paper is the first part of a trilogy and gives an overview of the DWD/BfG-HYRAS-PRE data base. In the two following papers, which are in preparation, applications of the data sets are presented. In the second paper an evaluation of the COSMO-CLM by comparison with HYRAS-PRE (Brienen et al., in preparation) can be found and in the third paper downscaling and bias correction of regional climate projections using the HYRAS-PRE data set will be introduced (Plagemann et al., in preparation). The main focus in this paper is the description of the data base and the gridding method of the HYRAS-PRE data (Sections 2 and 3). In Section 4 some examples and climatological features of the data set are presented. The validation by means of cross-validation and Jackknifing is described and the comparison with other data sets is shown in Section 5. A conclusion including an outlook is given in Section 6.

2 Description of the data base

The selected time period and region were chosen specifically to support the goals and aims laid out in the KLIWAS research programme. The data used here extend more than 50 years from 1951 to 2006, nearly twice the minimum period (i.e. 30 years) recommended for climatological investigations by the World Meteorological Organization. The data set includes all river basins within Germany as well as data of most neighbouring countries with shared basins (i.e. Rhine, Danube and Elbe). This area is henceforth referred to as the KLIWAS domain. Rain gauge data from Poland for the Oder catchment areas were not yet available for this study, but it is planned to include them in a future version of the HYRAS data set.

2.1 Data collection

Rain gauge data were required and obtained from a number of national meteorological services and other institutions. In addition to Germany, data were received from: the Netherlands (Royal Netherlands Meteorological Institute, KNMI), Belgium (Royal Meteorological Institute, RMI), Luxembourg (LUX Airport and Centre de Recherche Public Gabriel Lippmann), France (Météo-France), Switzerland (MeteoSchweiz), Austria (Central Institution for Meteorology and Geodynamics (ZAMG) and Hydrographical Survey (HD)) and the Czech Republic (Czech Hydrological Institute, CHMI). All available observations were used for the creation of the DWD/BfG-HYRAS-PRE data set. An overview of the total number of available stations and their temporal distribution is shown in Fig. 1. As can be seen, the total number of observations varies significantly over time, though offsets are particularly prominent:

- a near-tripling of the number of Swiss stations in 1961,
- about 1000 additional German stations in 1969, and
- a strong increase of about 500 stations in Austria in 1971.

The total maximum number of stations is about 6200 in the early 1990’s. To present the differences in spatial station distribution, the coverage in 1951 and 1991 is shown in Fig. 2. Note the significantly increased number of stations in Switzerland, Austria and Eastern Germany for 1991 and the sparse density of available stations in the Czech Republic for this study, which remains relatively constant. Between 4000 and 6000 daily reports are available for any particular day of the reference period (1961–1990) in the HYRAS-PRE data set. But in general it should be noted that spatially-variable observation networks have a significant influence on climatic averages (Willmott et al., 1991).
interpreting the results of climatological analyses (e.g. SEVRUK, 2004). In this context it is also important to know that the station distribution with elevation is often sub-optimal in mountainous areas. More stations are located in valleys than atop mountains because the support and measurement conditions at high altitudes are very difficult (e.g. SEVRUK, 1997). Furthermore, there are notable differences in the observing practices within and between the different networks (see for example GROSISMAN et al., 1991; FREI and SCHAR, 1998; ZOLINA et al., 2008). On the one hand, various rain-gauge types are used and in the last decade automated operation was introduced in most countries. On the other hand, different measurement times are common: 8:00 UTC (NL), 6:30 UTC (CH) and 6:00 UTC (all other KLIWAS countries, thus far known). In the following analysis inconsistencies due to the different rain gauge types and due to the different measurement times have been neglected to obtain the maximum data base for the gridded data set.

2.2 Quality control

By applying quality control checks, large errors in the time series can be detected and, if possible, corrected. Common errors are documented e.g. by WIJNGAARD et al. (2003) and ZURBENKO et al. (1996). Generally, there are two different types of errors in time series. On the one hand, there are errors from reading, coding and the encryption of the data, as well as problems with the data transfer itself. Typically, only single values of a time series are affected and become outliers. On the other hand, a time series is called inhomogeneous if the variations are not only caused by natural variability (CONRAD and POLLACK, 1950). Inhomogeneities may be due to changes in the observer and/or observing practices, changes in the instrumentation or changes in the measurement environment (for more details see PETERSON et al., 1998). In combination with the natural variations of precipitation the climate change signal of the time series can be influenced by such interventions. An in-depth description and analysis of quality control and homogeneity of precipitation data in Europe can be found in BLÜMEL et al. (2001) and GONZALEZ-ROUCO et al. (2001). In addition, the data quality varies between institutions (e.g. FREI and SCHAR, 1998). Commonly, erroneous daily precipitation amounts (e.g. WIJNGAARD et al. (2003) proposed values less than 0.0 mm or greater than 300 mm) are removed and inhomogeneities as well as inconsistencies flagged and corrected or removed. But an objective data control scheme for both types of errors is very difficult to implement, especially for precipitation because its large natural variability in time and space makes it very difficult to separate inhomogeneities or outliers from real extremes. Although automated control is still ongoing work (SCHERRER et al., 2011) we nevertheless performed a uniform quality control of all precipitation data in the KLIWAS project for which control-rules and -results will be presented in the following subsections. Some data providers perform their own quality control and/or provide homogenised time series, but details of the individual methods used are not known in most instances.
Apart from these non-systematic errors, the precipitation measurements are also affected by a bias in accuracy. This bias depends on the precipitation type, the hydrometer size, the wind speed and temperature as well as the resulting evaporation errors. Generally, the true precipitation amount is underestimated by at least 10% (or more) (SEVRIUK, 1982). Bias-corrected precipitation data are often used in hydrological applications, but the calculations for the bias correction require sufficient metadata (e.g. position and exposition of the station). Up to now no bias correction has been applied in this data set.

### 2.2.1 Outliers

Outliers were found by using the interquartile-adjusted method described by EISCHEID et al., 1995. They define an outlier to be greater than a threshold depending on the statistical properties of each individual rain gauge:

\[ y_{\text{outlier}} > y_{\text{threshold}} = q_{25} + f \cdot (q_{75} - q_{25}) \]  \hspace{1cm} (2.1)

where \( q_i \) is the \( i \)th quantile, \( (q_{75} - q_{25}) \) the interquartile range and \( f \) an arbitrary parameter. A value of \( f = 15 \) was specified from consultations with the extreme precipitation maps for Germany (KOSTRA-DWD-2000, MALITZ, 2000) and applied for all data series. To avoid the removal of real extreme values, outliers were flagged and only removed if their values proved implausible in comparison to neighbouring stations or within the interpolated field.

### 2.2.2 Inhomogeneities

Four different homogeneity tests were performed on each observation time series longer than 30 years to identify inhomogeneities caused by non-natural changes. Due to the large daily variability, the tests were performed using yearly precipitation amounts. The selection and application of the tests was based on WIJNGAARD et al. (2003), who used these tests for the European Climate Assessment daily precipitation data sets (ECAD). Only days with more than 1 mm precipitation were included in the calculation of the yearly precipitation amounts to reduce the variability. The resulting time series of yearly values were then tested with the Standard Normal Homogeneity Test (ALEXANDERSSON, 1986), the Pettitt Test (PETTITT, 1979), the Buishand Test (BUISHAND, 1982) and the von Neumann Test (VON NEUMANN, 1941). Each time series was tested against the null hypothesis that the series is homogeneous with a significance level of 95%. Two additional criteria were used to verify the inhomogeneities: First, the inhomogeneities should not appear in the first or last five years of the time series, because of the potential to yield uncertain results in the tests. Second, inhomogeneities were neglected if the differences between the mean precipitation before and after the inhomogeneities were smaller than 100 mm. Time series rejecting more than two of the four tests were classified as “suspect,” series rejecting two as “doubtful”, and all other time series were classified as “useful” (WIJNGAARD et al., 2003). As Table 1 shows, about 87% of the time series were declared as useful, which is comparable to findings from other data sets e.g. the ECA data set (BEGERT et al., 2008; KLOK and TANK, 2009). For the background field described in Section 3.1, only stations with homogeneous time series were included, whereas all values were used in the interpolation process of the daily data to incorporate the largest database possible. Due to the large effort required for such a voluminous daily data set, we refrained from using relative homogeneity testing as described e.g. by PERSON et al. (1998) and ROHADES and SALINGER (1993). In such tests the time series is tested against neighbouring stations, which has the additional benefit of detecting changes in a larger region e.g. caused by upgrades in the network. Most available gridded daily data sets are based on non-homogenised time series (e.g. FREI and SCHAR, 1998, HAYLOCK et al., 2008) because there are general difficulties with the homogenisation process as well as large efforts required to homogenise all time series (VENEMA et al., 2012).

### 3 Interpolation method

The irregularly-spaced station observations were interpolated to create a regularly-gridded precipitation data set, DWD/BIG-HYRAS v2.0. In this paper, version 2.0 is presented, although we are currently working on further improvements. The data set uses the Lambert Conformal...
Conic Coordinate Reference of the European Terrestrial Reference System 1989 (ETRS89-LCC). As shown by Hewitson and Crane (2005) and Hofstra et al. (2008), the best interpolation method depends on several factors such as the variable of interest, the desired resolution of the gridded data set, the point accuracy of the interpolation method, the orographical complexity of the area of interest, the data quality and the density of the observational network. For the HYRAS-PRE data set, the interpolation is based on a combination of multiple linear regression (MLR) and inverse distance weights (IDW). This method, which is called REGNIE at the DWD (“REgionalisierte NIEDerschlagshöhe”, engl. regionalised precipitation amount), is composed of two main steps. First, mean background fields are calculated (see Section 3.1) and second, the daily data are interpolated as a ratio of the total precipitation to the climatology (see Section 3.2). The assumption of this method is that the quantities of precipitation are partly determined by geographical factors (like altitude, aspect, and slope) and otherwise by daily atmospheric circumstances (like fronts or convection). Therefore, the background monthly climatology fields and their daily anomalies bring these aspects together. An overview of different interpolation methods for meteorological data can be found in Szentimrey et al. (2007). As shown in previous studies, using the ratio for the interpolation instead of the total precipitation itself gives a better representation of the spatial distribution of precipitation, especially for orographically complex areas (Chen et al., 2002; Xie et al., 2007; Haylock et al., 2008). The combination of MLR with IDW is often used in meteorology (e.g. Widmann and Bretherton, 2000; Perry and Hollis, 2005). In the studies of Nalder and Wein (1998) and Brown and Comrie (2002) this combination was shown to yield the lowest errors for both temperature and precipitation. In contrast, Hofstra et al. (2008) found that global kriging was the best-performing method in their comparison of six (global and local kriging, angular distance weighting, natural neighbour interpolation, thin plate splines and conditional interpolation) for temperature, precipitation and pressure. As illustrated in Figures 1 and 2 the station density in this study is very unequally distributed in time and space. The REGNIE method was developed to support hydrometeorological and hydrological applications at DWD and has been used successfully for many years. The main advantage of the REGNIE method is that the measured precipitation amounts are conserved, which means that, in contrast to other interpolation methods with smoothing (e.g. Haylock et al., 2008), observed extreme precipitation events as well as non-precipitation events can be found unchanged in the gridded field.

3.1 Background fields

Interpolated background precipitation for the period 1961–1990 was calculated using the stations that passed the homogeneity testing as “useful” (see Section 2.2.2). About 4000 stations for the whole KLIWAS domain were included in these background fields. The first step to calculating the background fields is a multiple linear regression (MLR). This regression was performed for each calendar month:

\[ y_i = a_0 x_{i0} + a_1 x_{i1} + a_2 x_{i2} + a_3 x_{i3} + a_4 x_{i4} + a_5 x_{i5} + e_{reg_i} \]

(3.1)

where \( y_i \) are the \( k = 1, \ldots, 5 \) explanatory variables at station \( i \) with \( x_{i0} \equiv 1 \), \( y_i \) the response variable, \( a_k \) the regression coefficients at station \( i \) for the explanatory variables \( k \), \( e_i \) the residuum and \( reg_i \), the result of the “pure” regression. The five explanatory variables consist of geographical longitude and latitude, height above sea level, exposition and mountain slope at the stations. The hillside parameters are determined using the elevation data of the Digital Elevation Model (GTOPO30) from the United States Geological Survey USGS (1993). At the end of the procedure, the regression and the residuum of each station were calculated for each calendar month as the mean of the period 1961–1990. Only stations with homogeneous monthly time series were used. The use of MLR with respect to geographic and topographic factors has widely been demonstrated to add considerable value to spatial interpolation (Agnew and Palutikof, 2000; Vicente-Serrano et al., 2003). The explanatory and response variables are known and the regression coefficients can be calculated using the least squares method. All available (at least 60) stations in one area were used to calculate the coefficients for that respective area. One of the main points of the regression is the classification of different climatological areas to optimise the explained variance of the MLR. With a cluster analysis based on ANOVA (Analysis of Variance), these areas (named clusters in the following) were identified. The clustering method of Ward (Wilks, 2005) begins with \( n \) clusters of size one and continues merging until all the observations are included in one cluster (so called agglomerative clustering). The error sum of squares and coefficient of determination were stepwise computed. The combination of two observations that yield the smallest sum of squares error formed the first cluster. Thus, at each step of the algorithm, observations were combined in such a way as to minimize the results of error from the squares. To achieve the optimum for the HYRAS dataset the whole KLIWAS domain was divided into 30 clusters for every calendar month. Within each cluster the regression coefficients were determined for all stations. The number of 30 regions is a good compromise between a too small scaled fragmentation and a well-explained variance in the different regions. In Fig. 3 the distribution of the cluster is shown for September. The pattern of the clusters does not differ strongly between the months. Only areas with pronounced orography (Alps or German Central Uplands) and border areas of the KLIWAS domain show differences in clustering for different months. The explained variance
of the MLR in the clusters is about 60% ± 20% (mean and standard deviation). Regression coefficients and residua were applied separately for each cluster. The homoscedasticity of residua, tested by the Goldfeld-Quandt-Test for each cluster (GOLDFELD and QUANDT, 1965) revealed that about 60% of all clusters were homoscedastic with a significance level of 95%. More than 80% of all residua were found to be within a range of ±10% deviation from the observed station value, though the residua can reach higher amounts in mountainous regions. Altogether, the MLR model is less representative for stations in Alpine valleys, leeward areas or stow relief rainfall influenced regions, i.e. areas with mesoscale climates that are, spatially, highly-versatile.

To obtain the background field at grid points without observations the residua of the MLR (eᵢ) and the result of the regression (regᵢ) were interpolated using IDW. Therefore, the following distance metric was used:

\[ \tilde{z}_i = \sum_{k=1}^{n} \frac{z_k}{d_{ki}^2} \]

where \( \tilde{z}_i \) is the interpolated value of \( e_i \) or \( reg_i \) at the grid point \( i \), \( z_k \) the \( e_i \) or \( reg_i \) at the station \( k \), which is calculated by Eq. 3.1. The distance between the centre of the grid \( k \) and the station \( i \) is \( d_{ki} \) and \( n \) the number of stations included for the interpolation. For the calculation, all stations within a maximum distance of 20 km were included. If there were no stations within this radius, the radius was extended to 30 km. To obtain the monthly background field, the residuum was added to the result of the regression for grid points without observations. Otherwise the regᵢ and eᵢ values calculated from Eq. 3.1 were used.

Despite the larger extension of the KLIWAS domain there are two main differences between the gridding procedure used in KLIWAS for the HYRAS-PRE data set and the standard REGNIE method used in the routine applications for Germany at DWD. Both lie in the calculation of the background fields: First, slightly different elevation data were used. Second, the classification of the clusters, which were combined for linear regression, was based on a different spatial aggregation in the standard REGNIE procedure for the German data set.

3.2 Daily data set

The daily precipitation at grid points without stations was calculated using the following three step process:

- The daily precipitation at a station was divided by the value of the background field of the appropriate month and grid point.
- For grid points without stations, the dimensionless ratio was interpolated via distance-weighting (see Equation 3.2) using the four closest stations.
- The daily precipitation distribution was determined by multiplying the dimensionless ratio with the background field.

For grid points with stations, the observed precipitation values were used. Note that due to the high spatial resolution of 1 km², two stations could never be assigned to the same grid point. One basic consideration concerning the quality of gridded data sets is independent from the gridding method: the density of the usable stations varies strongly, which influences the quality of the gridded data set. For our method, the quality of the background fields (Section 3.1) also plays an important role in the daily gridded data. Especially in areas of the KLIWAS domain where the precipitation is not dominated by orographic structures and local conditions, the regression coefficients of the background field are less certain, e.g. in the North German Plain.

4 Examples and climatology

Many climate indices, which are important for hydrometeorological and hydrological applications, can be calculated from the daily precipitation values. As a first overview of the data set, two exemplary daily fields and some climatological features are discussed: first,
4.1 Event-based comparison with radar-based precipitation data

Figures 4 and 5 show two examples of daily precipitation. For a qualitative comparison, daily fields of precipitation from weather radar are also shown (named RADOLAN). The RADOLAN method combines the reflectivity from radar with rain gauge measurements (for more details see WINTERRATH et al., 2012). A frontal event from December 16, 2005 is shown in Fig. 4. The general weather situation was characterised by the arriving low pressure system “Dorian,” which caused very high daily precipitation amounts of up to 100 mm in the North-Alpine region. The precipitation area covered most of the KLIWAS domain with maxima in regions of higher elevation. In the RADOLAN product, the spatial distribution is very similar to the HYRAS-PRE data. However, there are local differences and the intensity of the precipitation can be seen to vary. Larger differences between both methods can be found in the second example. The daily precipitation amounts of June 25, 2005, were mostly generated by convection (Fig. 5). The dominating weather event in this case was the storm “Theo,” which was responsible for local hail and heavy precipitation in Saxony and Bavaria. For very small areas, daily precipitation amounts clearly exceeded 100 mm.

Here, the RADOLAN product shows greater detail in the local structures e.g. in the western and northern part of the area, which are not detected by the HYRAS-PRE data. It is not surprising that in this case the differences between the two methods are much larger. One of the largest advantages of the HYRAS-PRE product is the direct measurement of the required variable, although only the precipitation events that are actually recorded by a station can be included. In contrast, the radar is able to scan the whole area and record all small events if there are no obstacles. Mountains, for example, can lead to a partial shadowing of the radar beam (so-called partial beam blockings), and ground and fixed echoes can falsely simulate precipitation where none has fallen. Additionally, if the heavy rain is directly above the radar the measurements are falsified (e.g. in Hamburg for the example in Fig. 5) because the water on the radome corrupts the radar signal of the precipitation and leads to an overestimation.

These two examples show that the radar with calibration from ground precipitation stations is a good alternative to analyse single precipitation events with high temporal resolution (see also SCHUURMANS et al., 2008; WINTERRATH et al., 2012). However, Radar precipitation climatology at DWD is still under development and time series remain too short for some climate applications. There is thus still a need for high resolution precipitation climatologies based solely on surface measurements, such as e.g. in the KLIWAS research programme.
4.2 Climatology

From the HYRAS-PRE data set a number of climatological studies were performed (e.g. calculation of climate indices). The main focus of this paper is the description of the method and the validation; therefore only a few aspects of the climatological results will be presented here. In Fig. 6 the yearly mean precipitation from 1971–2000 is shown to give an overview of the mean characteristics in the KLIWAS domain. As can be seen in the figure, the mean precipitation is very inhomogeneous. In the Alps as well as in the Black Forest the yearly precipitation sum tops 2000 mm and exceeds this value in the higher mountain areas. In contrast only precipitation sums of less than 700 mm are reached in the eastern part of the domain, the Elbe basin. In the western regions yearly precipitation amounts up to 1000 mm are common. Apart from these larger scale patterns, the German Central Uplands (e.g. Bavarian Forest, Harz, Ore Mountains, Eifel) are characterised by larger values than the surrounding areas. Furthermore, the Upper Rhine Rift with Vosges and Black Forest is a very prominent spatial structure of the mean precipitation with low precipitation amounts in the valley and higher values in the mountainous areas on either side. This strong variability is a challenge for the gridding procedure.

The results of a trend analysis performed for precipitation data in the winter and summer seasons, respectively, are presented in Fig. 7. We calculated the linear trends and their significances between 1952–2005 for the mean precipitation of second-order catchment areas, which are one of the concerted spatial division of the KLIWAS project. In contrast to studies of the cooperative
project KLIWA (climate change and its impact to water resource management, www.kliwa.de), in which trends of the hydrological half years in the catchment areas of Southern Germany were investigated between 1931–2010 (KLIWA, 2011), here, the trends on the meteorological seasons were examined. In Fig. 7 the trends (top) and their significance levels (bottom) are shown for summer and winter. There is a decline in summer precipitation (left part of Fig. 7) with decreases up to 20% observed. However, only in the northwest of the domain (excluding the coastal region) are the decreases significant. These results are generally consistent with other studies for Germany and Western Europe, where summer trends are also less significant than in winter (e.g. KLIWA, 2011; ZOLINA et al., 2008; MOBERG and JONES, 2005). The region has also experienced notable decreases.
in the frequency of heavy precipitation events of more than 10, 20 and 30 mm, respectively (not shown). These results, in combination with the decline in maximum observed values, which are also observed in Germany and the western half of Central Europe, imply that heavier events are occurring less frequently there. In contrast to summer, the mean precipitation is generally increasing (20–40%) in winter months (right part of Fig. 7) across the majority of Germany and Central Europe, while relatively weak, non-significant decreases of magnitudes less than about 10% have occurred in the southern Alpine regions of the domain. There is a tendency for larger relative changes toward the northwest of Central Europe (i.e. most of Germany) were the trends are highly significant. Trends are also strong across the German Central Uplands from the Meuse and Mosel basins in the west to the Elbe basin in the Czech Republic (east), although with somewhat lower significance values. Again, it must be mentioned that the station density varies with time (see Fig. 1) and outliers and inhomogeneities may still exist in the station data. Both can influence the trends, but due to averaging in time and space the trends and their signs are very robust. Furthermore, we have performed station data analyses which have shown the similar trend results for the mean precipitation (not shown). Comparable results were also found e.g. by Zolina et al. (2008).

5 Validation

The quality of the data set was analysed using the methods described in Sections 5.1 to 5.3. First, the results of a cross-validation are presented. By means of these error measures the users of the data set are able to assess the interpolation error, i.e. the quality of the data set and its reliability for different regions and seasons. Second, Jack-knifing results show the general influence of the station density on the gridded dataset. Third, a comparison with other existing climatologies allows one to identify the characteristics of the data sets. These validation results enable the assessment of uncertainties due to the gridded data set in such applications as e.g. evaluation of climate models, bias correction of climate models, and hydrological impact modelling.

5.1 Cross-validation

As mentioned already in Section 2, the number and spatial distribution of stations, on which the gridding is based, essentially influences the quality of a data set. We applied the method of cross-validation to estimate the interpolation error. During the cross-validation, one or several station values were removed from the sample and the field was recalculated. Afterwards, the results of the reduced sample field were compared with those of the full sample or the calculated values of the reduced data product were compared directly with the removed values (Wilks, 2005). Due to the large computation time needed to calculate the daily gridded data set over such a large area, we randomly removed 20% of the stations in each recalculation instead of removing every single station for each calculation and repeating the calculation. This percentage of 20% is an acceptable compromise between a reduction in computation time and a sufficient conservation of the interpolation quality and is based on test results (not shown). This procedure was repeated five times to ensure, on average, that every station was statistically removed once. To calculate the interpolation error, the removed station values were compared with the interpolated values calculated without these stations. For all interpolation error calculations more than 20 values per day with precipitation are necessary to ensure stable cross-validation results. To condense the results, we took the mean of the differences to determine the mean error per day. It must be noted that only daily precipitation values (PREC) exceeding 1 mm per day were investigated to avoid the distortion of the results by small precipitation amounts. The smaller values (PREC < 1 mm/day) were analysed with scores based on contingency tables. About 60% of all days in the station data are so called dry days with PREC less than 1 mm/day.

Fig. 8a shows a pronounced seasonal cycle for the mean absolute error (MAE, see Equation A.1 in Appendix A) of each calendar month. The median is smaller than 1.5 mm/day between October and April and approaches 2.5 mm/day in summer. The seasonal cycle is caused by different seasonal precipitation amounts and also by the different dominating precipitation mechanisms. In summer, the total precipitation is generally larger and the precipitation patterns are more patchy due to convection than in winter. Different quantiles (10%, 25%, 75% and 90%) are also presented in Fig. 8. The upper quantiles show that the errors can exceed two times the mean. As can be seen from the lower quantiles, there are also many days with smaller MAE.

With this error measure, however, it is not possible to differentiate if the gridded precipitation amounts are systematically under- or overestimated compared to the station values. From the mean relative error (MRE) (see Equation A.2 in Appendix A) shown in Fig. 8b it can be seen that the majority of MRE values are positive. This means that the station precipitation amounts are smaller than the gridded values: there is an overestimation of precipitation in the gridded field due to a reduction of stations in the gridding procedure. In summer months the overestimation is larger: more than 75% of the MRE values are greater than zero, which means that the 25%-quantile can be found above zero. This could be caused by the dominance of convective precipitation events with large precipitation amounts, which are highly localised. Summer precipitation is more often smoothed out in the surrounding grid cells than in winter, where the precipitation patterns generally have a larger extent. In winter, more than half of the days show an underestimation. We assume that the larger-scale precipitation
induced by frontal systems can be better interpolated with our gridding method and the underestimation of up to 25% of the MRE values is due to smoothing effects. With the comparison between the MRE and MAE, it is possible to separate the effects of the seasonal dependence of the total precipitation from the effects of different precipitation patterns. The MRE is defined such that the seasonal dependence of the total precipitation amount is removed by the normalisation. On account of the remaining seasonal cycle in the MRE, the precipitation patterns due to different precipitation mechanisms influence the error measures more than the total precipitation amount.

The correlation (see Equation A.3 in Appendix A) shows large values for all months, which implies that the spatial distribution is well-reproduced in the gridded data over all seasons (see Fig. 8c). However, from the spread of the correlation and the larger values in winter than in summer, one may induce that the type of precipitation largely influences the quality of the interpolation result (i.e. frontal events are much more precisely reproduced than convective events). Further investigations have shown that the correlation decreases with height (not shown), but it must be noted that the station density and their representativity are also lower in mountainous areas than in lowland areas.

For precipitation amounts smaller than 1 mm/day the bias score (BSC) (see Equation A.4 in Appendix A) was calculated. This score compares the frequency of events in the gridded field with the frequency of events in the station data. More than 90% of the calculated BSC values are smaller than one (see Fig. 8d), indicating that in the station data, more values less than 1 mm/day exist than in the interpolated precipitation values. The gridding procedure tends to interpolate more precipitation across the area than is measured, which means that the number of days with precipitation smaller than 1 mm/day are underestimated. This feature is slightly stronger in summer and winter seasons than in spring and autumn.

To analyse the spatial distribution of the cross-validation errors they were also calculated as averages over second-order catchments areas. The mean of the MAE and MRE are shown in Fig. 9. We want to emphasise that the individual daily interpolation errors can differ enormously, as can be seen in the quantile values in Fig. 8. The largest MAE exists in the Alps and other mountainous areas. In flat and coastal areas, the error is smaller because of less orographic complexity, which can significantly influence the processes of precipitation generation. In the eastern part of the KLIWAS domain, total precipitation is generally lower and the MAE consequently smaller. The MRE, in which the dependence of the total precipitation amount is removed by the normalisation, shows values between $-2\%$ and $-6\%$ in most parts of the KLIWAS domain. This implies that the precipitation is often underestimated in the daily gridded data. Only in the Alps are there areas with overestimations up to $2\%$. Here, the MRE is clearly smaller because the total precipitation amount is generally larger than in the rest of the area. The unclear patterns in the Czech republic and in some parts of Austria are perhaps due to the lower number of available measurements (see Fig. 2). The spatial distribution of the correlation is very uniform; only in the south-east are the values smaller (not shown). This could be attributed to different reasons: First, there are lower total precipitation amounts and a lower number of precipitation events. Second, the precipitation mechanism may be different because large precipitation events in this area are mostly caused by more continental processes, which means that a large part of the total precipitation is not caused by Atlantic low
pressure systems. Furthermore and as mentioned above, the lower station density in the Czech Republic and in some parts of Austria places a probabilistic limit on the likeliness of event observation.

5.2 Jackknifing

The influence of station density was investigated using the Jackknifing method described in (Wilks, 2005). Stepwise, more and more stations used in the interpolation were iteratively removed from the data set to demonstrate the evolution of the error. For the calculation of the error measures, the data of the field with fewer stations were compared with the full analysis for daily precipitation (greater than 1 mm/day only). It is possible to estimate the minimum number of stations required for a certain error, but the error itself always depends on the quality of the full data product. As shown in Fig. 1, the number of stations is not constant over time (1951 – 2006). Therefore the number of stations is reduced relative to the full data product. Note that the reduction steps are 5% and 10%, respectively. The error increases with the reduction level almost linearly, which means that the increase of the MAE between the 10% and 20% station reductions relative to the total number of stations has approximately the same magnitude as the increase between 60% and 70%. A seasonal influence can be seen in all levels of reduction, with the largest mean absolute error in summer and the smallest values from October to April (see Fig. 10). The values of summer are nearly double those in winter. It has to be noted that seasonal differences are smaller than the differences due to the reduction of the stations by 50%. From these results it is clear that a reduced station density increases the MAE very quickly.

For the months January and July the spatial distribution of the MRE is shown in Fig. 11 for reductions of 10%, 50% and 70%. As mentioned above, the errors generally increase with the reduction in station density, although there are strong dependencies on the location, i.e. the geographical conditions as well as the total station density available in the surrounding area. In all cases the effects of single stations are clearly visible by strongly increasing or decreasing errors (named bull’s eye patterns). In the comparison of the seasons, the larger errors in summer are also visible as in the results of the

Figure 9: Different error measures of the cross-validation calculated as the mean for the whole time period (1951–2005) and catchments areas of the second order: mean absolute error (MAE) in mm/day (left) and mean relative error (MRE) in % (right).

Figure 10: Mean absolute error (MAE) in mm/day calculated with the Jackknifing method and averaged over each month and the KLIWAS domain. Different densities of stations (10%–70%) are used for the calculation and indicated by different colours, where e.g. 10% means that 10% of the stations were removed before recalculating the gridded data set.
The main point of this analysis, however, is the spatial distribution: a reduction of only 10% causes large negative MREs in the Alpine region, which dominate the errors of the whole KLIWAS domain and indicate an underestimation of the precipitation. In contrast to these results, a stronger reduction of station density produces (apart from the Alpine region for up to 50% reduction) positive MREs. The precipitation is overestimated in comparison to the full data product, which means that the precipitation measured at a station is dispersed into the surrounding area. The different behaviour in the Alpine region may be due to the complex orography, which strongly influences the background field. Furthermore, the reduced station density in the Czech Republic contributes to larger errors than in the rest of the area. The reduction of 70% impressively demonstrates that with such a low network density, the generation of a high resolution gridded field is futile. Generally, the need for a high station density is evident, although it is not possible to determine a minimum station density. Because all results are relative to the full data set, it is therefore necessary to compare the product based on rain gauge data with other independent data sets. Unfortunately satellite data do not yet have the required quality and radar data time series are still too short for climatological studies. Additionally, there are large uncertainties in the algorithms for converting radiometric measurements into precipitation rates at the surface (e.g. Krajewski et al. (2010)). At the moment, only the comparison with other gridded data sets is possible for investigating climatological features (see next section).

5.3 Comparison with existing climatologies

Although several climatologies currently exist for Europe, the HYRAS data set was developed specially to address the requirements of the KLIWAS research.
programme with a high spatial and temporal resolution across the KLIWAS domain. Nevertheless, the HYRAS-PRE data set was compared with other data sets to gain insight into the variability of regionalised precipitation data sets based on different interpolation methods, spatial resolutions and topographic data. First, the precipitation distribution of the whole KLIWAS domain is presented in this section. Second, we focus on two regions for the comparison, (i) the Alps and (ii) Germany as a whole. A description of the data sets used can be found in Table 2.

### 5.3.1 Precipitation distribution

The probability density functions or histograms of the daily precipitation amounts provide information on how well the relative intensities of the daily precipitation amounts are reproduced in the gridded field. In Fig. 12, the distributions for the station data, the HYRAS-PRE data set and also for the EOBS data set are shown (HAYLOCK et al., 2008). For the different classes, which are also used by CHEN et al. (2008), the daily precipitation values of the station and gridded data were counted and scaled by the total number of events. Note that the original spatial resolution of each gridded data set is used in the calculation. The main characteristics of the station and the HYRAS-PRE data are generally very similar and differences are generally only found for precipitation amounts smaller than 3 mm. The station data show more non-precipitation events, while the HYRAS-PRE data set shows more precipitation events in the following two classes with larger amounts up to 3 mm. This behaviour can be explained by the gridding, where relatively frequent small precipitation amounts are smoothed and spread out over the surrounding grid cells without stations, causing an underestimation of non-precipitation events and an overestimation of small precipitation values. With our method it is only possible to create grids with no precipitation if there is a measurement with 0 mm/day at the grid point, or if all surrounding stations included in the interpolation show no precipitation. In contrast to the high resolution of the HYRAS-PRE data set (1 km), the EOBS data are based on a 25 km grid. With the coarser resolution, precipitation events with daily amounts larger than 10 mm are not resolved and events between 1 and 10 mm are clearly underestimated. This results in a strong overestimation with more than three times more events up to 1 mm. The non-precipitation events are similar to those in the station data set, which can be due to coarse resolution. More than one station can be found inside a grid point and therefore the smoothing of small precipitation values into the surrounding field occurs less frequently. The results show that the high spatial resolution plays an important role for heavy precipitation events and that the conservation of the station values within the gridded field enables the analysis of such events. Nevertheless, the distinction between non-precipitation and small precipitation events is blurred in the gridded data set, which has also been documented for other gridding procedures (e.g. CHEN et al., 2008). This feature of the gridded data must be considered when analysing, for example, both dry and wet days.

### 5.3.2 Alpine region

In the KLIWAS domain the Alpine region, due to its complex orography, is the most ambitious region for the regionalisation (see also DUMOLARD, 2007). All available data sets in this region, i.e. ALPIMP (EFTHymiADis et al., 2006), PRISM (SCHWARB, 2000) and E-OBS
(HAYLOCK et al., 2008), are listed with the version, temporal and spatial resolution, period and references in Table 2. For the comparison, the common period of 1971–1990 and the ALPIMP grid were used. In Fig. 13a the monthly mean values are shown. The seasonal behaviour of all data sets is very similar. The largest precipitation amounts of more than 120 mm can be found in June and small values less than 85 mm between October and May. The EOBS data set shows smaller precipitation amounts during all months. We assume that the coarser resolution of all investigated data sets and the partially reduced station density in some data sets are the main reasons for this. The strongest similarity between the data sets can be found between the PRISM and the ALPIMP data sets. Both use additional weightings in the interpolation method to take into account elevation, distance and angular information between the stations.

Between these two data sets the mean absolute error (MAE) is smaller than 5 mm/month (Fig. 13b). The MAE between the HYRAS-PRE data set and both Alpine climatologies is also small with 5–10 mm/month. The largest differences between the data sets occur when compared to the EOBS data set, where the MAE is larger than 10 mm/month. For all data sets there is no clear seasonal cycle in the MAE. We also investigated the spatial correlation (not shown) between the data sets, which (excluding the EOBS data) are larger than 0.95, whereas the values for the comparisons with the EOBS data are between 0.7 and 0.9. In spite of the good agreement in the mean values there are systematic differences between the HYRAS-PRE data set and, for example, the PRISM data set. As seen in Fig. 14, the HYRAS-PRE data set shows smaller yearly precipitation sums in the Eastern and Southern Alps of about 100 mm, but larger

**Figure 13:** Comparisons of monthly mean values between HYRAS-PRE and other data sets (1971–1990) for the Alpine region (top, a+b) and Germany (bottom, c+d). On the left side (a+c) the monthly mean precipitation in mm/month is shown and on the right side the mean absolute error (MAE) in mm/month (b+d). Note the different y-axis for the monthly mean precipitation.
amounts in the Western part of the area. A similar pattern in the spatial distribution of the differences is found in the comparison between daily values of the HYRAS-PRE and EOBS data set (see Fig. 15). In addition, the HYRAS-PRE data set shows smaller values in the valleys and larger ones atop mountains compared to PRISM. The observed differences could be due to different station density, interpolation method and topographic data and are an indicator for the uncertainty for the gridded precipitation data set.

5.3.3 Germany

Since most of the KLIWAS domain covers Germany the HYRAS-PRE data set was compared with other data sets of Germany. In Fig. 13c a comparison of monthly mean values between the HYRAS-PRE, EOBS (HAYLOCK et al., 2008) and the DWD MONTHLY climatology (MüLLER-WESTERMEIER, 1995) is shown. The analysed period is 1971–1990 and the common grid is the EOBS grid. The differences between the data sets are small and not as clear as in the Alps. For all months, the HYRAS-PRE data show the largest precipitation values, which can be explained by the higher station density and the gridding method with station precipitation amount conservation. The seasonal variation is smaller than in the Alpine region and the monthly sums vary between 50 and 100 mm. The MAE is small with 5 to 12 mm/month (see Fig. 13d). An investigation of the whole (1951–2006) period shows similar results. The average correlation of daily precipitation amounts (not shown) between the HYRAS-PRE and the EOBS data set for the 1951–2006 period is about 0.8, which means that the data sets aggregated on a coarse resolution result, on average, in fields of similar precipitation amounts with similar spatial structures. The mean daily differences confirm this (see Fig. 15). The differences in Germany are smaller than 10 mm/day for most grid points.

6 Summary and outlook

A precipitation climatology covering Germany and neighbouring river basins, the DWD/BfG-HYRAS v2.0 precipitation data set (HYRAS-PRE), was successfully developed at the DWD. In contrast to other existing data sets, the high spatial and temporal resolution as well as the domain are unique and necessary for the hydrometeorological and hydrological applications in the KLIWAS project. Within the project and beyond, the HYRAS-PRE data set can be used for the bias correction of regional climate model output, hydrological modelling, studies of precipitation climatology and other hydrologically-relevant indicators. The first successful application of the data sets was produced by BERG et al. (2012).

It has been observed that the REGNIE method presented in this paper works particularly well with a dense station network. A slight variation of the station density or the relocation of stations influences the quality of the gridded data only marginally. In contrast to other procedures, this method reproduces the observed daily precipitation amounts in the respective grid cells, which includes heavy precipitation as well as non-precipitation events. Performing a detailed validation enabled the quantification of the interpolation errors with respect to time and region, which is important information for all following applications. Generally, the results of the cross-validation showed that precipitation greater than
1 mm/day is more often than not overestimated and that small precipitation amounts are mostly underestimated in the gridded field. Furthermore, the results of the Jackknifing procedure demonstrated the importance of high station density. In comparison with other data sets, a general agreement of the precipitation amount and the spatial distribution was found. Larger differences were found in more orographically complex areas. These differences are indicative of the uncertainties due to the differences in station density, interpolation method and topographic data. Additionally, the advantages in high spatial resolution and high station density were also demonstrated. Within the KLIWAS project, the data are delivered to impact modellers in different resolutions: 1x1 km² and 5x5 km². These analyses are in progress and an evaluation of a potential added value of the high resolution dataset will be carried out in due time.

In the future, more detailed climatological studies are planned; only the first results were presented in this paper. We found a clear increase in winter precipitation of up to 40% (1952–2005) and indications of light decreases in summer precipitation. Both results varied in the trend magnitude and their significance across the KLIWAS domain.

Furthermore there are also several ideas which could improve the quality and accuracy of the gridded data set. The background fields can be improved by:

- introducing objective weather types to classify the background fields, which introduces more physical information (e.g. Schiemann and Frei, 2010),
- using the regression coefficients for the interpolation instead of the regression results,
- introducing a smoothing function if there are very large differences between the regression and interpolation results.

Additionally, the distance metric can be extended by using an additional weighting and/or including the height difference between station and target grid cell for the distance calculation. Alternatively, angular distance weighting or directional weighting can be used to take into account that not all surrounding stations used in the interpolation have the same representativeness for the grid point (e.g. the PRISM method, Schwarp, 2000).

Beside the precipitation data set (HYRAS-PRE), gridded data sets for other hydrometeorological parameters are underway within in the KLIWAS research programme. For the daily mean temperature, the solar radiation, and the relative humidity, the gridding is achieved by Universal Kriging. At the moment, the validation and improvement of these data sets are ongoing work.

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Appendix A

The following error measures were used to quantify the quality of the data set for precipitation values greater than 1 mm:

Mean absolute error:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |x_i - y_i|$$ (A.1)

Mean relative error:

$$MRE = \frac{1}{N} \sum_{i=1}^{N} \left(100 \frac{x_i}{y_i} - 100\right)$$ (A.2)

Correlation:

$$COR = \frac{\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \bar{x})^2 \sum_{i=1}^{N} (y_i - \bar{y})^2}}$$ (A.3)

where $N$ is the number of values, $x_i$ the value of the gridded field, $y_i$ the observation at the station and $\bar{x}$ and $\bar{y}$ the mean of gridded and station values, respectively.

To quantify the precipitation amounts below 1 mm, the bias score was used:

$$BSC = \frac{\text{hits + false alarms}}{\text{hits + misses}}$$ (A.4)