



Article **Precipitation Atlas for Germany (GePrA)**

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Abstract: A new approach for modeling daily precipitation (*RR*) at very high spatial resolution (25 m × 25 m) was introduced. It was used to develop the Precipitation Atlas for Germany (GePrA). GePrA is based on 2357 *RR* time series measured in the period 1981–2018. It provides monthly percentiles (*p*) of the large-scale *RR* patterns which were mapped by a thin plate spline interpolation (TPS). A least-squares boosting (LSBoost) approach and orographic predictor variables (PV) were applied to integrate the small-scale precipitation variability in GePrA. Then, a Weibull distribution (Wei) was fitted to *RR*_p. It was found that the mean monthly sum of *RR* (*RR*_{sum}) is highest in July (84 mm) and lowest in April (49 mm). A great dependency of *RR* on the elevation (ε) was found and quantified. Model validation at 425 stations showed a mean coefficient of determination (*R*²) of 0.80 and a mean absolute error (*MAE*) of less than 10 mm in all months. The high spatial resolution, including the effects of the local orography, make GePrA a valuable tool for various applications, the results of this study enable the seasonal differentiation between dry and wet period at small scales.

Keywords: Weibull distribution; least-squares boosting; annual cycle; thin plate spline interpolation

1. Introduction

Precipitation impacts the environment in a number of ways. It drives the water cycle by determining the availability of water [1] and by affecting the exchange of water between the atmosphere and the land surface [2]. With increasing intensity, precipitation may trigger floods and increase soil vulnerability to erosion [3]. Many sectors, including forestry, agriculture, water resource management, food security, hydropower, and disaster management, depend on the spatiotemporal dynamics of precipitation regimes [2,4]. Thus, they are in need of accurate, local information on the statistical properties of precipitation [5].

However, the high spatiotemporal variability of precipitation is a major constraint for the statistical description of precipitation distributions [6]. On spatial scales, precipitation patterns are influenced by the orography [6–10] and land cover [11,12]. On temporal scales, precipitation patterns are driven by different temporal cycles of the large-scale atmospheric circulation [13] and diurnal warming [14].

To statistically consider the complexity of precipitation regimes in large areas, a large number of long-term precipitation measurements is required. Unfortunately, the density of precipitation gauges is often too sparse for a detailed representation of the small-scale precipitation variability [1,7,15]. Precipitation models with a high spatial resolution can fill the gaps that occur in low-density networks [16]. In general, the modeling approaches can be differentiated into two categories: (1) Atmospheric circulation models and (2) statistical models. Atmospheric circulation models are useful tools for characterizing and investigating physical processes leading to precipitation. Applying atmospheric circulation models requires deep knowledge of a large number of input parameters. Their initialization and parameterization can thus be very complex.

In contrast, statistical models are based on precipitation measurements and a variety of predictor variables associated with the precipitation pattern in certain regions. Statistical approaches do not provide deep insight into the underlying physical processes driving precipitation formation but can describe the precipitation pattern at a very high spatial resolution, even when only a limited number of precipitation measuring stations exists [8].

There are numerous investigations on the parameterization of statistical precipitation models. For instance, a linear regression model was developed to describe the variability of winter precipitation in Great Britain [17]. In another study, the monthly precipitation was modeled at a spatial resolution of $1 \text{ km} \times 1 \text{ km}$ by applying a statistical downscaling approach [1]. Recently, a method for stochastic simulation of precipitation was developed based on a linear theory, which described the orographic precipitation and additional functions that consider synoptic and convective precipitation [18]. Statistical downscaling techniques were also used to build a precipitation model using satellite and land surface data [19].

Based on currently known statistical approaches, a model was developed in this study which enabled the mapping of the entire statistical precipitation distribution at a very high spatial resolution (25 m \times 25 m) in a large study area. To depict the annual cycle of the precipitation regime, the model was monthly parameterized. For model development, a theoretical distribution capable to accurately mimic the empirical precipitation distribution was found, which made it possible to quantify the strong dependence of precipitation on elevation (ε).

2. Material and Methods

2.1. Overview

The development of GePrA was composed of the following main steps (Figure 1): (1) Obtaining daily precipitation data (parametrization data) provided by the German Meteorological Service for the period 1981–2018; (2) fitting of 18 theoretical distributions to the precipitation time series and evaluation of their goodness-of-fit; (3) building of predictor variables representing the local orography based on a digital elevation model; (4) high spatial resolution modeling (25 m × 25 m) of the percentiles by a least-squares boosting approach and thin plate spline interpolation; (5) fitting of Weibull distributions, which provide the best fits, to the modeled precipitation percentiles; and (6) model validation by independent precipitation data (validation data).



Figure 1. Overview of the methodology applied to develop the Precipitation Atlas for Germany (GePrA).

2.2. Study Area and Precipitation Data

Germany has a size of about 357,000 km². The country consists of the four large natural areas: The North German Plain, Central German Plain, Alpine Foothills, and Alps in southern Germany [20]. Its topography is complex and ε ranges from below 0 m to nearly 3000 m (Figure 2). Besides the high mountain range of the Alps, there are numerous low mountain ranges (500 m < ε < 1500 m). The highest and largest contiguous low mountain range is the Black Forest in the southwest.



Figure 2. Precipitation (*RR*) measurement sites subdivided into a parameterization dataset (DS1) and validation dataset (DS2). Elevation (ε) in the study area varies between -216 m and 2964 m (top of the mountain Zugspitze). For the points labeled "Grünow" and "Zugspitze", more results are presented in Figure 5. The figure inset highlights a region in the Black Forest for which detailed results are presented in Figure 9.

The study was based on daily precipitation (*RR*) measurements of the period 1981–2018 available from the German Meteorological Service climate data center [21]. Depending on the availability of *RR* data (*DA*), *RR* time series were assigned to either the parameterization dataset (DS1) or to the validation dataset (DS2). DS1 contained 2357 *RR* time series with *DA* > 50%. DS2 included 425 *RR* time series with *DA* being in the range of 40.0% to 49.9%. All other and less complete time series were not considered for further analysis.

The selection of suitable theoretical distributions is of great importance for the accurate description of the statistical properties of precipitation time series. Thus, different statistical distributions used in previous studies [22,23] were tested. From these distributions, those with less than four parameters were selected (Table 1). The distributions were fitted to monthly empirical cumulative distribution functions (ecdf) of *RR* included in DS1 by applying the maximum likelihood method. As there is often a very high proportion of *RR* = 0 mm, the distributions were only fitted to *RR* > 0 mm. The goodness-of-fit (GoF) of each theoretical distribution was assessed by the Kolmogorov-Smirnov statistic (*KS*), the coefficient of determination related to the cumulative probability (R_{PP}^2), and the coefficient of determination related to the quantiles (R_{OO}^2) [24].

Distribution	Abbreviation	Parameters	
Beta	Be	shape, shape	
Birnbaum-Saunders	BS	shape, scale	
Burr	Bu shape, scale		
Epsilon Skew Normal	ESN	scale, location, skewness	
Extreme Value	EV	location, scale	
Gamma	Gam	shape, scale	
Generalized Extreme Value	GEV	shape, scale, location	
Generalized Pareto	GP	shape, scale, location	
Inverse Gaussian	IG	scale, shape	
Logistic	L	mean, scale	
Log-logistic	LL	mean, scale (of logarithmic values)	
Lognormal	LN	mean, standard deviation (of logarithmic values)	
Nakagami	Na	shape, scale	
Normal	Ν	mean, standard deviation	
Poisson	Р	mean	
Rician	R	non-centrality, scale	
t-Location Scale	tLS	location, scale, shape	
Weibull	Wei	shape, scale	

Table 1. Theoretical distributions fitted to daily precipitation (*RR*) including their parameters [25].

The distribution fitting was made using Mathworks' Matlab[®] Software Statistics and Machine Learning Toolbox (Release 2019a; The MathWorks Inc., Natick, MA, USA).

2.4. Predictor Variables

The orographic features (Table 2) were represented by 22 predictor variables (PV) derived from the digital elevation model EU-DEM v.1 at a 25 m × 25 m spatial resolution [26]. The relative elevation (η) was developed by subtracting the mean elevation of an outer circle of each grid cell from the grid cell-specific ε value [27]. Four η variants with outer-circle radii of 1000 m (η_{1000}), 3000 m (η_{3000}), 5000 m (η_{5000}), and 7500 m (η_{7500}) were built. For the eight main compass directions, η was modeled with a 3000 m radius. Furthermore, the orographic sheltering (σ) was quantified. It was derived by calculating the angles between grid cell-specific elevation and the visible horizon up to a distance of 1000 m [27].

Table 2. Orographic features used as predictor variables (PV) for modeling daily precipitation (RR).

Symbol	Name	Sector (°)	Distance (m)	Data Source
lon	longitude	-	-	-
lat	latitude	-	-	-
ε	elevation	-	-	EU-DEM v.1
η_{1000}	relative elevation	1-360	1000	EU-DEM v.1
η_{3000}	relative elevation	1–360	3000	EU-DEM v.1

Symbol	Name	Sector (°)	Distance (m)	Data Source
η_{5000}	relative elevation	1-360	5000	EU-DEM v.1
η ₇₅₀₀	relative elevation	1-360	7500	EU-DEM v.1
η_n	relative elevation	337.5-22.4	3000	EU-DEM v.1
η_{ne}	relative elevation	22.5-67.4	3000	EU-DEM v.1
η_e	relative elevation	67.5-112.4	3000	EU-DEM v.1
η_{se}	relative elevation	112.5-157.4	3000	EU-DEM v.1
η_s	relative elevation	157.5-202.4	3000	EU-DEM v.1
η_{sw}	relative elevation	202.5-247.4	3000	EU-DEM v.1
η_w	relative elevation	247.5-292.4	3000	EU-DEM v.1
η_{nw}	relative elevation	292.5-337.4	3000	EU-DEM v.1
σ_n	sheltering	337.5-22.4	1000	EU-DEM v.1
σ_{ne}	sheltering	22.5-67.4	1000	EU-DEM v.1
σ_e	sheltering	67.5-112.4	1000	EU-DEM v.1
σ_{se}	sheltering	112.5-157.4	1000	EU-DEM v.1
σ_s	sheltering	157.5-202.4	1000	EU-DEM v.1
σ_{sw}	sheltering	202.5-247.4	1000	EU-DEM v.1
σ_w	sheltering	247.5-292.4	1000	EU-DEM v.1
σ_{nw}	sheltering	292.5-337.4	1000	EU-DEM v.1
σ_{sum}	sheltering	1–360	1000	EU-DEM v.1

Table 2. Cont.

2.5. LS-Boost Modeling (LSBoost) and Thin Plate Spline Interpolation (TPS)

The *RR* percentiles (*RR*_{*p*}), being $p = \{1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 99\}$, were modeled in a two-step procedure: (1) A least-squares boosting (LSBoost) algorithm was trained for *RR* included in DS1 using PV; and (2) the remaining DS1 residuals were further reduced by applying a thin plate spline interpolation (TPS). The modeling of *RR* return times associated with greater p > 99 (corresponding to a return period of 100 days) was omitted because they would exceed the limitations with which a reliable model can be developed given the length of the available dataset and would require an extreme value analysis [28].

The LSBoost model is a sequence of regression trees (*B*), i.e., decision trees with binary splits for regression [29–31]. The LSBoost model strives to reduce the mean squared error (*MSE*) between RR_p and the aggregated RR_p prediction (\hat{RR}_p) of *B*. Starting with the median of RR_p (\tilde{RR}_p) of all DS1 stations, the regression trees B_1, \ldots, B_m were combined in a weighted manner [29–31] to minimize *MSE*. Mathematically, the LSBoost algorithm is described as:

$$\widehat{RR}_p(PV) = \widetilde{RR}_p(PV) + v \sum_{m=1}^M p_m B_m(PV),$$
(1)

where p_m is the weight for model *m*, *M* is the total number of regression trees, and $0 < v \le 1$ is the learning rate.

More than 5000 predictor variable combinations (PVC) were tested for their predictive power. Evaluation of the five-fold cross-validated R^2 revealed the most powerful PVC associated with DS1. The applied LSBoost algorithm was available from the Matlab[®] Software Statistics and Machine Learning Toolbox (Release 2019a; The Math Works Inc., Natick, MA, USA).

The predictors *lon* and *lat*, which describe the geographic location of a measurement station, were used as input for TPS [32]. The applied TPS algorithm was implemented in the Matlab[®] Software Curve Fitting Toolbox (Release 2019a; The Math Works Inc., Natick, MA, USA).

Wet days were defined when $\hat{RR}_p > 0$ (PR_{wet}). Wei, which was found to provide the best fitting accuracy, was fitted to \hat{RR}_p on wet days applying the least-squares estimation method [33] The probability density function of Wei (f(RR)) is defined as [33]:

$$f(RR;\alpha,k) = \frac{k}{\alpha} \left(\frac{RR}{\alpha}\right)^{k-1} exp\left[-\left(\frac{RR}{\alpha}\right)^k\right],\tag{2}$$

where *k* is the shape parameter and α is the scale parameter. From *PR*_{wet} and *f*(*RR*), the mean monthly precipitation sum (\overline{RR}_{sum}) was then calculated:

$$\overline{RR}_{sum} = \alpha \Gamma \left(1 + \frac{1}{k} \right) \cdot nm \cdot RR_{wet}, \tag{3}$$

where Γ is the Gamma function and *nm* is the number of days per month.

After completion of RR_p modeling and distribution fitting, the model was validated for RR_{sum} calculation using DS2. The model quality was assessed by applying R^2 , mean absolute error (*MAE*), and mean error (*ME*).

2.6. Inter-Area Variability

The variability of *RR*_{sum} within the study area was quantified by the interarea variability (*IAV*) according to:

$$IAV = \frac{S}{\langle \overline{RR}_{sum} \rangle},\tag{4}$$

where *S* is the standard deviation of \overline{RR}_{sum} , and $\langle \overline{RR}_{sum} \rangle$ is the mean of \overline{RR}_{sum} in the study area.

3. Results and Discussion

3.1. Proportion of Wet Days (PR_{wet})

The monthly PR_{wet} is displayed in Figure 3. The mean PR_{wet} in the study area ($\langle PR_{wet} \rangle$) was lowest ($\langle PR_{wet} \rangle = 33\%$) in April (Figure 3d) and highest ($\langle PR_{wet} \rangle = 44\%$) in December (Figure 3l). In addition to the temporal PR_{wet} variability, there was also a strongly pronounced spatial PR_{wet} pattern. In January (Figure 3a), February (Figure 3b), March (Figure 3c), October (Figure 3j), November (Figure 3k), and December, the highest PR_{wet} values occurred in the west ($PR_{wet} > 50\%$). The precipitation in these months was mainly caused by precipitation fronts from the west. In contrast, in May (Figure 3e), June (Figure 3f), and July (Figure 3g), the highest PR_{wet} values occurred in the Alps ($PR_{wet} > 50\%$). During summer, the high PR_{wet} values in this area were caused by a high frequency of convective precipitation events [34].



Figure 3. Monthly proportion of wet days (*PR*_{wet}) in (**a**) January; (**b**) February; (**c**) March; (**d**) April; (**e**) May; (**f**) June; (**g**) July; (**h**) August; (**i**) September; (**j**) October; (**k**) November; and (**l**) December.

3.2. Distribution Fitting

Results from the GoF evaluation are summarized in Figure 4 for all months. Out of the 18 candidate theoretical distributions, Gam, Wei, GP, and BS could be fitted to all empirical distributions in all months yielding accurate fits. All other theoretical distributions could either not be fitted to all *RR* time series or their GoF was low.

According to *KS*, Wei was the best fitting theoretical distribution (Figure 4a). The median *KS* of Wei was 0.055, the first quartile was 0.047, and the third quartile was equal to 0.065. For Gam, GP, and BS, median *KS* varied between 0.063 and 0.097. Similar results were found for R_{PP}^2 (Figure 4b). The median R_{PP}^2 for Wei was 0.996 and was thus close to a perfect match between the theoretical and empirical distribution. For Gam and GP, the median R_{PP}^2 was only slightly worse (0.994 resp. 0.995). The outliers obtained by Wei were not lower than 0.97, indicating a reliable fitting accuracy. The third calculated GoF confirms the capability of Wei to mimic *f*(*RR*) (Figure 4c). Its median R_{QQ}^2 was 0.992. A similarly high GoF could only be achieved by Gam (median of $R_{QQ}^2 = 0.991$). Based on the GoF evaluation, Wei was assumed to be generally able to reproduce *f*(*RR*) on wet days.



Figure 4. Goodness-of-fit (GoF) of theoretical distributions fitted to daily precipitation (*RR*) on wet days evaluated by (**a**) the Kolmogorov-Smirnov statistic (*KS*); (**b**) the coefficient of determination related to the cumulative probabilities (R_{PP}^2); (**c**) the coefficient of determination related to the quantiles (R_{QQ}^2). The boxplots include results from all DS1 measurement stations and months.

All of the *RR* probability density functions had similar shapes. In general, (1) the lowest *RR* values have the highest probability density, and (2) the probability density decreases with increasing *RR*. As an example of the coincidence of the empirical probability density and Wei, the results for two different locations in summer (Jun–Aug, JJA) and winter (Dec–Feb, DJF) are presented in Figure 5.

For the city of Grünow, which is located in the northeast of the study area, f(RR) is shown for August (Figure 5a). From this, it can be inferred that Grünow was very dry during summer. The frequency of RR < 1.5 mm was highest (0.305). During summer, RR rarely exceeded 20 mm (0.027). The Wei function reproduced the shape of the histograms very accurately.

The second example shows f(RR) in August for Germany's highest peak, the Zugspitze (Figure 5b). Overall, the probability density of high *RR* was much higher compared to Grünow. For instance, *f* (*RR* = 0 mm) was 0.148 and *f* (*RR* > 20 mm) was 0.125.

In December, the probability density of low *RR* values increased in Grünow (Figure 5c), with f(RR) = 1 mm being 0.42. The exceedance probability of 10.4 mm was only 0.01, indicating that high *RR* values were extremely rare.

On the Zugspitze, the differences between f(RR) in August and f(RR) in December were marginal (Figure 5d). The probability density of f(RR) > 10.4 mm was even higher (0.35) in December. The examples show a broad spectrum of different *RR* regimes. Nevertheless, the fitting of Wei was always very close to the empirical histogram.



Figure 5. Weibull (Wei) probability density functions fitted to the empirical daily precipitation (*RR*) on wet days in (**a**) Grünow in August; (**b**) Zugspitze in August, (**c**) Grünow in December; (**d**) Zugspitze in December.

3.3. Heavy Precipitation

As an example of heavy precipitation, \hat{R}_{99} is shown in Figure 6. It corresponds to a return period of 100 days. Similar to PR_{wet} , summer months were more precipitous than all other months. In July, the highest \hat{R}_{99} values generally occurred. The mean \hat{R}_{99} in the study area ($\langle \hat{R}_{99} \rangle$) in July was equal to 28.3 mm (Figure 6g). In contrast, $\langle \hat{R}_{99} \rangle$ in February was only 16.0 mm (Figure 6b). In May and September, $\langle \hat{R}_{99} \rangle$ corresponded to 23.3 mm, whereas in March, April, and November, $\langle \hat{R}_{99} \rangle < 20$ mm.



Figure 6. Heavy precipitation indicated by the 99th percentile of daily precipitation ($\hat{R}R_{99}$) in (**a**) January; (**b**) February; (**c**) March; (**d**) April; (**e**) May; (**f**) June; (**g**) July; (**h**) August; (**i**) September; (**j**) October; (**k**) November; (**l**) December.

The \hat{R}_{99} gradient in DJF is west-east oriented whereas in the summer months it is more northwest-southeast oriented. An important reason for this could be that heavy precipitation in winter is mainly stratiform [35] and predominantly from western directions. In summer, precipitation is predominantly convective. However, there are also regions in DJF were \hat{R}_{99} is very high. In the low mountain ranges, especially on their west-east oriented slopes, \hat{R}_{99} is often higher in winter than in the summer. In December, \hat{R}_{899} frequently exceeds 50 mm in the Black Forest and near the Alps (Figure 6l). By comparison, in eastern Germany, \hat{R}_{899} is clearly lower at less than 15 mm. Overall, the \hat{R}_{899} variability is greater in winter than in summer. This indicates that the small-scale properties of the orography determine the heavy precipitation pattern in winter. In Figure 7, \overline{RR}_{sum} is presented. The large-scale spatial pattern shows similarities to the \widehat{RR}_{99} pattern. In January (Figure 7a) and December (Figure 7l), \overline{RR}_{sum} was highest on the west–east oriented slopes of the western low mountain ranges, where it often exceeded 150 mm. In contrast, in the eastern parts of Germany, \overline{RR}_{sum} was frequently below 50 mm.



Figure 7. Mean monthly precipitation sum (\overline{RR}_{sum}) in (**a**) January; (**b**) February; (**c**) March; (**d**) April; (**e**) May; (**f**) June; (**g**) July; (**h**) August; (**i**) September; (**j**) October; (**k**) November; (**l**) December.

In the study area, \overline{RR}_{sum} was highest ($\langle \overline{RR}_{sum} \rangle = 84$ mm) in July (Figure 7g) and lowest ($\langle \overline{RR}_{sum} \rangle = 49$ mm) in April (Figure 7d). The annual \overline{RR}_{sum} cycle in the study area had two maxima: One in July and a second in December. At the regional scale, the annual \overline{RR}_{sum} cycle may differ from $\langle \overline{RR}_{sum} \rangle$. For instance, in the vicinity of the Alps, \overline{RR}_{sum} was often more than twice as high in JJA compared to DJF. In contrast, in some areas of the western low mountain ranges, the maximum \overline{RR}_{sum} was modeled in December.

The interarea variability of \overline{RR}_{sum} in the study area was highest (IAV = 3.6) in September (Figure 7i), October (Figure 7j), and November (Figure 7k). This indicates that both the large-scale and orographic

influence on RR_{sum} in these months were strong. In contrast, RR_{sum} was more evenly distributed (*IAV* = 2.9) in April (Figure 7d).

The mean annual precipitation sum ($\overline{RR}_{sum,yr}$) is displayed in Figure 8. In the study area, it corresponded to $\langle \overline{RR}_{sum,yr} \rangle = 790$ mm and tended to increase toward the south and decrease toward the east. In most of the low mountain ranges, $\overline{RR}_{sum,yr}$ usually exceeded 1000 mm. In the southern low mountain ranges and close to the Alps, $\overline{RR}_{sum,yr}$ often exceeded 1500 mm. At individual sites, $\overline{RR}_{sum,yr}$ may even be higher than 2000 mm.



Figure 8. Mean annual precipitation sum ($\overline{RR}_{sum,yr}$).

3.5. Orographic Influence on Precipitation Sums

The small-scale variability of precipitation over the course of the year is highlighted for the low mountain range of the Black Forest in Figure 9. In January, \overline{RR}_{sum} varied from ≈ 50 mm to almost 200 mm over a distance of less than 30 km (Figure 9a). The highest \overline{RR}_{sum} values occurred on the high mountain slopes exposed to the west. The lowest \overline{RR}_{sum} values can be found in the lowest regions of the map extract. The spatial pattern of \overline{RR}_{sum} remained similar in April (Figure 9b). However, the \overline{RR}_{sum} variability decreased compared to January. This was mainly due to the fact that \overline{RR}_{sum} was lower at high elevations compared to January. In July, \overline{RR}_{sum} increased in the entire study area (Figure 9c). In almost the entire map extract, $\overline{RR}_{sum} > 90$ mm. In the high elevation regions, \overline{RR}_{sum} was slightly lower compared to January. In October, \overline{RR}_{sum} tendencies remained similar to the other months (Figure 9d). \overline{RR}_{sum} ranged from 75 mm to 160 mm. From the presented figure, it can be deduced that (1) elevation had a significant influence on \overline{RR}_{sum} and (2) its effect on \overline{RR}_{sum} varied over the course of the year.

To quantify the dependency of \overline{RR}_{sum} on ε , boxplots of \overline{RR}_{sum} as a function of ε are shown in Figure 10. In January, \overline{RR}_{sum} increased only slightly, with increasing ε until 600 m (Figure 10a). Above 800 m, \overline{RR}_{sum} rapidly increased. At $\varepsilon > 1200$ m, \overline{RR}_{sum} remained quasi-constant. The variability of

 \overline{RR}_{sum} was greatest at $\varepsilon \approx 1200$ m. A possible reason for this is that the orographic features (e.g., orientation, inclination) are very diverse in this elevation range.



Figure 9. Map extracts displaying the mean monthly precipitation sum (\overline{RR}_{sum}) in (**a**) January; (**b**) April; (**c**) July; (**d**) October in the low mountain range of the Black Forest.



Figure 10. Boxplots of the mean monthly precipitation sum (\overline{RR}_{sum}) as a function of elevation (ε) in (**a**) January; (**b**) April; (**c**) July; (**d**) October.

In April, the interquartile range of \overline{RR}_{sum} was lower, especially at low ε (Figure 10b). In July, the rate of \overline{RR}_{sum} change as a function of ε was greatest (Figure 10c). The median \overline{RR}_{sum} increased from 71 mm at ε = 200 m to 205 mm at ε > 1200 m. In addition, \overline{RR}_{sum} variability also increased. Both the general \overline{RR}_{sum} level and the variability of \overline{RR}_{sum} decreased in October (Figure 10d). The median of \overline{RR}_{sum} increased from 53 mm at ε = 200 m to 124 mm at ε > 1200 m.

3.6. Model Validation

Results from model validation are summarized in Table 3. From this summary, it can be seen that the R^2 ranged from 0.70 in February to 0.87 in June and July. In 11 months, the R^2 exceeded 0.75. From May to September, $R^2 > 0.80$, which indicates that the accuracy of the model used to simulate \overline{RR}_{sum} was higher in summer than in winter. The $\overline{RR}_{sum,yr}$ model had the highest accuracy ($R^2 = 0.91$). Further, *MAE* indicates that the accuracy of the models was very good (below 10 mm in all months). For $\overline{RR}_{sum,yr}$, *MAE* = 9 mm. *ME* indicates that there was no bias in the models, because it was either 0 mm or 1 mm in all months and on the annual scale.

Table 3. Model validation evaluated by the coefficient of determination (R^2), the mean absolute error (*MAE*), and mean error (*ME*) calculated for the mean monthly precipitation sum (\overline{RR}_{sum}) and the mean annual precipitation sum ($\overline{RR}_{sum,yr}$).

R^2	MAE (mm)	<i>ME</i> (mm)
0.78	9	1
0.70	8	1
0.76	9	1
0.75	7	1
0.83	8	0
0.87	8	0
0.87	9	0
0.85	8	0
0.80	8	0
0.79	8	1
0.75	8	0
0.78	9	0
0.91	9	1
	R ² 0.78 0.70 0.76 0.75 0.83 0.87 0.85 0.80 0.79 0.75 0.78 0.91	R ² MAE (mm) 0.78 9 0.70 8 0.76 9 0.75 7 0.83 8 0.87 8 0.87 8 0.87 8 0.79 8 0.75 8 0.79 8 0.75 8 0.75 9 0.75 9

4. Conclusions

In this study, daily precipitation was modeled monthly at a very high resolution in Germany. It was demonstrated that the annual precipitation cycle depends on regions and orographic properties such as elevation, relative elevation, and topographic sheltering. The high resolution provided the foundation for a very detailed detection of local precipitation regimes. According to the rigorous goodness-of-fit evaluation using a parametrization dataset and a validation dataset, the accuracy of the models built was good. The coefficient of determination reached values up to 0.91, which was achieved by evaluating the results from modeling the mean annual precipitation sum.

One important feature of GePrA is that it is not limited to the mapping of large-scale precipitation patterns. It can also be used to quantify the effects of the local orography on monthly and annual precipitation. Moreover, GePrA does not only reproduce the monthly and annual precipitation sums, but also the entire monthly precipitation distributions. The two parameters of the Weibull distribution used to fit the empirical precipitation distributions and the share of wet days are available monthly for all grid cells in the study area. Using the monthly Weibull parameters and the share of wet days, it was possible to calculate any percentile and the monthly precipitation sum.

Although the developed models reflect the monthly distribution of precipitation very well, the results and the approach are not without limitations. GePrA does not indicate precipitation intensity on sub-monthly scales. The statistical approach of GePra does not allow the mapping of

daily precipitation conditions. No direct relationship can be established between individual synoptic conditions and the simulated precipitation sums. Furthermore, it is not possible to map extreme heavy precipitation events with return periods exceeding 100 days. It is possible to transfer the proposed approach to the analysis of extreme precipitation events, but that would require longer time series than those used in this study.

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