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Closing the Latency Gap for Operational Flood Forecasting: Near-Real-Time 1-km Hourly Gridded Forcing in Germany

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Abstract. Operational flood forecasting using spatially distributed hydrological models requires accurate, high-resolution gridded meteorological forcing delivered in near real time, particularly for systems operating on hourly update cycles. To support this application, this study evaluates four spatial interpolation methods—inverse distance weighting (IDW), ordinary kriging (OK), external drift kriging (EDK), and a Gaussian copula-based approach—for producing high-resolution gridded meteorological fields across Germany. Performance is assessed using station-based cross-validation and benchmarking against high-resolution reference datasets from the German Weather Service (DWD). Results show that hourly precipitation exhibits clear climatological variogram structures but limited instantaneous spatial coherence. Consequently, IDW and OK show very similar performance for most situations, with OK providing only modest improvements during high-intensity or more spatially coherent events. For daily totals derived from the hourly fields, relative to HYRAS, the station-based products showed lower errors than the unadjusted RADOLAN product used here, particularly for the selected events. In contrast to precipitation, temperature fields exhibit stronger spatial coherence and smoother spatial structure, making them particularly well suited to multivariate dependence modelling. Consequently, the Gaussian copula approach captures spatial patterns more accurately than IDW and kriging-based methods, resulting in substantial improvements in interpolation accuracy. Evaluation against the hourly reference grids of the German Weather Service (DWD) shows that the copula method reliably reproduces large-scale spatial patterns and achieves an RMSE of 1.19 °C over 1995–2024. These results are obtained without explicitly accounting for land-use-dependent variables, highlighting the efficiency of the approach for near-real-time applications. To examine suitability for operational use, the methods are further tested under extreme conditions, with case studies centred on the July 2021 flood and the summer 2024 flood events. Two recent heavy-rainfall events associated with flooding (Ahr 2021 and Fils 2024) further show that OK captures the spatial structure of extreme precipitation slightly better than the other methods, although IDW performs similarly and both substantially outperform RADOLAN. Overall, the study shows that hourly precipitation interpolation remains fundamentally constrained by weak event-scale spatial dependence and station density, which limits the benefits of more advanced methods, whereas temperature fields benefit strongly from copula-based modelling. Method choice should therefore depend on the vari-

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able of interest: for hourly precipitation, advanced interpolation provides only limited gains over simpler approaches, whereas for temperature, copula-based modelling offers clear advantages.

1 Introduction

Operational flood forecasting is fundamentally constrained by rapid rainfall–runoff response, particularly in small and medium-sized catchments, where discharge can rise sharply and peak within hours. This is especially the case during convective storms with highly localized precipitation (Wetterhall et al., 2011; Lyu et al., 2018). As a result, operational forecasting with large-domain, spatially distributed hydrological models such as mHM and LISFLOOD depends strongly on high-frequency, near-real-time (NRT) observations to capture event-scale forcing and update hydrological initial conditions(Maina et al., 2020; Sun et al., 2020; Najafi et al., 2024). However, many high-quality gridded reference products are released with daily-to-monthly latency, which limits their value for real-time initialization and operational flood forecasting. Generating high-resolution, NRT gridded hourly precipitation and temperature fields from station observations can bridge this latency gap, reduce forcing delays, and better support end-to-end operational forecasting workflows (Najafi et al., 2025b). Similar efforts to extend climatological gridded datasets into NRT for hydrological forecasting have demonstrated the operational value of such approaches (Van Osnabrugge et al., 2017).

In Germany, operational flood forecasting is increasingly moving toward hourly and sub-hourly update cycles, supported by rapid-update DWD forecast products such as SINFONY (Seamless INtegrated FOrecastiNg sYstem), which combines nowcasting and numerical weather prediction (Bondy et al., 2025; Deutscher Wetterdienst (DWD), 2025). This shift is particularly important for localized convective storms, whose timing and spatial structure can evolve rapidly and therefore require meteorological forcing at hourly or even shorter intervals. A central challenge is the timely generation of spatially consistent, high-resolution gridded forcing fields for operational hydrological models. Gauge-based gridded products such as HYRAS (Rauthe et al., 2013) provide an important benchmark because of their broad use and quality-controlled station basis, but their daily temporal resolution and update cycle limit their suitability for forecasting systems operating at sub-daily time scales. For hourly applications, RADOLAN (Winterrath et al., 2012) provides near-real-time radar-based precipitation estimates, yet these can underestimate event totals in some situations and may require adjustment before hydrological use (Kreklow et al., 2020; Hammoudeh et al., 2025). Operational flood forecasting therefore benefits from the parallel use and evaluation of multiple forcing sources (Trömel et al., 2025). This motivates the systematic assessment of station-based interpolation methods for generating near-real-time, high-resolution hourly forcing fields suitable for operational hydrological forecasting.

For air temperature, the bottleneck is even more pronounced: state-of-the-art hourly gridded temperature fields HOchaufgelöste STündliche RAsterDAtensatz (HOSTRADA; Krähenmann et al., 2018) are typically available only with a lag of at least one month, limiting their use for real-time model initialization and continuous operational forecasting. This combination (i.e., daily NRT precipitation totals, under-estimated hourly radar precipitation, and delayed hourly temperature grids) creates a persistent barrier to producing consistent, high-resolution, near-real-time forcing for operational flood forecasting using fully gridded hydrological models (e.g. see (Najafi et al., 2025a)). Accurate NRT gridded forcing is essential to specify model initial conditions

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(e.g., soil moisture, snow state) and to convert meteorological forecasts into skillful hydrological predictions. Deficiencies in the forcing datasets or in initial conditions are consistently identified as a leading source of forecast error in operational flood forecasting systems (Antonetti et al., 2019; Berg et al., 2021). In particular, rainfall uncertainty has been shown to dominate predictive uncertainty in hydrological modeling, and conditional simulation frameworks provide a systematic way to characterize and propagate these errors (Renard et al., 2011).

A practical way to close this gap is to generate near-real-time, observation-based gridded forcing directly from station networks at the required spatiotemporal resolution. However, producing *hourly* fields at *1 km* is challenging. Hourly precipitation is intermittent and highly non-Gaussian, with rapidly evolving spatial structure that can be weak or unstable from one hour to the next, challenging methods that rely on smooth variograms or stationary dependence assumptions. In addition, the temporal correlation structure of precipitation plays a critical role in shaping spatial ensemble characteristics and uncertainty propagation, particularly at sub-daily scales (Rakovec et al., 2012). Neglecting these dependencies can lead to unrealistic spatial variability and misrepresentation of event dynamics. Furthermore, gauge measurements themselves are subject to sampling uncertainty due to spatial variability at scales smaller than the network resolution, which can introduce additional errors in gridded products derived solely from station data (Villarini et al., 2008). Hourly temperature exhibits stronger spatial coherence, but is strongly modulated by elevation, land-surface heterogeneity, and boundary-layer processes, which can induce local anomalies that simple lapse-rate or diurnal-curve parameterizations fail to capture. These characteristics motivate a systematic evaluation of interpolation approaches across a range of complexity to determine what is robust and skillful under genuine NRT constraints.

Previous research has investigated a wide range of approaches for interpolating hourly precipitation and temperature from station observations to continuous grids. For precipitation, Haberlandt (2007) evaluated several geostatistical methods and showed that External Drift Kriging (EDK) and External Drift Indicator Kriging (EDIK) can outperform simpler approaches when auxiliary information such as radar data is available. Their analysis, however, was limited to a subregion of Germany and focused primarily on extreme rainfall events under conditions where radar information could be assimilated, which constrains its applicability to purely gauge-based, near-real-time settings. An alternative line of research has explored copula-based interpolation methods for precipitation. Bárdossy and Li (2008) introduced the use of copulas to explicitly separate marginal precipitation distributions from spatial dependence, enabling more flexible modeling of non-Gaussian and intermittent rainfall fields. Subsequent studies further developed this framework and demonstrated its potential for precipitation interpolation and infilling, particularly at daily or aggregated timescales (Bárdossy and Pegram, 2013, 2014). Despite these advantages, copula-based approaches are computationally demanding and their effectiveness for hourly precipitation, characterized by strong intermittency and rapidly evolving storm structures, remains uncertain.

For temperature, several studies have examined the interpolation of station observations to gridded products at hourly resolution. Berndt and Haberlandt (2018) investigated spatial interpolation of hourly temperature over parts of Germany and showed that interpolation performance is strongly affected by station density and local physiographic conditions. Other approaches have relied on idealized diurnal temperature curves (Luedeling, 2018) or functional representations derived from daily minimum and maximum temperatures, such as linear, parabolic, or sinusoidal models (Eccel et al., 2010). While these methods

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reproduce the mean diurnal cycle reasonably well, they are limited in their ability to represent short-term temperature anomalies caused by cloud cover, radiative effects, cold-air pooling, or urban influences, which are not fully captured by smooth diurnal parameterizations. As a result, their performance degrades in complex terrain and heterogeneous land-surface conditions, and they are less suitable for applications requiring spatially consistent, near-real-time temperature fields at high temporal resolution. The HOSTRADA dataset currently represents the state of the art for gridded hourly temperature data in Germany. It combines nonlinear temperature profiles adapted to regional climatic conditions with a non-Euclidean representation of station influence, yielding improved spatial consistency and relatively low average errors (Frei, 2014). Nevertheless, HOSTRADA is produced retrospectively and updated monthly, which limits its applicability for near-real-time operational flood forecasting (Krähenmann et al., 2018). As a result, despite substantial progress in temperature interpolation methodologies, a clear gap remains between high-quality retrospective products and the requirements of real-time hydrological applications.

The primary objective of this study is to identify the most suitable method for generating near-real-time, high-resolution (1 km) gridded hourly precipitation and temperature fields for Germany by evaluating different interpolation approaches against reference datasets over a historical period. Specifically, we aim to: (1) compare the performance of multiple interpolation approaches, Inverse Distance Weighting (IDW), Ordinary Kriging (OK), External Drift Kriging (EDK), and a Gaussian copula framework, and assess whether more complex methods provide tangible advantages over simpler techniques for highly variable hourly precipitation; and (2) examine the spatial dependence structure of hourly precipitation to determine whether advanced interpolation methods can effectively exploit it, and validate the resulting gridded products against established reference datasets (HOSTRADA, HYRAS), with particular emphasis on performance during extreme precipitation events. Thus, this study contributes not only a comparison of interpolation methods, but also an operationally feasible forcing-generation strategy that identifies which level of methodological complexity is justified for each meteorological variable under near-real-time constraints.

2 Methods and Metrics

To ensure consistent validation against the reference datasets described in Section 3, all methods are configured to produce gridded fields at 1 km spatial resolution and hourly temporal resolution. IDW is a purely distance-based technique that assumes similarity decreases monotonically with distance and does not explicitly account for spatial autocorrelation or underlying physical controls, which can limit its performance in heterogeneous environments (Isaaks et al., 1989). OK explicitly models spatial dependence through a variogram and provides the best linear unbiased prediction under second-order stationarity assumptions (Goovaerts, 1997). EDK extends this framework by incorporating auxiliary variables, such as elevation, to represent deterministic spatial trends and has been shown to improve interpolation performance in regions with complex topography or systematic gradients (Goovaerts, 2000; Haberlandt, 2007). The Gaussian copula approach differs fundamentally from kriging-based methods by modeling spatial dependence independently of the marginal distributions, allowing greater flexibility in representing non-Gaussian behavior while preserving rank correlations between stations (Bárdossy and Li, 2008).

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This separation of marginal and dependence structures can be advantageous when the assumptions of Gaussianity or stable covariance required by kriging are violated.

2.1 Inverse Distance Weighting

The IDW method (Shepard, 1968) is a deterministic interpolation technique in which the value at an unsampled location is estimated as a weighted average of values from nearby observation points. The weights assigned to each observation are inversely related to their distance from the target location, typically governed by a power parameter q. Formally, for a given location $\mathbf{x}$, the interpolated value $\hat{z}(\mathbf{x},t)$ is calculated as:

$$\hat{z}(\mathbf{x},t) = \sum_{i=1}^{n} \lambda_i z(\mathbf{x}_i,t) \tag{1}$$

with weights defined by:

$$\lambda_i = \frac{1}{d(\mathbf{x}_i,\mathbf{x})^q} \bigg/ \sum_{j=1}^{n} \frac{1}{d(\mathbf{x}_j,\mathbf{x})^q} \tag{2}$$

where $d(\mathbf{x}_i,\mathbf{x})$ denotes the distance between the observation point $\mathbf{x}_i$ and the location $\mathbf{x}$. A fixed number n of the nearest stations is used to ensure stability of the estimate. In this work, for both precipitation and average temperature, $q = 3$ is applied, as proven by cross-validation on a range $q \in [0.5, 5]$.

2.2 Ordinary and External Drift kriging

Given a specified variogram model (e.g., exponential, spherical, or Gaussian), Ordinary Kriging (OK) and External Drift Kriging (EDK) provide linear unbiased estimates of a spatial variable at an unsampled location (Metheron, 1963; Goovaerts, 1997). The estimate at location $\mathbf{x}$ and time t is expressed as a weighted sum of neighboring observations,

$$\hat{z}(\mathbf{x},t) = \sum_{i=1}^{n} \lambda_i \cdot z(\mathbf{x}_i,t), \tag{3}$$

where the kriging weights $\boldsymbol{\lambda}$ are obtained by solving the kriging system,

$$\mathbf{A} \cdot \lambda = \mathbf{b} \tag{4}$$

.

Here, $\mathbf{A}$ denotes the kriging covariance (or variogram) matrix augmented with the unbiasedness constraints, and $\mathbf{b}$ is the covariance (or variogram) vector between the prediction location and the neighboring observations. In EDK, additional constraints are included to account for auxiliary variables (e.g., elevation), allowing large-scale trends to be incorporated into the interpolation (Goovaerts, 1997; Samaniego et al., 2011).

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2.3 Gaussian Copula

Copulas provide a flexible framework for modeling spatial dependence independently of marginal distributions, making them particularly suitable for non-Gaussian variables such as precipitation. In this study, we apply a Gaussian copula for precipitation interpolation following Bárdossy and Li (2008). The Gaussian copula is derived from the multivariate normal distribution and captures linear dependence via a correlation matrix while allowing arbitrary marginal distributions. Although it does not explicitly model tail dependence (an important limitation for extreme precipitation), it remains computationally efficient and widely used in hydroclimatic applications.

Let $z_i, i \in \{0, \ldots, n\}$ denote the observed variable at location $\mathbf{x}_i$ with marginal distribution $F_i(z) = \mathbb{P}(Z_i \le z)$. Based on Sklar's theorem, the joint cumulative distribution of Z_0, $Z_1, \ldots, Z_n$ can be written as

$$F(z_0, z_1, \ldots, z_n) = C\left(F_0(z_0), F_1(z_1), \ldots, F_n(z_n)\right), \tag{5}$$

where C is a copula function. Assuming a Gaussian copula, the dependence structure is modeled using a multivariate normal distribution with correlation matrix Σ.

Each marginal is transformed to the Gaussian space as

$$T_i = \Phi^{-1}(U_i) = \Phi^{-1}(F_i(Z_i)), \tag{6}$$

where Φ^{-1} is the inverse standard normal Cumulative Distribution Function (CDF). Note that the random variable $U_i = F_i(Z_i)$ has a uniform distribution $U(0,1)$.

Conditional Gaussian theory is used to estimate the latent variable T_0 at an unobserved location x_0, yielding a conditional mean and variance

$$\mu_0 = \boldsymbol{\sigma}_{n\times 1}^{\top} \Sigma_{n\times n}^{-1} \mathbf{T}_{\text{obs}}, \quad \sigma_0^2 = 1 - \boldsymbol{\sigma}_{n\times 1}^{\top} \Sigma_{n\times n}^{-1} \boldsymbol{\sigma}_{n\times 1} \tag{7}$$

The prediction is finally transformed back to the original space using the inverse marginal CDF

$$\hat{z}_0 = F_0^{-1}\left(\Phi(\mu_0)\right). \tag{8}$$

2.3.1 Dependence Structure and Marginals

The correlation matrix Σ is estimated parametrically using an exponential spatial correlation model with range ρ and nugget τ (Bárdossy and Pegram, 2013):

$$C_{ij} = (1-\tau) \times \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{\rho}\right) \tag{9}$$

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A parametric approach is preferred here due to the high variability and intermittency of hourly precipitation, which complicates stable empirical covariance estimation.

Hourly precipitation marginals are modeled using a zero-inflated gamma distribution, accounting for the mixed discrete–continuous nature of precipitation:

$$F(z) = \begin{cases} p_0 & \text{if } z = 0 \\ p_0 + G(z)\cdot(1-p_0) & \text{if } z > 0 \end{cases} \tag{10}$$

where p_0 is the probability of zero precipitation and $G(z)$ is the gamma CDF for positive values.

2.4 Nonparametric assessment of spatial dependence using rank correlation

Before applying advanced copula models, we assess whether measurable spatial dependence exists in observed precipitation fields. The analysis is based on rank correlations, which provide a nonparametric and distribution-free measure of dependence that depends only on the copula and not on the marginal distributions (Sklar, 1959; Genest and Favre, 2007).

For each time step, precipitation observations across stations are transformed to ranks. Pairwise Spearman rank correlations are then computed between all station pairs, yielding a copula-based dependence measure invariant under monotonic transformations (Genest and Favre, 2007). Correlations are grouped by inter-station distance and summarized using robust statistics to obtain a distance-dependent dependence function.

The analysis is repeated conditionally on subsets of time steps corresponding to heavy precipitation events, identified using high spatial quantiles and a minimum number of wet stations to ensure spatial coherence. Event-conditional rank correlations provide a direct diagnostic of whether spatial dependence strengthens under extreme conditions without assuming a specific parametric copula or tail-dependence structure (Bárdossy and Pegram, 2009; Vandenberghe et al., 2010).

2.5 Performance Metrics

To evaluate the performance of the interpolation methods applied to precipitation and temperature, several commonly used statistical metrics were employed. Let z_i and $\hat{z}_i$ denote the observed and simulated (or interpolated) values, respectively, and n the total number of data points. The average observed and simulated values are represented by $\bar{z}$ and $\bar{\hat{z}}$, respectively:

Root Mean Square Error (RMSE) measures the magnitude of the prediction error and penalizes larger errors more than smaller ones:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{z}_i - z_i)^2}. \tag{11}$$

Mean Absolute Error (MAE) evaluates the average magnitude of the absolute errors, providing a more robust measure against outliers than RMSE:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{z}_i - z_i|. \tag{12}$$

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Nash–Sutcliffe Efficiency (NSE) assesses how well the interpolated values match observations:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(\hat{z}_i - z_i)^2}{\sum_{i=1}^{n}(z_i - \bar{z})^2}. \tag{13}$$

Values range from $-\infty$ to 1, where 1 indicates a perfect match.

Kling–Gupta Efficiency (KGE) provides a balanced evaluation of correlation, bias, and variability:

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}, \tag{14}$$

where

$$r = \frac{\sum_{i=1}^{n}(\hat{z}_i - \bar{\hat{z}})(z_i - \bar{z})}{\sqrt{\sum_{i=1}^{n}(\hat{z}_i - \bar{\hat{z}})^2 \sum_{i=1}^{n}(z_i - \bar{z})^2}}, \tag{15}$$

$$\beta = \frac{\bar{\hat{z}}}{\bar{z}}, \qquad \gamma = \frac{\sigma_{\hat{z}}}{\sigma_z}, \tag{16}$$

and $\sigma_{\hat{z}}$ and σ_z denote the standard deviations of simulated and observed values, respectively.

Relative Bias (Rbias) measures the fractional bias of the model in representing the mean of the observations:

$$\mathrm{Rbias} = \frac{\bar{\hat{z}} - \bar{z}}{\bar{z}}, \tag{17}$$

where positive values indicate over-estimation and negative values indicate underestimation.

Finally, additive bias (Bias) quantifies the systematic overestimation or underestimation of a model relative to a reference dataset. It is defined as the arithmetic mean of the pointwise differences between the model estimates $\hat{z}$ and the reference values z. A positive bias indicates that the model overestimates the reference on average, whereas a negative bias indicates systematic underestimation. Formally,

$$\mathrm{Bias} = \frac{1}{n}\sum_{i=1}^{n}(\hat{z}_i - z_i) \tag{18}$$

where n is the number of valid data pairs.

2.6 Distinguishing Climatological and Event-Scale Spatial Structure

In this study, we explicitly distinguish between climatological spatial structure and the instantaneous spatial coherence of individual precipitation and temperature fields, as these represent fundamentally different aspects of spatial dependence (Goovaerts, 1997; Cressie, 2015):

1. *Climatological variogram structure*, defined as the empirical variogram estimated by aggregating observations over long time periods. This structure reflects long-term statistical dependence and mean spatial organization, and may appear stable even when individual realizations differ substantially (Pegram and Clothier, 2001; Berne et al., 2004; Haberlandt, 2007).

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2. *Instantaneous spatial coherence*, which describes the spatial footprint and continuity of a variable at a specific time step (e.g., an hourly precipitation field). This coherence can be weak for short-duration or convective precipitation events, where rainfall is highly localized and intermittent (Fabry, 1996; Berne et al., 2004).

Hourly precipitation over Germany exhibits a well-defined climatological variogram when averaged over many years, yet individual storm events (particularly convective systems) often show limited spatial continuity and low spatial autocorrelation at short distances (Fabry, 1996; Berne et al., 2004; Kreklow et al., 2020). In contrast, near-surface air temperature typically displays noisier or less stable variogram estimates at fine temporal scales, while instantaneous temperature fields remain spatially coherent due to dominant large-scale atmospheric controls and surface energy balance processes (Berndt and Haberlandt, 2018). Recognizing this distinction is essential for interpreting cross-validation results and for understanding the relative performance of interpolation methods applied to different variables and temporal scales.

3 Datasets

This study relies on a combination of station observations and gridded reference products to evaluate interpolation methods for hourly precipitation and temperature in Germany. While the evaluation spans a long-term historical period (1991–2024 for temperature and 2007–2024 for precipitation), this historical analysis is conducted to validate methods intended for use in operational workflows. By establishing the long-term performance and robustness of these techniques, we demonstrate their suitability for generating high-resolution, near-real-time (NRT) forcing fields required for operational flood forecasting.

3.1 Station observations

Hourly precipitation and temperature observations were obtained from the Deutscher Wetterdienst's (DWD) operational surface station network. The network provides near-real-time access to quality-controlled measurements and serves as the primary data source for time-critical hydrological applications in Germany.

For cross-validation, only stations with continuous records and sufficient data availability over the study period were retained to ensure robust and reliable validation results. In contrast, the final interpolation was performed using all available station data. For hourly temperature, 123 stations (out of 577 available), that have more than 90 % data availability for the period 1991–2024, were considered. For precipitation, 1438 historical stations in Germany provide hourly precipitation records, but only 973 have less than 10 % missing data for the period 2007–2024. For precipitation, the study is restricted to the years 2007–2024, because RADOLAN-adjusted hourly precipitation is currently the only reliable gridded reference dataset at hourly resolution for Germany, and it has been consistently available only since mid-2006. The spatial variability of hourly precipitation necessitates an even denser observation network. Relying solely on sparse station measurements for precipitation interpolation introduces significant errors across large grid areas (Terink et al., 2018; Berndt and Haberlandt, 2018).

3.2 RADOLAN hourly precipitation

As a reference and benchmark for precipitation, the radar-based RAdar-OnLine-ANeichung (RADOLAN) product provided by DWD was used. RADOLAN combines weather radar observations with rain gauge measurements to produce gridded hourly precipitation fields at approximately 1 km spatial resolution over Germany (Winterrath et al., 2012).

While RADOLAN is available in near-real-time, its gauge adjustment is finalized only at the end of each day using daily precipitation totals. As a result, hourly RADOLAN fields available in real time are known to underestimate precipitation intensities, particularly during extreme events, and should be regarded as preliminary products rather than fully quality-controlled reference data (Kreklow et al., 2020; Hammoudeh et al., 2025). Despite these limitations, RADOLAN represents the only nationwide gridded hourly precipitation dataset available in an operational context and is therefore included for comparison.

3.3 HYRAS daily precipitation

For retrospective validation of accumulated precipitation, the Hydrometeorological Raster Dataset (HYRAS) was used (Rauthe et al., 2013). The HYRAS is the official 1 km gridded precipitation dataset over Germany of the German Weather Service (DWD), derived from a dense observational network and based on established regionalisation and interpolation procedures (Rauthe et al., 2013). The dataset undergoes extensive quality control, including consistency checks, gap filling, and homogenization, ensuring a high level of reliability for climatological and hydrological applications. HYRAS has been widely used in climate modeling, impact studies, and hydrological research across Germany (Zink et al., 2017; Ehmele et al., 2022; Hammoudeh et al., 2025), supporting its suitability as a benchmark dataset. However, it should be noted that HYRAS itself is an interpolated product and therefore subject to inherent uncertainties, particularly related to the smoothing of spatial variability and potential underestimation of extreme precipitation events. These limitations are important to consider when interpreting differences between interpolation methods.

3.4 HOSTRADA hourly temperature

Hourly temperature interpolation results were evaluated against the HOchaufgelöste STündliche RAsterDAtensatz (HOSTRADA) dataset (Krähenmann et al., 2018). HOSTRADA provides gridded hourly air temperature at 1 km resolution across Germany and represents the current state-of-the-art retrospective temperature product.

HOSTRADA combines nonlinear diurnal temperature profiles with a non-Euclidean representation of station influence, yielding spatially consistent and physically plausible temperature fields (Frei, 2014). However, the dataset is produced retrospectively and updated monthly, which precludes its direct use in operational flood forecasting. In this study, HOSTRADA serves solely as a reference dataset for assessing the accuracy and spatial consistency of the proposed near-real-time temperature interpolation methods.

3.5 Heavy Rainfall Events

The analysis covers two major heavy rainfall events that led to flooding: the July 2021 at Ahr (Mohr et al., 2022; Ludwig et al., 2023; Seidel et al., 2023; Vorogushyn et al., 2024) and the June 2024 at Fils (Junghänel et al., 2024). The first case corresponds to the Ahr valley flood on 14 July 2021, and the second to the Fils catchment flood occurring between 30 May and 2 June 2024. These events were selected to evaluate interpolation performance under extreme precipitation conditions that are particularly relevant for operational flood forecasting.

For all near-real-time analyses, only information available within the respective hour at the stations was used. Daily-adjusted or retrospectively corrected datasets (e.g., HYRAS, RADOLAN, HOSTRADA) were employed exclusively for validation purposes and not as inputs to the interpolation procedures.

4 Interpolation of Hourly Temperature

Temperature is commonly regarded as well-suited for kriging-based interpolation because it typically varies smoothly in space and is often reasonably approximated by a Gaussian random field (Goovaerts, 1997; Cressie, 2015). Under these assumptions, Ordinary Kriging (OK) and External Drift Kriging (EDK) provide the best linear unbiased prediction (BLUP) when the variogram is well defined and adequately represents the underlying spatial dependence (Metheron, 1963). In practice, however, kriging performance is highly sensitive to the quality and stability of the estimated variogram and to observation density. For hourly temperature, variograms can become noisy or weakly structured in regions with sparse station coverage, complex topography, or pronounced microclimatic effects, thereby limiting the predictive skill of both OK and EDK, even when auxiliary variables such as elevation are included (Frei, 2014; Berndt and Haberlandt, 2018). Gaussian copula interpolation offers an alternative framework by explicitly decoupling the marginal distribution of temperature from its spatial dependence structure (Bárdossy and Li, 2008). Although hourly temperature often approximates Gaussian behavior at larger scales, local radiative processes, land–surface interactions, and topographic contrasts can introduce skewness and other deviations from normality (Dunn et al., 2019; Rojas Muñoz et al., 2021; Gubler et al., 2023). The copula approach represents spatial dependence through rank-based correlations, which tend to be more stable than covariance-based measures when variograms are poorly defined or affected by local heterogeneity (Genest and Favre, 2007; Bárdossy and Pegram, 2013). This property makes copula-based interpolation more robust in heterogeneous landscapes and under conditions where kriging performance may degrade due to variogram mis-specification.

4.1 Cross Validation

Leave-one-out cross-validation (Zacharias et al., 2011) was used to compare the performance of the three interpolation methods. The upper part of Table 1 summarizes the results for hourly average temperature. For all methods, the 12 nearest stations were used for interpolation to ensure comparability.

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In our experiments, EDK with an exponential variogram performed best for hourly temperature, among OK and EDK. Other variogram families yielded slightly poorer results, so only EDK with the exponential model is included in Table 1. The hourly empirical and fitted theoretical variograms are depicted in Fig.1 (top) for temperature. For the Gaussian copula method, the marginal distributions at each station were estimated by fitting a normal distribution to its hourly temperature series, yielding station-specific mean and standard deviation parameters. Spatial dependence among the transformed (Gaussianized) observations was modeled using the exponential covariance function in Eq. 9 with a nugget term. The range and nugget parameters were estimated globally from empirical spatial correlations, yielding $\tau = 0.019$ and $\rho = 200000$.

Table 1. Performance metrics for inverse distance weighting (IDW), external drift kriging with exponential variogram (EDK-exp), and the Gaussian copula-based interpolation from leave-one-out cross-validation for hourly and daily air temperature interpolation. Reported values (mean $\pm$ standard deviation) summarize errors between interpolated and observed temperatures across all stations and time steps.

Type	Method	RMSE (°C)	MAE (°C)	NSE	KGE	Rbias
Hourly	IDW	1.72 ± 1.32	1.43 ± 1.28	0.91 ± 0.28	0.85 ± 0.31	-1.56 ± 34.9
	EDK-exp	1.33 ± 0.92	0.97 ± 0.67	0.95 ± 0.19	0.94 ± 0.11	-0.78 ± 7.43
	Gaussian copula	$\mathbf{1.24 \pm 0.50}$	$\mathbf{0.90 \pm 0.39}$	$\mathbf{0.96 \pm 0.02}$	$\mathbf{0.98 \pm 0.01}$	$\mathbf{0.002 \pm 0.27}$
Daily	IDW	1.08 ± 0.99	0.91 ± 0.96	0.95 ± 0.18	0.90 ± 0.21	-0.61 ± 23.47
	EDK-exp	0.79 ± 0.63	0.59 ± 0.46	0.97 ± 0.11	0.96 ± 0.06	-0.37 ± 5.63
	Gaussian copula	$\mathbf{0.75 \pm 0.37}$	$\mathbf{0.55 \pm 0.27}$	$\mathbf{0.98 \pm 0.02}$	$\mathbf{0.98 \pm 0.01}$	$\mathbf{0.06 \pm 0.91}$

Table 1 shows that the Gaussian copula method provides the strongest overall performance for hourly average temperature, despite the fact that the empirical variograms for temperature are relatively weak and noisy as indicated in Fig.1. This is important because both OK and EDK rely heavily on a well-defined variogram structure; when variograms lack a clear sill or range, kriging tends to oversmooth or misrepresent spatial dependence. The Gaussian copula, by contrast, is less sensitive to such issues because it models dependence through rank correlations, which remain more stable across stations even when covariance estimates fluctuate. This helps explain why the copula achieves the lowest RMSE and MAE, the highest NSE and KGE, and almost zero bias. Compared to IDW, the Gaussian copula reduces RMSE by roughly 28 %, and even relative to the best kriging variant (EDK-exp), the improvement is still around 7 %. The narrow spread of NSE and KGE also suggests highly consistent performance across stations, in contrast to kriging, whose accuracy varies depending on local variogram instability. The method's near-zero relative bias (0.002 ± 0.27) means it introduces virtually no systematic offset, which reduces the need for downstream bias corrections. EDK with an exponential variogram performs considerably better than IDW, but its performance still reflects the limitations imposed by the noisy hourly variogram: prediction accuracy varies strongly from station to station, and the method struggles where local thermal anomalies are not captured by the drift variable (elevation). IDW shows the weakest performance overall, as expected for a method that imposes neither large-scale structure nor local terrain effects. The main drawback of the Gaussian copula is its computational expense. Fitting station-specific marginals and

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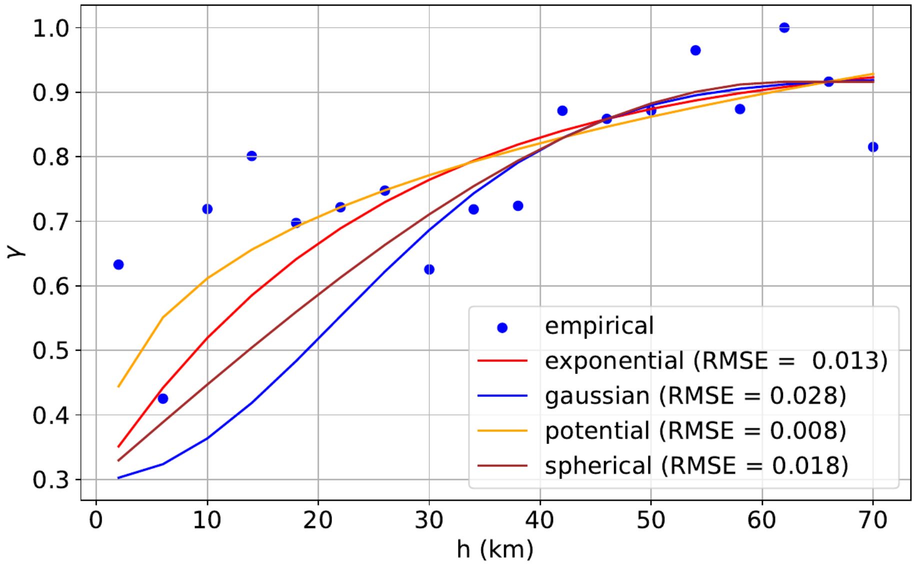

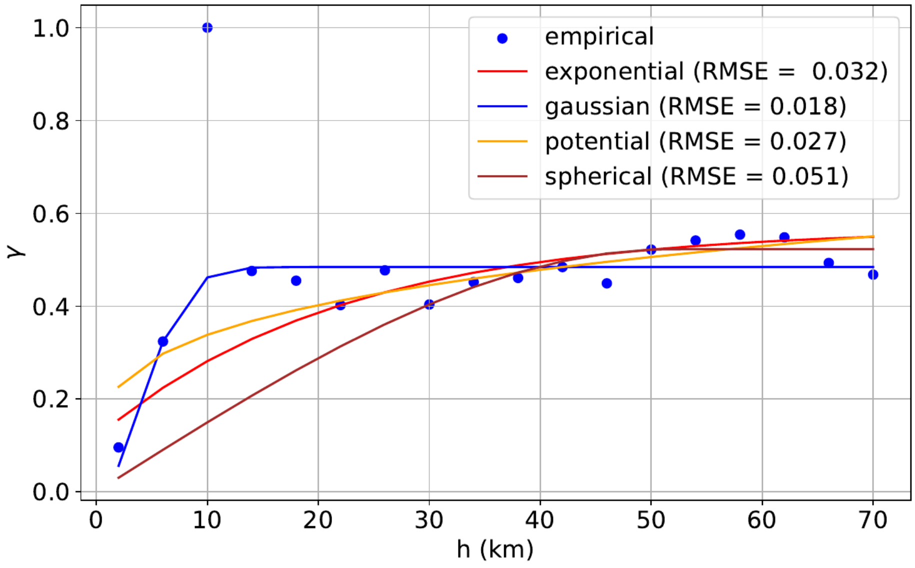

Figure 1. Empirical and theoretical variograms for hourly (top) and daily (bottom) temperature for 1991-2024, based on 577 hourly and 928 daily stations

modeling spatial dependence in the copula domain is more time-consuming than kriging. Nonetheless, the strong reduction in bias and the high station-to-station consistency often justify the additional cost in operational settings.

A similar cross-validation was conducted for daily average temperature (Table 1) using 329 stations with at least 90 % data availability over the period 1991–2024. As expected, all methods perform better at daily resolution because the spatial structure of temperature becomes smoother, and the daily variograms show clearer ranges than their hourly counterparts. The Gaussian copula again outperforms EDK, although the margin is slightly smaller (approximately 5 % RMSE improvement compared to approximately 7 % at hourly scale).

Thus, the ranking of methods is consistent across temporal scales: Gaussian copula > EDK-exp > IDW. The results emphasize that when variograms are weak (common for hourly temperature due to microclimates, radiative variability, and topographic complexity) rank-based dependence modeling offers a clear advantage over conventional geostatistics.

4.2 Evaluation of Gridded Hourly Average Temperature

The Gaussian-copula–interpolated temperature fields were compared with the HOSTRADA average temperature dataset from DWD for the period 1995–2024. The mean RMSE between the two products is 1.19 °C. The largest systematic differences occur in regions where HOSTRADA incorporates additional spatial information, most notably urban heat island adjustments, topographic corrections, and land-surface characteristics, that are not explicitly represented in the copula-based interpolation. To examine these differences more closely, a monthly climatology of interpolation errors was created by computing the long-term average of the HOSTRADA–copula differences for each calendar month (Fig.2). These climatological error maps reveal that the discrepancies vary seasonally and regionally, reflecting physical processes represented in HOSTRADA but absent from the purely station-based copula method.

5 Interpolation of Hourly Precipitation

For precipitation interpolation, factors such as circulation patterns (Bárdossy et al., 2021) and topographic influences are known to improve performance over longer accumulation periods. However, both effects weaken substantially at hourly resolution: the correlation between precipitation and topography increases with the length of the temporal aggregation (Ly et al., 2011; Bárdossy and Pegram, 2013). Because this study focuses specifically on short-term (hourly) precipitation, topographic predictors were not included. Likewise, incorporating circulation patterns would significantly increase model complexity and is not well suited for short-duration precipitation fields, so this aspect was also omitted from the present analysis.

5.1 Cross Validation

Leave-one-out cross-validation (Zacharias et al., 2011) was used to evaluate the performance of the interpolation methods. The top section of Table 2 summarizes the results for hourly precipitation. For each method, the 12 nearest stations to the withheld location were used for interpolation. The choice between OK and EDK with different variogram models was informed by cross-validation, and the empirical and fitted variograms are shown in Fig. 3 (top). For the Gaussian copula approach, the parameters of the parametric covariance model (Eq. 9) were estimated as $\tau = 0.418$ and $\rho = 162582.19$.

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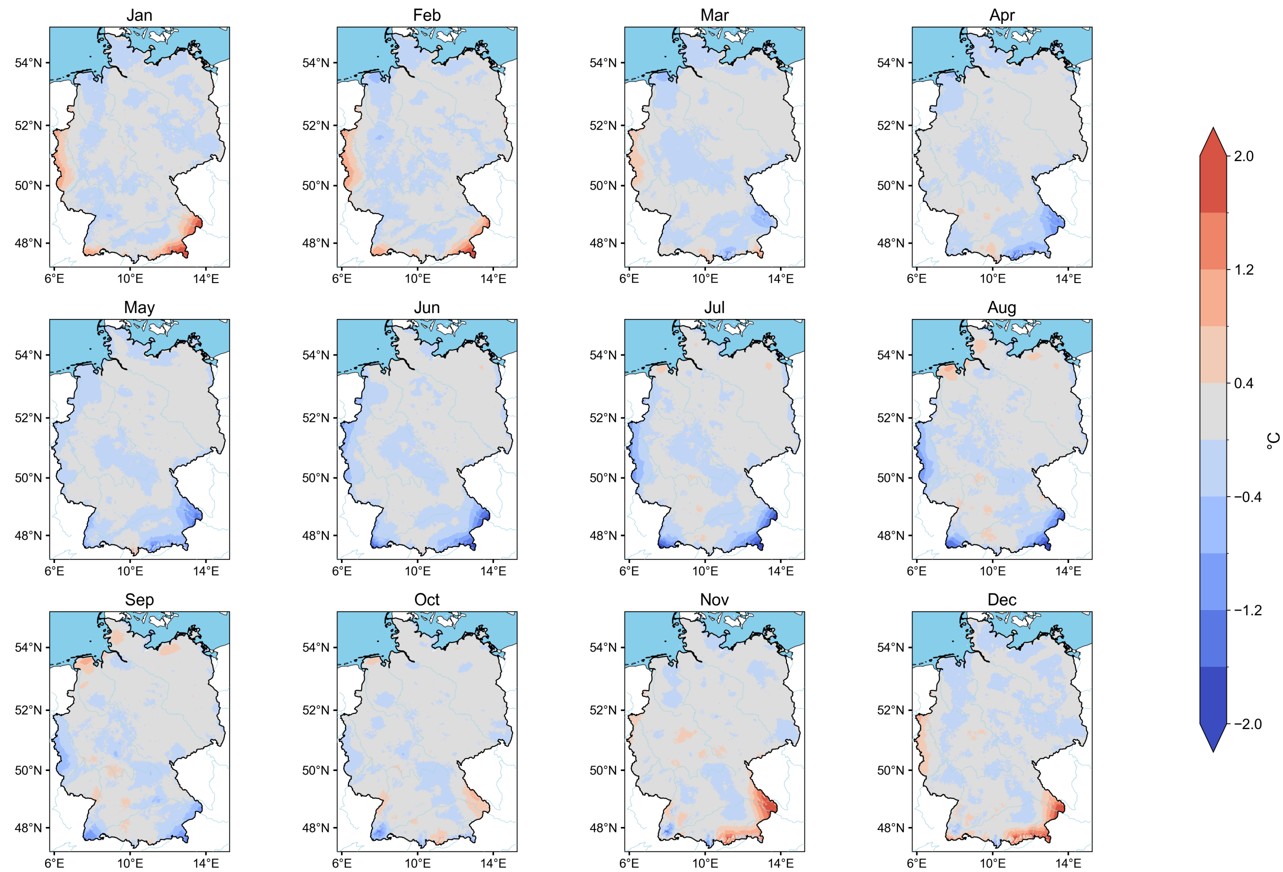

Figure 2. Monthly climatology of temperature differences between the Gaussian copula-based interpolation and the HOSTRADA dataset over the period 1991–2024. Differences are computed at each grid cell as (Copula − HOSTRADA) for hourly temperature, and subsequently averaged over all hours within each month and over all years to obtain a monthly mean difference. The interpolation is based on n = 577 stations, of which 123 stations have less than 10% missing values.

Although hourly precipitation exhibits a much clearer spatial variogram signal than temperature, the cross-validation results in Table 2 show that the three interpolation methods perform similarly in terms of RMSE, MAE, and NSE. OK with an exponential variogram (OK-exp) achieves slightly lower bias than the other approaches, whereas the Gaussian copula exhibits a large negative relative bias and reduced skill (notably lower KGE). This indicates that, at the hourly resolution, the dependence structure is too irregular for the parametric copula model to capture reliably, even though the variogram is well-defined.

To test whether this limitation arises from the short temporal aggregation interval, the same methods were applied to daily precipitation. The results, summarized in the bottom section of Table 2, use the same station set and are accompanied by empirical and fitted variograms in Fig.3 (bottom). As expected, daily precipitation exhibits a more even and smoother spatial structure, reflected in substantially improved interpolation performance across all methods.

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Table 2. Performance metrics from leave-one-out cross-validation for hourly and daily accumulated precipitation interpolation. Reported values (mean ± standard deviation) summarize errors between interpolated and observed precipitation across all stations and time steps. Results are shown for inverse distance weighting (IDW), ordinary kriging with exponential variogram (OK-exp), and the Gaussian copula-based interpolation.

Type	Method	RMSE ($\mathrm{mm\,h^{-1}}$)	MAE ($\mathrm{mm\,h^{-1}}$)	NSE	KGE	Rbias
Hourly	IDW	$\mathbf{0.36 \pm 0.05}$	$\mathbf{0.06 \pm 0.01}$	$\mathbf{0.49 \pm 0.08}$	0.56 ± 0.09	2.09 ± 10.39
	OK-exp	$\mathbf{0.36 \pm 0.05}$	$\mathbf{0.06 \pm 0.01}$	$\mathbf{0.49 \pm 0.08}$	$\mathbf{0.56 \pm 0.07}$	$\mathbf{1.64 \pm 10.45}$
	Gaussian copula	0.38 ± 0.05	0.06 ± 0.02	0.45 ± 0.06	0.33 ± 0.09	-28.78 ± 17.82
		RMSE ($\mathrm{mm\,d^{-1}}$)	**MAE** ($\mathrm{mm\,d^{-1}}$)	**NSE**	**KGE**	**Rbias**
Daily	IDW	2.19 ± 0.6	0.95 ± 0.26	0.78 ± 0.06	0.73 ± 0.07	3.14 ± 11.95
	OK-exp	$\mathbf{1.81 \pm 0.49}$	$\mathbf{0.68 \pm 0.22}$	$\mathbf{0.85 \pm 0.05}$	$\mathbf{0.86 \pm 0.05}$	$\mathbf{1.07 \pm 8.42}$
	Gaussian copula	1.98 ± 0.48	0.72 ± 0.24	0.82 ± 0.04	0.76 ± 0.05	-10.05 ± 6.44

In Table 2, OK-exp clearly outperforms IDW and the Gaussian copula across all metrics. In contrast to the hourly case, IDW performs worse, consistent with the stronger spatial structure at daily resolution. The copula method improves noticeably over the hourly case but still trails OK, suggesting that although the dependence structure becomes more regular at the daily scale, the parametric copula formulation used here does not exploit the available spatial information as effectively as kriging.

Taken together, the comparison across temporal scales indicates that:

- Hourly precipitation does have a meaningful spatial variogram, much stronger than temperature, but still too intermittent for the copula model to capture reliably.
- The similarity in performance between IDW and OK at hourly resolution suggests that the spatial structure is not strong enough to give kriging a consistent advantage over simple distance-based interpolation.
- The clear separation between methods at daily resolution confirms that the strength of spatial structure increases with the aggregation interval and that more sophisticated dependence models (including more flexible copulas) may be required to extract additional skill for hourly data.

Preliminary tests with more flexible copula formulations, including nonparametric and vine-copula approaches, did not yield substantial performance improvements. It remains unclear whether this is due to limitations in the methods themselves or to the specific implementation choices made here. Consequently, further work is needed to determine whether alternative copula architectures can meaningfully capture the spatial complexity of short-duration precipitation, or whether fundamentally different modeling strategies are required.

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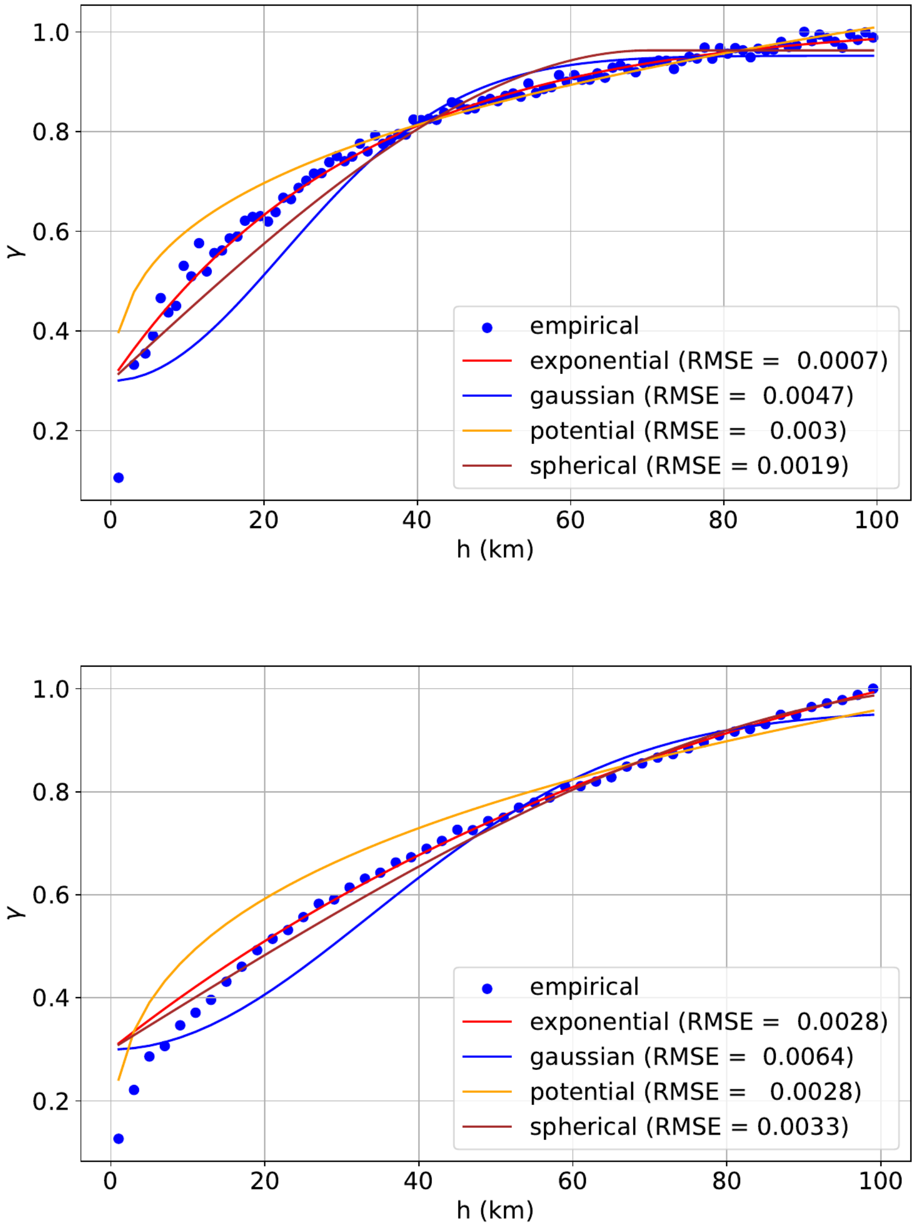

Figure 3. Empirical and theoretical variograms for hourly (top) and daily (bottom) precipitation for 2007-2024, based on 1438 hourly and 2771 daily stations

5.2 Interpolation of Precipitation using IDW and OK

This section presents interpolation results for hourly precipitation from 2007 to 2024 using IDW and OK. Due to the comparatively poor cross-validation performance of the Gaussian copula (Table 2) and its high computational cost for long, high-resolution time series, we did not include this method in the full interpolation.

Based on cross-validation results (Section 5.1), OK-exp was selected as the best-performing kriging configuration. The fitted global variogram exhibits a clear spatial structure (stronger than that seen for temperature) with the following parameters: nugget = 0.29, sill = 0.71, and range = 0.32×10^5 m.

5.2.1 Comparison with HYRAS

When aggregated to daily totals, IDW and OK yield comparable errors: approximately $1.25\ \mathrm{mm\,d^{-1}}$ and $1.27\ \mathrm{mm\,d^{-1}}$, respectively, when evaluated against HYRAS daily precipitation. For context, daily precipitation errors on the order of ± 0.5 to $\pm 1\ \mathrm{mm\,d^{-1}}$ are commonly reported for high-quality gridded datasets over Germany and correspond to roughly 10–20 % of typical wet-day totals (5–10 $\mathrm{mm\,d^{-1}}$) (Rauthe et al., 2013). Both methods exceed this range on average, suggesting that neither method fully captures the fine-scale spatial variability characteristic of convective precipitation events (Bárdossy and Pegram, 2014).

Despite the relatively well-behaved empirical variogram, IDW and OK produce fields that are strikingly similar. Uncertainty analyses and direct inspection show that, under conditions of high small-scale variability, modest station density, and intermittent spatial correlation, OK effectively collapses toward a distance-weighted predictor. In these circumstances, kriging's theoretical optimality provides limited practical advantage, and both methods converge to nearly identical interpolation surfaces.

5.2.2 Seasonal patterns

Fig.4 shows that interpolation errors from OK are consistently higher during the winter months (November–February). This seasonal pattern is associated with a shift from convective to predominantly stratiform precipitation systems in winter, which are characterized by lower rain intensities and weaker spatial contrasts (Berne et al., 2004; Winterrath et al., 2012). Under such conditions, the signal-to-noise ratio of gauge observations decreases, and measurement uncertainty becomes relatively more important, reducing the effectiveness of spatial interpolation based solely on distance or covariance structure (Haberlandt, 2007). In addition, winter precipitation in Germany is often influenced by large-scale frontal systems with embedded small-scale variability, which further complicates the representation of spatial dependence using stationary variograms (Kreklow et al., 2020).

5.2.3 Annual accumulation bias

A more critical limitation of IDW and OK appears when annual totals are examined. At some grid cells, yearly accumulated precipitation can deviate by ± 1000 mm from HYRAS. These large long-term biases arise from the compounding of small

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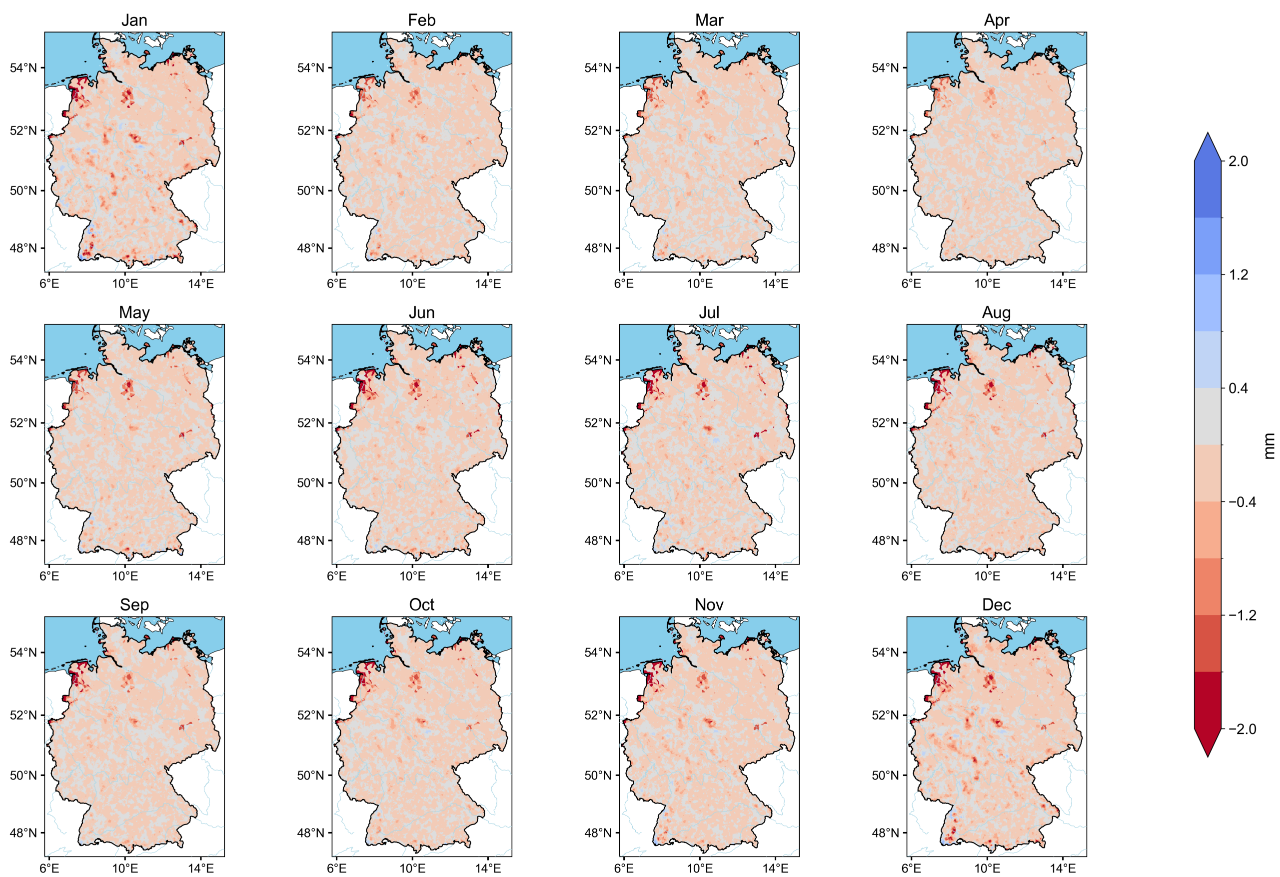

Figure 4. Spatial distribution of monthly mean precipitation differences between Ordinary Kriging and HYRAS over Germany for the period 1991–2024. Hourly interpolated precipitation was first aggregated to daily totals to match the temporal resolution of HYRAS. Differences were computed at each grid cell as Ordinary Kriging minus HYRAS (OK − HYRAS) and then averaged over all days within each calendar month and across all years to obtain a monthly climatology. Positive values indicate higher precipitation in Ordinary Kriging than in HYRAS. The interpolation is based on $n = 1438$ stations, including 973 stations with less than 10% missing data.

timing and spatial-placement errors in hourly rainfall, especially in regions influenced by convective storms or orographic enhancement. For short-term operational applications, such as real-time flood forecasting where horizons are < 24 h, these long-term biases are less consequential, and a dedicated bias-correction step is not applied due to computational constraints.

430 #### 5.2.4 Comparison with RADOLAN

For real-time hydrological initialization, both IDW and OK outperform raw RADOLAN products over the evaluation period. RADOLAN exhibits an RMSE of 2.28 $\mathrm{mm\,d^{-1}}$ relative to HYRAS (2007–2024), primarily due to known radar-based bi-

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ases. Nevertheless, for non–real-time applications, bias-adjusted RADOLAN (corrected against HYRAS) remains a strong alternative.

5.3 Limitations of advanced copula models for precipitation interpolation

Cross-validation experiments using a Gaussian copula formulation (2) yielded suboptimal interpolation performance, motivating a closer examination of the underlying spatial dependence structure of precipitation fields. Accordingly, the rank-based spatial dependence diagnostics introduced in section 2.4 were applied to hourly and daily precipitation fields to assess whether instantaneous spatial dependence in precipitation amounts is sufficiently strong to justify the use of more advanced copula models. The results indicate that rank correlations of precipitation amounts are negligible (near zero) across all distance classes and this holds consistently for climatological conditions, normal precipitation days, and heavy precipitation events. These findings imply that the joint distribution of precipitation amounts exhibits near-independence in copula space, such that more flexible or tail-dependent copula families cannot effectively exploit additional dependence structure. In this setting, the reported success of copula-based precipitation interpolation methods in the literature (Bárdossy and Pegram, 2009) is likely attributable to spatial coherence in precipitation occurrence and marginal distributions, rather than to strong cross-sectional dependence in precipitation magnitudes. Consequently, increasing copula complexity is unlikely to yield substantial improvements.

5.4 Heavy Rainfall Case Study

This section examines two extreme precipitation events that produced major floods in Germany. Hourly precipitation fields interpolated using IDW, OK, and the Gaussian copula, along with RADOLAN radar data, were aggregated to daily totals and compared against the HYRAS reference dataset. For the Fils event, 31 May 2024 is shown as a representative day. The resulting comparisons are presented in Fig.5 and Fig.6.

Across both events, ordinary kriging consistently performs best among the interpolation methods. Visual inspection indicates that OK reduces local over- and underestimation compared to IDW and yields smoother, more coherent precipitation fields. RADOLAN shows the largest deviations from HYRAS in both cases, with errors concentrated around convective cores and radar beam–shaded regions. The Gaussian copula performs noticeably worse than OK and IDW during extreme rainfall. This is consistent with the cross-validation findings: although climatological precipitation variograms are well-defined, the instantaneous spatial structure of short-duration convective storms is highly irregular. As a result, the parametric dependence model used in the copula struggles to reproduce localized extremes.

To complement the visual assessment, event-scale quantitative error metrics were computed from the HYRAS difference fields (Tables 3. For the Ahr 2021 event, OK achieves the lowest RMSE ($5.49\,\mathrm{mm\,d^{-1}}$) and MAE ($3.03\,\mathrm{mm\,d^{-1}}$), and it also substantially reduces large deviations (P90 error = $6.91\ \mathrm{mm\,d^{-1}}$). IDW performs similarly but consistently slightly worse. Both interpolation methods outperform RADOLAN, which exhibits large maximum errors ($119\,\mathrm{mm\,d^{-1}}$) and heavy-tailed error distributions (typical of radar underestimation and displacement errors during convective storms). The Gaussian copula shows degraded performance, with RMSE and P90 values more than double those of OK.

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Table 3. Event-scale error metrics for precipitation estimates during the Ahr (14 July 2021) and Fils (31 May 2024) flood events, using HYRAS as the reference dataset. Differences are computed as (product − HYRAS), where all datasets are expressed as daily accumulated precipitation totals derived from hourly data. Metrics are calculated over all grid cells and time steps within each event using the resulting difference fields. All values are given in $\mathrm{mm\,d^{-1}}$.

Event	Method	RMSE	MAE	Max error	P90 error	Bias
Ahr-2021	IDW	6.91	3.6	44.81	8.19	**0.1**
	OK-exp	**5.49**	**3.03**	**32.67**	**6.91**	-0.16
	Gaussian copula	16.22	9.41	66.66	27.21	-8.42
	RADOLAN	16.3	10.66	119.29	28.30	-10.42
Fils-2024	IDW	5.06	2.4	43.64	6.3	0.77
	OK-exp	**4.52**	**2.24**	**39.97**	**5.88**	**0.61**
	Gaussian copula	9.11	5.24	88.95	13.47	-4.65
	RADOLAN	14.04	9.52	73.19	22.94	-9.43

The Fils 2024 results follow the same pattern: OK again yields the smallest RMSE and MAE and the lowest P90, while IDW remains a close second. The Gaussian copula performs moderately for light and moderate rainfall but fails to capture localized extremes (maximum error 88.95 $\mathrm{mm\,d^{-1}}$). RADOLAN again shows the largest biases and spatially concentrated errors.

Overall, both events confirm that:

- Kriging provides the most reliable reconstruction of extreme-event precipitation when HYRAS is taken as reference.
- IDW performs similarly to OK in many locations but cannot match kriging's reduction of large localized errors.
- Gaussian copula methods are not suited for reconstructing extreme convective rainfall under the current modeling assumptions.
- Radar data require bias adjustment to achieve accuracy comparable to station-based interpolation (see Table.3).

These case studies therefore reinforce the broader conclusion that, despite the weak instantaneous spatial coherence of hourly precipitation, OK maintains a consistent advantage over IDW and performs considerably better than both the Gaussian copula and unadjusted RADOLAN during flood-generating extreme events.

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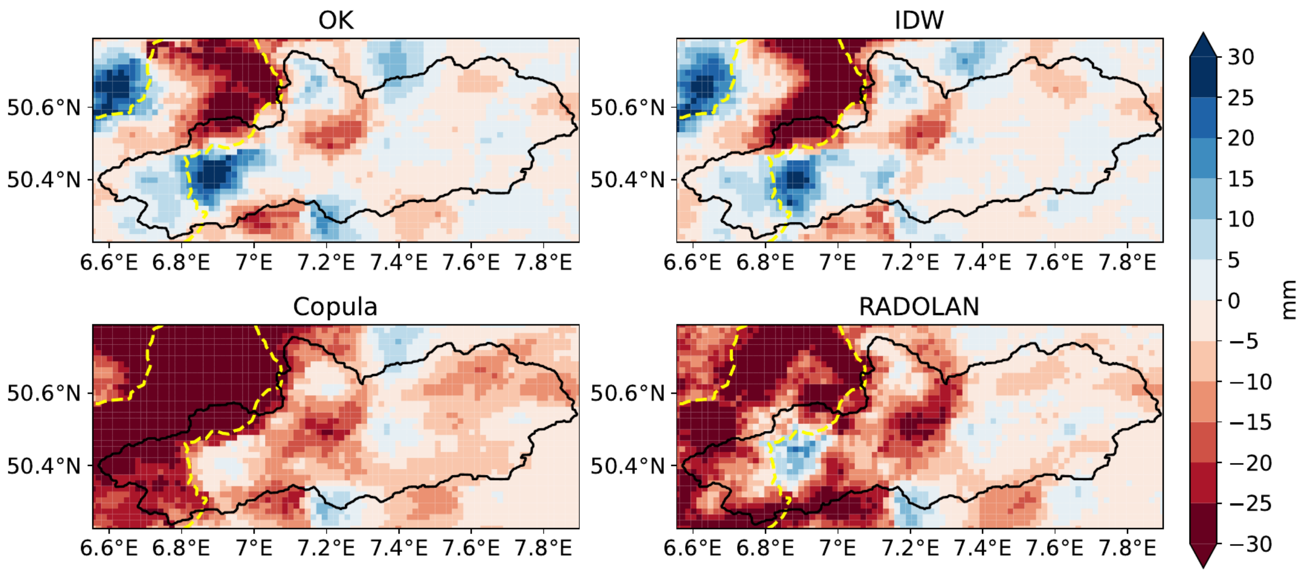

Figure 5. Spatial distribution of daily precipitation differences between four interpolation-based products and the HYRAS dataset for the extreme rainfall event of 14 July 2021 in the Ahr basin. Precipitation from the interpolation methods is aggregated from hourly to daily totals to match the temporal resolution of HYRAS, and differences are computed as (product − HYRAS). The yellow contour delineates areas where HYRAS precipitation exceeds 100 $\mathrm{mm\,d^{-1}}$ during the event.

6 Discussion

6.1 Hourly precipitation: good variograms but limited interpolation skill due to network density and unresolved small-scale variability

An unexpected outcome of this study was the disconnect between the well-behaved variograms of hourly precipitation and the relatively weak interpolation performance, particularly in terms of annual accumulated precipitation and systematic bias in certain regions. The empirical variograms consistently showed interpretable spatial structures (clear nugget, sill, and range) suggesting that hourly precipitation exhibits coherent spatial dependence that should, in principle, support kriging-based interpolation. However, the actual predictive skill remained modest.

This result directly addresses the question raised in the Introduction regarding whether reliable spatial structure exists for hourly precipitation that advanced interpolation techniques can effectively exploit. Although the variograms indicate well-

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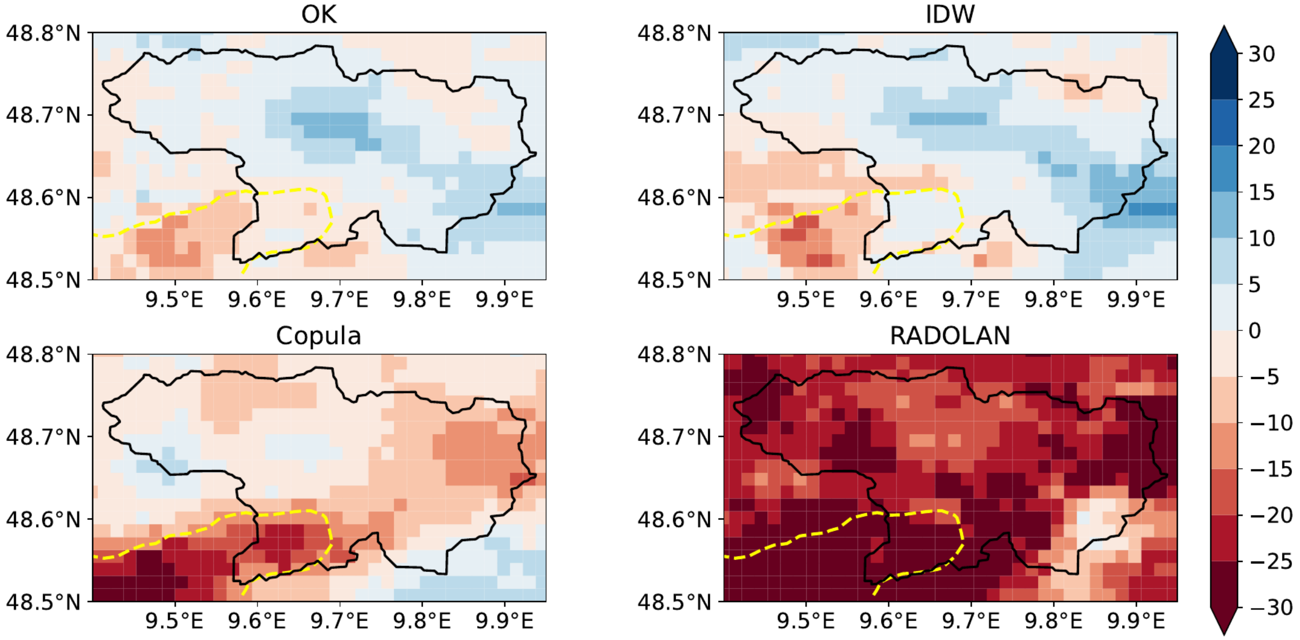

Figure 6. Spatial distribution of daily precipitation differences between four interpolation-based products and the HYRAS dataset for the rainfall event of 31 May 2024 in the Fils basin. Interpolated precipitation is first aggregated from hourly to daily totals for consistency with HYRAS, and differences are computed as (product − HYRAS). The yellow contour delineates areas where HYRAS precipitation exceeds $80\ \mathrm{mm\,d^{-1}}$ during the event.

defined climatological spatial dependence, the limited interpolation skill demonstrates that such structure is insufficient for resolving event-scale variability relevant for operational flood forecasting.

The main explanation lies not in the lack of spatial dependence but in the density and spatial configuration of the observation network relative to the true variability of hourly rainfall. Hourly precipitation in Germany is strongly influenced by short-lived convective cells with spatial scales often far below the 10–20 km spacing of the station network (Fabry, 1996; Berne et al., 2004; Peleg et al., 2018). Even though the variograms summarise average spatial structure across the network, individual convective features are typically undersampled or not sampled at all by the stations. As a result, the "good" variogram describes a smoothed, climatological dependence structure rather than the fine-scale heterogeneity responsible for most interpolation errors.

OK performs well for intense rainfall events when stations happen to sample the core of convective cells, but this success is event-dependent. In the flood case studies (Ahr 2021 and Fils 2024), OK outperformed RADOLAN because station coverage happened to capture key parts of the storm structures. Under such conditions, the variogram structure becomes truly informative, allowing OK to accurately interpolate high intensities. However, this does not generalize across the entire year, when many convective peaks fall between stations. This explains why IDW and OK performed similarly on average, despite OK benefiting

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from valid variogram models. OK's theoretical advantage materializes primarily when convective features intersect the station network, while IDW suffers from fewer structural assumptions and performs surprisingly robustly when spatial dependence is too short-ranged for the kriging model to make meaningful distinctions. The systematic underperformance of EDK further illustrates the challenge. Although variograms were well defined, the external drift predictors (mainly elevation or large-scale coordinate trends) do not meaningfully describe hourly convective activity. Instead of reducing uncertainty, they introduce spurious broad-scale gradients that may intensify the smoothing effect, thereby worsening bias in accumulated precipitation.

Similarly, the Gaussian copula method struggled because the spatial rank correlation of hourly rainfall is inherently weak, even when the variogram suggests coherent second-order structure. Copulas rely on stable rank dependence, but the dominance of intermittent zero rainfall and localized peaks causes rank relationships to fluctuate strongly in space and time. This directly confirms the uncertainty mentioned in the Introduction regarding the applicability of copula-based methods to hourly precipitation. While copulas have demonstrated skill at aggregated timescales, the weak and unstable rank dependence at the hourly scale limits their effectiveness for near-real-time precipitation interpolation.

The comparison with RADOLAN further underscores these findings: despite being radar-based, RADOLAN showed substantial underestimation in extreme cases. During the Ahr 2021 and Fils 2024 events, OK was able to provide higher and more realistic peak intensities. This suggests that a well-calibrated station-based interpolation method can outperform radar products in specific extreme conditions, particularly when radar correction processes smooth or truncate peak values.

From an operational hydrological perspective, this finding is critical: even when high-resolution (1 km) grids are produced, unresolved convective-scale variability at the hourly timescale limits the ability of station-based interpolation to fully meet the forcing requirements of rapidly responding catchments highlighted in the Introduction (Maina et al., 2020; Sun et al., 2020; Najafi et al., 2024).

Overall, the key limitation is not the quality of the variograms but the inability of the observation network to resolve small-scale precipitation variability at the hourly time scale. This leads to spatial smoothing that explains both the modest interpolation performance and the bias in annual accumulations. The results suggest that further gains will require either denser observational networks, radar–station merging techniques, or fundamentally different approaches to modeling convective-scale variability.

6.2 Temperature: weak variogram structure but strong large-scale coherence benefits the copula method

In contrast to precipitation, one might expect temperature to show a strong and smooth spatial dependence that supports classical geostatistical models. However, the hourly temperature variograms in this study were noisy, irregular, and often lacked a clear sill or range. This reflects the fact that temperature at the hourly scale is influenced by a mixture of local processes (radiative effects, land cover heterogeneity, urban heat signals, valley–ridge contrasts) that can disrupt the smooth synoptic gradients typically visible at coarser temporal scales. As a result, the covariance structure becomes difficult to model accurately using standard kriging assumptions. Despite this weak variogram behavior, the Gaussian copula method consistently produced the best interpolation performance. This initially counterintuitive result can be explained by the distinction between second-order dependence (used in kriging) and rank-based dependence (used in the copula approach). Although the variograms lack a

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stable structure, the rank relationships among stations remain robust because temperature fields (even with local noise) preserve their large-scale ordering. Stations that are generally colder or warmer than others tend to maintain that ordering over time, even if the precise covariance structure fluctuates. This makes the Gaussian copula particularly suitable for hourly temperature interpolation. The method leverages the stable ordinal relationships between station temperatures while allowing the marginals to follow the observed distributions exactly. This helps avoid the smoothing and bias typical of kriging when variograms are noisy or mis-specified. The result is an interpolation method that remains accurate even when classical geostatistics struggle to characterize the underlying covariance model.

Importantly, the copula-based temperature fields approach the accuracy of HOSTRADA while avoiding its retrospective production cycle. This directly addresses the operational gap identified in the Introduction between high-quality monthly products and the need for near-real-time forcing in flood forecasting systems.

By comparison, OK performed reasonably well but was limited by the poor variogram quality. With no clear range or sill, OK tends to impose artificial smoothness and produces biases, particularly near areas of steep temperature contrasts such as urban–rural boundaries or complex topography. EDK performed somewhat better than OK only when elevation was strongly correlated with temperature (e.g., winter conditions). However, elevation alone cannot capture diurnal and radiative influences, limiting the method's consistency across seasons. IDW, being purely distance-based, showed stable but inferior performance. It avoids variogram mis-specification but cannot capture the broad thermal gradients that dominate Germany's temperature field. Thus, the success of the copula method arises not from strong covariance structure, which is absent, but from the robust spatial ordering and distributional consistency of hourly temperature. This makes it a particularly effective tool for generating high-resolution temperature fields in real time, even under conditions where classical geostatistics are disadvantaged.

6.3 Implications for operational hydrology

As noted in the Introduction, forecasting chains in Germany are increasingly moving toward rapid-update systems such as SINFONY, which aim to combine nowcasting and numerical weather prediction into seamless, high-frequency meteorological guidance. To make full use of such systems in hydrological forecasting, distributed hydrological models require timely, high-resolution gridded forcing for updating initial conditions, including soil moisture, snow state, and antecedent discharge. While near-real-time station observations are available, the key challenge is how to transform these point measurements into spatially consistent gridded fields at the resolution required by distributed hydrological models. This is particularly relevant for hourly temperature, for which high-quality gridded reference products such as HOSTRADA are available only retrospectively, limiting their direct use in operational forecasting. Our results show that the Gaussian copula approach can help close this gap by generating accurate, near-real-time gridded temperature fields from station observations.

These findings support a variable-dependent strategy for operational workflows:

– For temperature: We show that distribution-aware methods like the Gaussian copula provide robust, high-quality gridded fields in near-real-time, even when spatial dependence is noisy. This is a critical finding for regional water authori-

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ties, as it enables the updating of temperature-dependent processes at 15 to 60-minute intervals, such as snowmelt and evapotranspiration, that were previously constrained by the multi-week latency of traditional gridded products.

- The study shows that station-only interpolation provides a practical near-real-time forcing option, while the benefit of more complex methods is constrained at hourly time scales by the localized and intermittent nature of precipitation. OK performs slightly better during the selected flood-generating events, whereas IDW remains competitive under many conditions. This suggests that, for operational station-based gridded precipitation products, method selection should be guided by robustness, reproducibility, latency requirements, and event-scale performance rather than methodological complexity alone.

Overall, this research provides the methodological evidence needed to align hydrological initial conditions with the sub-hourly tempo of state-of-the-art meteorological forcing. By enabling the generation of near-real-time, high-resolution gridded inputs, these findings support the transition toward "impact-based" warning systems. Such systems allow regional water authorities to update flood risk assessments frequently, providing the actionable lead time required to respond to the rapid evolution of localized, convective flood events. Taken together, these results directly answer the study objectives outlined in the Introduction by demonstrating that interpolation performance at the hourly scale is strongly dependent on the variability of the data and constrained by the physical process scales relative to the network density.

While the impact of different interpolation methods on simulated streamflow and flood hydrographs is highly relevant for operational flood forecasting, it is beyond the scope of the present study. Here, we focus on the preceding and necessary step: evaluating whether near-real-time station-based interpolation methods can generate reliable high-resolution meteorological forcing fields for hydrological applications. A hydrograph-based assessment would require a dedicated hydrological modelling experiment, including catchment-specific model setup, routing, and discharge validation. We therefore consider the propagation of interpolation differences into flood magnitude, peak timing, and hydrograph shape as an important follow-up study.

7 Conclusion

The primary contribution of this work is providing operational insights into which interpolation methods can reliably produce high-resolution gridded hourly data (1 km) from station observations in near real time for flood forecasting. Beyond comparing interpolation methods, this study provides an operationally feasible forcing-generation strategy that identifies which level of methodological complexity is justified for each meteorological variable under near-real-time constraints. By evaluating these techniques against high-quality retrospective benchmarks, the study supports ongoing research-to-operations activities and provides a clear framework for generating the real-time hydrometeorological forcing required for impact-based early warning systems.

Four interpolation methods (IDW, OK, EDK, and a Gaussian copula approach) were systematically evaluated with respect to accuracy, robustness, and operational suitability. For hourly precipitation, the results show that no interpolation method can fully overcome the weak instantaneous spatial coherence of rainfall at the hourly scale, particularly for convective events.

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Among the tested approaches, OK provided the most consistent overall performance, including during the Ahr (2021) and Fils (2024) flood events, and yielded more reliable extremes than the radar-based RADOLAN product in these cases. However, IDW performed comparably to OK for most stations, indicating that the added complexity of geostatistical methods provides only marginal benefits under the high spatial variability and low autocorrelation typical of hourly precipitation. EDK and the Gaussian copula approach did not demonstrate systematic advantages for precipitation and are therefore not recommended for near-real-time operational use in this context. These findings confirm that, while a climatological spatial structure exists for hourly precipitation, it is often not representative of individual events and limits the effectiveness of advanced interpolation techniques. For hourly temperature, the situation differs markedly. Temperature fields exhibit strong instantaneous spatial coherence, which can be effectively exploited by advanced dependence models. The Gaussian copula method consistently outperformed IDW, OK, and EDK, producing the lowest errors and minimal bias across Germany. Its performance was comparable to the established HOSTRADA dataset, while offering the crucial advantage of near-real-time applicability, making it well-suited for operational forecasting. This is particularly relevant for flood forecasting in snow-affected and temperature-sensitive catchments, where biases in thermal forcing directly influence hydrological model states and forecast skill. Validation against reference datasets (HYRAS and HOSTRADA) and targeted flood-event analyses demonstrate that variable-specific interpolation strategies are essential. Complex methods do not necessarily improve results for highly variable hourly precipitation, whereas they offer clear benefits for spatially coherent variables such as temperature. Overall, this study demonstrates that a national, near-real-time hydrometeorological forcing dataset can be derived directly from station data, provided that interpolation methods are tailored to each variable's physical characteristics. A pragmatic combination of OK for hourly precipitation and Gaussian copula interpolation for temperature provides a computationally feasible and operationally robust solution that effectively addresses the gap between existing retrospective products and the requirements of real-time flood forecasting in Germany. Future work should prioritize hybrid radar–station merging approaches, as the present rank-based diagnostics indicate that instantaneous spatial dependence of precipitation amounts is negligible even at short inter-station distances. These results suggest that further improvements from increasingly complex copula formulations for station-based interpolation alone are unlikely. Nevertheless, targeted investigations of copula models that explicitly separate precipitation occurrence from amount, or that adapt dependence structures to specific meteorological regimes, may still provide limited benefits in well-defined settings. More broadly, the observed limitations appear to reflect the inherent stochasticity of rainfall at short timescales rather than deficiencies of the interpolation framework itself.

Code and data availability. The meteorological datasets used in this study, including hourly and daily station observations, the RADOLAN-RW hourly precipitation product, and the HYRAS-DE daily precipitation dataset, are provided by the German Weather Service (DWD). These are among the freely accessible geodata and geodata services available via the DWD Climate Data Center (CDC) (https://opendata.dwd.de). Data usage is governed by the "Ordinance on the Definition of the Terms of Use for the Provision of Federal Geodata (GeoNutzV)". The HOSTRADA temperature dataset is available from the DWD as a retrospective product upon request.

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All code used for interpolation, cross-validation, and figure generation is openly available on GitHub: https://github.com/Mattemathics/interpolation. The codes used for interpolation using ordinary and external drift kriging are available on Gitlab: https://git.ufz.de/chs/progs/edk_nc.

The hourly interpolated precipitation and temperature datasets generated in this study are publicly available via online data repositories and can be accessed using the following link for precipitation: https://doi.org/10.48758/ufz.16623 and the following links for temperature from 1991-2024:

Part 1 (1991–1994): https://doi.org/10.5281/zenodo.18738358,
Part 2 (1995–1998): https://doi.org/10.5281/zenodo.18799481,
Part 3 (1999–2002): https://doi.org/10.5281/zenodo.18801016,
Part 4 (2003–2006): https://doi.org/10.5281/zenodo.18833741,
Part 5 (2007–2010): https://doi.org/10.5281/zenodo.18860162,
Part 6 (2011–2014): https://doi.org/10.5281/zenodo.18860567,
Part 7 (2015–2018): https://doi.org/10.5281/zenodo.18924207,
Part 8 (2019–2022): https://doi.org/10.5281/zenodo.18924425,
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