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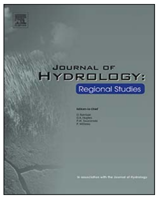

Spatial interpolation of climate variables in Northern Germany—Influence of temporal resolution and network density

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A R T I C L E I N F O

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A B S T R A C T

Study region: Region in Lower Saxony (North Germany) covered by the measuring range of the weather radar device located near Hanover (approx. 50.000 m^2).
Study focus: This study investigates the performance of various spatial interpolation techniques for climate variables. Meteorological observations are usually recorded as site-specific point information by weather stations and estimation accuracy for unobserved locations depends generally on station density, temporal resolution, spatial variation of the variable and choice of interpolation method. This work aims to evaluate the influence of these factors on interpolation performance of different climate variables. A cross validation analysis was performed for precipitation, temperature, humidity, cloud coverage, sunshine duration, and wind speed observations. Hourly to yearly temporal resolutions and different additional information were considered.
New hydrological insights: Geostatistical techniques provide a better performance for all climate variables compared to simple methods Radar data improves the estimation of rainfall with hourly temporal resolution, while topography is useful for weekly to yearly values and temperature in general. No helpful information was found for cloudiness, sunshine duration, and wind speed, while interpolation of humidity benefitted from additional temperature data. The influences of temporal resolution, spatial variability, and additional information appear to be stronger than station density effects. High spatial variability of hourly precipitation causes the highest error, followed by wind speed, cloud coverage and sunshine duration. Lowest errors occur for temperature and humidity.

1. Introduction

Climate or weather information more generally is usually recorded as site-specific point information by meteorological stations. However, the modelling of many processes in hydrology or environmental science requires areal input data, or in many cases, data for unobserved locations is needed. Spatial interpolation techniques are a reliable approach in order to estimate climate information for unobserved locations from nearby measurements.

Many different techniques have been proposed for various climate information, while the estimation performance depends not only on the selected interpolation method, but also on other factors like station network configuration, temporal data resolution, spatial variability of the variable, and whether a useful additional information can be incorporated into the interpolation procedure.

First investigations towards the issue of rainfall interpolation were carried out by Thiessen (1911), who used polygons drawn around the locations of rain gauges on a station network map in order to obtain an estimation of rainfall based on the nearest

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neighbouring station. Shepard (1968) proposed a technique, wherein the estimate is computed as a weighted average of adjacent rain gauges. The impact of each station is defined according to the inverse of its distance from the location to be estimated. Geostatistical methods like Kriging allow the consideration of the spatial correlation of adjacent observations for the estimation of unknown locations. Several studies reported that Ordinary Kriging can outperform simpler approaches (Dirks et al., 1998; Phillips et al., 1992; Tabios and Salas, 1985). Moreover, methods based on spline fitting have been applied (Hutchinson, 1998a). The fitting of three-variate splines even allows for the incorporation of elevation data (Hutchinson, 1998b). The consideration of elevation as additional information resulted in a significant improvement of interpolation performance at certain time scales. Annual or mean annual precipitation was predicted using regression (Daly et al., 1994; Nalder and Wein, 1998) and geostatistics (Hevesi et al., 1992a,b; Lloyd, 2005; Martínez-Cob, 1996). A study by Goovaerts (2000) reported that the incorporation of elevation in various Kriging methods can outperform linear regression as well as univariate interpolation for the estimation of monthly and annual rainfall.

Quantitative precipitation estimates from weather radar was proven to be useful additional information in the interpolation of short-term rainfall. However, radar data tends to be strongly biased (Seo et al., 1999) and is prone to a variety of different measuring errors, for instance a variation in the relationship between reflected energy and rainfall intensity, changes in precipitation particles before reaching the ground, anomalous beam propagation, attenuation, and clutter. Haberlandt (2007) as well as Verworn and Haberlandt (2011) applied Kriging with External Drift in addition to Indicator Kriging with External Drift for hourly data and achieved an improvement compared with univariate techniques. Cokriging was applied by Krajewski (1987) and provided slightly better estimation compared to using rain gauges only. A further technique to combine radar and rain gauge data is the so called Conditional Merging approach reported by Ehret (2003). According to Sinclair and Pegram (2005), it can efficiently reduce bias and error variance of quantitative precipitation estimates. Goudenhoofdt and Delobbe (2009) compared different merging algorithms using daily rainfall data and preferred geostatistical techniques over univariate rain gauge interpolation and radar data adjustment techniques like mean field bias correction (Smith and Krajewski, 1991). Overall, Kriging with External Drift performed best. Berndt et al. (2014) reported that Conditional Merging outperforms Kriging with External Drift and Indicator Kriging with External Drift for temporal resolutions from 10 min to 360 min.

Spline fitting (Price et al., 2000) as well as regression-based approaches (Nalder and Wein, 1998) taking into account the elevation were also applied for the estimation of air temperature and provided a better estimation quality than simple methods. Other techniques are based on a linear lapse rate (Dodson and Marks, 1997). Stahl et al. (2006) compared different approaches based on lapse rates and spatial interpolation They found that a combination of computing a regression based lapse rate and inverse-distance weighting performed best. Hudson and Wackernagel (1994) applied Kriging with External Drift for January averages of temperature and concluded that the incorporation of topography results in a substantial improvement of interpolation performance compared to univariate interpolation of station data. Other climate variables such as wind speed, humidity, and sunshine duration are less often studied regarding spatial interpolation issues. However, interpolation is often performed if exhaustive data sets are generated for a certain region (Jeffrey et al., 2001; Li et al., 2014).

Most of the previous work focused in improving the interpolation performance for one specific temporal resolution of a specific climate variable. A comparison of interpolation performances for different climate variables is difficult to find in the literature. Only some studies compare the interpolation performance among different station densities (Goudenhoofdt and Delobbe, 2009; Krajewski, 1987; Nanding et al., 2015; Yoon et al., 2012) and even fewer among different time scales (Bárdossy and Pegram, 2013; Dirks et al., 1998), although network density is considered to have a strong impact on the estimation accuracy. Additionally, the spatial variability of certain climate information depends significantly on the accumulation time. A combined evaluation of all influencing factors in order to provide a guidance for the choice of interpolation method depending on study area, climate variable, network configuration, temporal resolution, and intended data use is not available. This paper aims at evaluating the different impacts on the interpolation performance for a region in North Germany. Geostatistical techniques as well as simple methods are considered in the cross validation experiments that were performed here for observations of precipitation, temperature, relative humidity, cloud coverage, sunshine duration, and wind speed. Different station network density scenarios as well as temporal data resolutions ranging from 1 h to 1 year were taken into account.

The paper is organised as follows. Chapter 2 contains a brief description of all interpolation techniques. Geostatistical approaches were considered since they are widely applied in hydrology and environmental science. Simpler techniques, specifically Nearest Neighbour and Inverse-Distance Weighting are included as a standard for comparison. Chapter 3 describes the study region as well as data and their pre-processing. The cross validation strategy considering different network densities and the performance assessment of spatial estimation are presented in Ch. 4. All results of the analysis are shown and discussed in Ch. 5, while the main findings and conclusions are summarised in Ch. 6.

2. Interpolation methods

2.1. Simple interpolation techniques

The nearest neighbour interpolation technique (NN), also known as the Thiessen polygon method (Thiessen, 1911), is a basic interpolation approach that is often used for the spatial interpolation of rainfall data. It can be easily applied for the interpolation of other meteorological variables as well. Each location to be estimated within the regarded domain is simply assigned with the closest available observation.

Inverse-distance weighting (Shepard, 1968) is able to account for a simple spatial dependency in the interpolation of point observations. It does not require an a priori investigation of spatial variability for the regarded variable, in contrast to the more