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Kriging interpolation of precipitation for Lake Ćelije catchment

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The research analyzed the necessary conditions for the successful application of the Kriging method of spatial interpolation for the purposes of average annual precipitation interpolation on a certain area. The Kriging method is widely used in the field of interpolation of spatially distributed data, which also includes rainfall data. The paper analyzes the influence of the number of rainfall gauging stations, as well as model parameter adoption, on the results of spatial interpolation of precipitation. Precipitation interpolation was performed for the experimental catchment of Lake Ćelije, which is located on the Rasina River in the Republic of Serbia. The conducted research presents conclusionson on the influence of the number of rainfall gauging stations on the interpolation results, as well as the suggestions for the practical application of the mentioned method for the needs of spatial interpolation of average annual precipitation on a cathcment.

Keywords: Kriging, Average annual precipitation, Hydrology, Spatial interpolation

1. INTRODUCTION

Precipitation data plays a crucial role in hydrology modeling. Precipitation, in the form of rain, snow, or hail, is a primary input for hydrological models as it directly impacts the water balance of a region [1], [2]. Accurate and detailed precipitation data is essential for several reasons. Firstly, it helps in understanding the spatial and temporal patterns of precipitation, allowing identification of areas with high or low rainfall. This information is vital for water resource management, flood prediction, and drought monitoring [3].

Moreover, precipitation data is instrumental in estimating water runoff and streamflow, which are crucial components of hydrological modeling [4]. Precipitation data aids in calibrating and validating hydrological models by comparing simulated and observed precipitation values [5]. This iterative process improves the accuracy and reliability of the models, enabling better water resource planning and management decisions.

By incorporating accurate precipitation data into hydrological models, scientists can make informed decisions regarding water resource management, flood control, and drought mitigation strategies [6]. Precipitation data is therefore indispensable for hydrologists and plays a crucial role in ensuring sustainable water management practices [7].

Determining the average annual precipitation over a catchment can be a challenging task due to several factors. One of the main problems is the spatial variability of precipitation within the catchment [8]. Precipitation patterns can vary significantly over relatively short distances, making it difficult to accurately represent the average precipitation for the entire catchment. Rain gauges, which are commonly used to measure precipitation, are often sparsely distributed within a catchment, leading to limited coverage and potential inaccuracies in estimating the average.

Rainfall measurements are often subject to various sources of error, such as evaporation, wind effects, and gauge undercatch, which further complicate the estimation of average annual precipitation. Additionally, the impact of climate change introduces another layer of complexity. Climate change can alter precipitation patterns, leading to shifts in the timing, intensity, and duration of rainfall events. Historical precipitation records may not adequately represent future conditions, making it challenging to predict the average annual precipitation accurately [9].

Overcoming these problems employs various techniques and technologies. This includes the use of remote sensing data from satellites and radar systems to capture a broader spatial coverage of precipitation. Statistical methods, such as spatial interpolation and data assimilation techniques, are also employed to fill gaps in the measurements and improve the representation of average precipitation [10]. Climate models and downscaling techniques can provide insights into future precipitation trends, aiding in the estimation of average annual precipitation under changing climatic conditions.

Spatial interpolation methods are used to estimate precipitation values at locations where direct measurements are not available [11], [12]. These methods help fill data gaps, create continuous spatial representations of precipitation, and improve the accuracy of hydrological modeling.

When comparing spatial interpolation methods for precipitation data, several factors should be considered. Inverse Distance Weighting (IDW) is a simple and computationally efficient method that assigns weights to nearby points based on their distance. Kriging method take into account the spatial correlation between measurements and yield optimal estimates by minimizing the prediction error variance. Splines are a flexible interpolation method

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that fits smooth curves or surfaces through the measured points. They capture complex spatial patterns and can represent precipitation surfaces with high accuracy. The choice of interpolation method should be based on the specific characteristics of the data, the desired accuracy, and the trade-off between simplicity and computational complexity[13].

2. METHODS

Kriging is a widely used geostatistical interpolation method for spatially estimating values, including precipitation, based on a set of measured data points. It takes into account both the spatial correlation between points and the overall trend in the data. The fundamental concept behind Kriging is to provide optimal estimates by minimizing the prediction error variance[14].

The Kriging method was developed by the French mathematician Georges Matheron. Georges Matheron, inspired by Danie G. Kriges work in mining geology, sought to find a statistical approach to estimate ore deposits' spatial distribution. Matheron's key insight was that the spatial correlation between samples could be quantified and used to make optimal predictions at unmeasured locations. In the 1960s, Matheron developed the mathematical framework for Kriging, which he named after Danie G. Krige.

Kriging gained recognition for its ability to estimate values with minimum variance, making it an optimal interpolation technique [15]. Over the years, Kriging and geostatistics have evolved, finding applications beyond mining and ore estimation. The method has been widely adopted in various disciplines, including hydrology, environmental sciences, agriculture, and spatial analysis.

There are different types of Kriging methods, including Ordinary Kriging (OK) and Universal Kriging (UK). Ordinary Kriging assumes a constant mean and provides unbiased estimates. It is suitable when there is no systematic trend in the data [16]. Universal Kriging, on the other hand, incorporates additional predictor variables, such as elevation, to account for a spatial trend. In this research Ordinary Kriging (OK) has been used to interpolate annual precipitation over analysed catchment.

Kriging involves several equations that describe the estimation process based on the spatial correlation structure of the data. The Kriging estimate, Z^*, at an unmeasured location is calculated as a weighted sum of the measured values, Z_i, at the neighboring points, Equasion 1 and Figure 1:

$$Z^* = \sum_{i=1}^{n} \lambda_i * Z_i \tag{1}$$

where λ_i represents the weight assigned to each measured point.

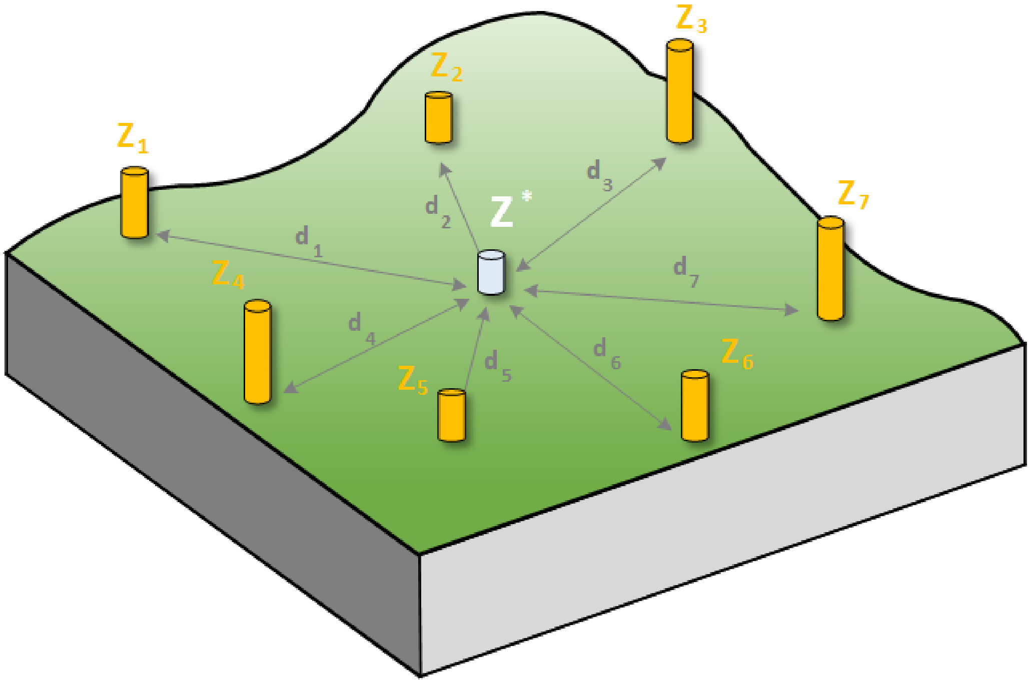

Figure 1: The Kriging method spatial interpolation basic principle

Kriging estimates the value at an unmeasured location by calculating weights for neighboring measured points. The weights, λ, are calculated using the following equation:

$$\lambda_i = \frac{1}{C^T} * \gamma_i \tag{2}$$

where C is the covariance matrix between the measured points and γ is the vector of variogram values between the measured points and the unmeasured location.

Kriging method involves constructing a variogram, which describes the spatial correlation between pairs of data points. The variogram provides information about the spatial dependence of the variable being interpolated, such as precipitation. The variogram, γ, quantifies the spatial correlation between pairs of data points as a function of their separation distance. It quantifies how the similarity between measurements decreases as the distance between them increases.

$$\gamma_i = \frac{(Z_j - Z_i)^2}{2} \tag{3}$$

where Z_i and Z_j are the values of the variable being interpolated (e.g., precipitation) at locations x and x+d, respectively. The variogram provides essential information about the spatial dependence and is used to model the spatial correlation in Kriging.

A semivariogram model is fitted to the calculated variogram to describe the relationship between the variogram and the distance. The semivariogram model allows extrapolation of the spatial correlation beyond the measured data points, Figure 2.

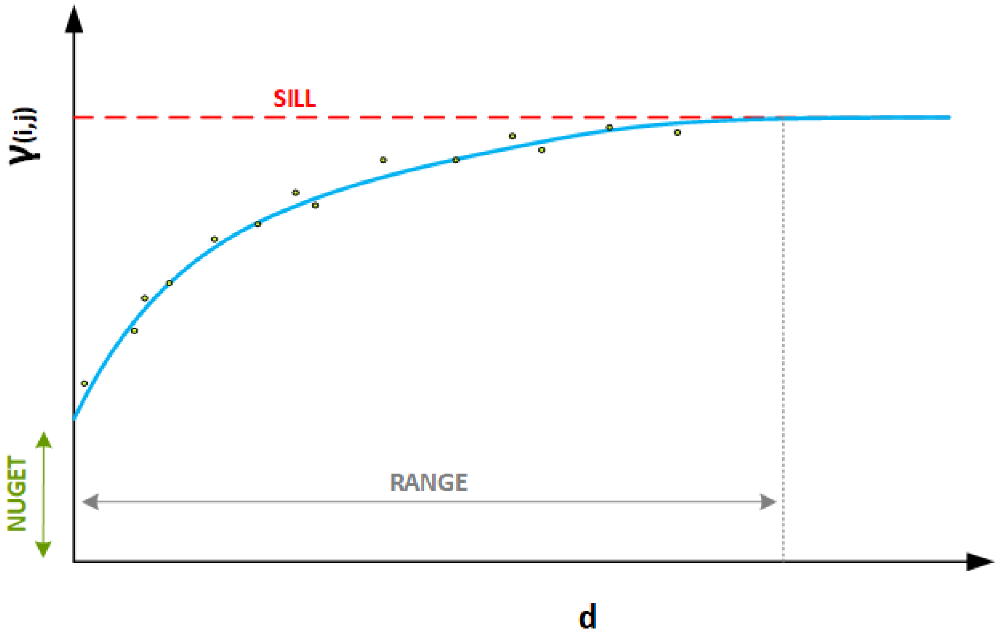

Figure 2: Semivariogram with characteristic values.

The Semivariogram characteristic values include: $RANGE\ (R)$ - the range represents the maximum distance beyond which the spatial correlation becomes negligible; $NUGGET\ (C_0)$ - the nugget represents the y-intercept of the semivariogram, or the semivariance at the origin (d = 0); $SILL\ (C)$ - the sill represents the semivariance at large distances (beyond the range) where the semivariogram levels off.

The semivariogram model parameters define the mathematical function that best fits the empirical semivariogram. These parameters may include the range, nugget, and additional parameters specific to the chosen model (e.g., slope, sill-to-nugget ratio). The model parameters help describe the shape of the semivariogram curve and are used for predicting semivariance at unmeasured distances. Commonly used models include exponential, spherical, Gaussian, and linear models. In this research linear model for prediction of semivariance has been used.

Once the variogram is determined, Kriging calculates weights for neighboring points based on their spatial relationship and the variogram model. Points that are closer to the target location receive higher weights since they are expected to have a stronger influence on the interpolation. The weights are then used to calculate a weighted average of the measured points, resulting in the estimated value at the target location.

3. MATERIALS

For the purposes of this research, the experimental catchment of the Rasina River up to the profile of the Ćelije dam was chosen. The analyzed catchment is located in the central part of the Republic of Serbia (Figure 3).

The river Rasina springs on Goč mountain, below the peak of Ržište at an altitude of about 1100m. Mount Goč is located in the north-western part of the analyzed catchment (Figure 3), northen from the mountains Željin and Kopaonik. Near the town of Brus, the Rasina River receives its large right tributary, the Graševačka River, which drains the waters from Kopaonik Mountain below Pnčićev Vrh (2017m). The river Rasina, near the town of Razbojna, receives its second large right tributary, the river Blatašnica, which collects surface water from the southern sides of the Jastrebac mountain below the peak of Karaula (849m).

In 1979, the valley of the river Rasina was dammed in its north-eastern part by the Ćelije dam, which formed the lake. The main purpose of the Ćelije lake is to collect water for the water supply of the city of Kruševac. The construction of the dam, with a building height of 55m, created a lake with a volume of 41 million m³ of water, a water surface of 2.85 km², an average and maximum depth of 14 and 41m, respectively.

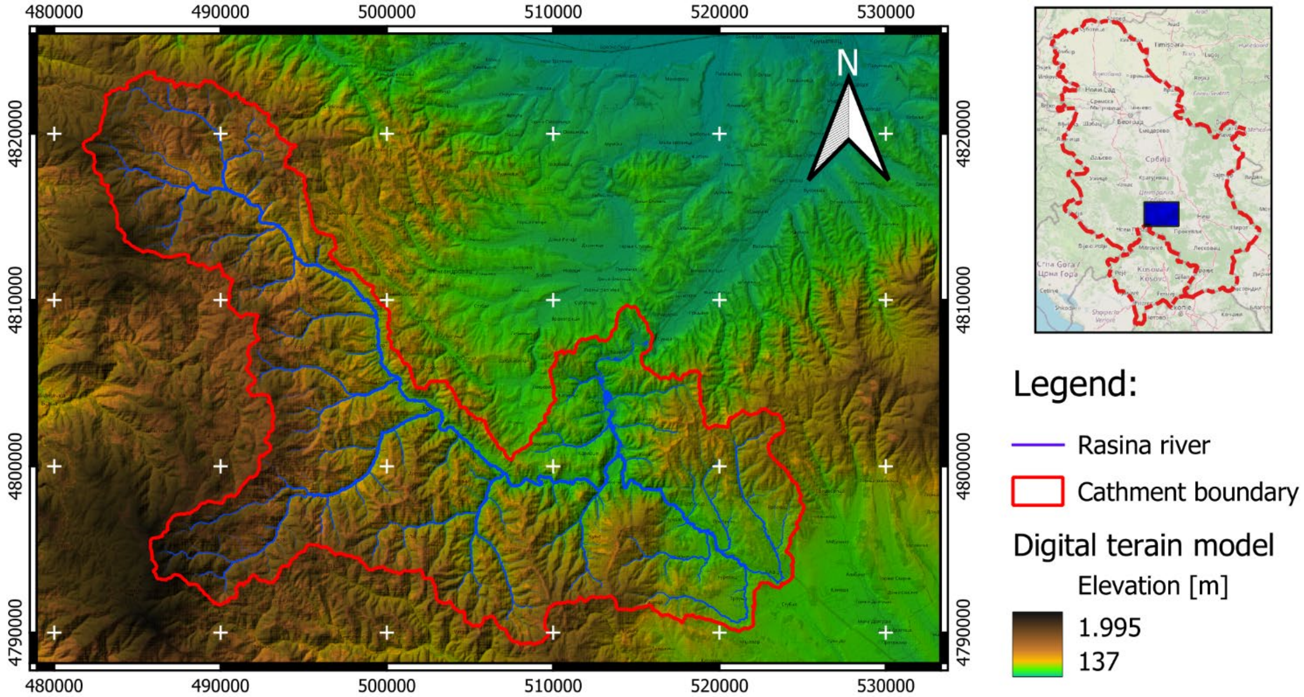

Figure 3: Rasina river cathcment

Due to the long period of exploitation of the water resource from Lake Ćelije, the reservoir area of the lake was filled with river sediment, which results in a reduction of the available volume of water in the lake for water supply. In recent years, there has been a need for the creation of a revitalization and silting project for Lake Ćelije. The first step of water management analyzes is the preparation of a hydrological study of the rainfall-runoff water balance on the analyzed catchment. One of the crucial data of the hydrological analysis is the determination of the average annual precipitation in the Rasina river basin.

In the preparation of hydrological studies, it is very common to analyze data only from measuring stations located in the considered watershed. As part of this research, a check of the previously presented approach and an analysis of the influence of the number and spatial distribution of rain gauge stations on the results of determining the average annual precipitation in the basin were carried out.

The catchment of the river Rasina up to the profile of the Ćelije dam was chosen as an experimental cathment due to the existence of a large number of rain gauge stations both in the basin itself and in its surroundings. For the purposes of analyzing the influence of the number of rain gauge stations on the calculation results of the mean annual precipitation in the analyzed catchment, the avalable rain gauge stations were grouped into four groups according to which four calculation scenarios were formed (Figure 4):

- Scenario 1: includes only rain gauge stations located in the analyzed catchment,
- Scenario 2: includes rain all rain gauge stations located on the catchment and up to 10 km from the border of the watershed,
- Scenario 3: includes rain all rain gauge stations located on the catchment and up to 20 km from the border of the watershed, and
- Scenario 4: includes rain all rain gauge stations located on the catchment and up to 30 km from the border of the watershed.

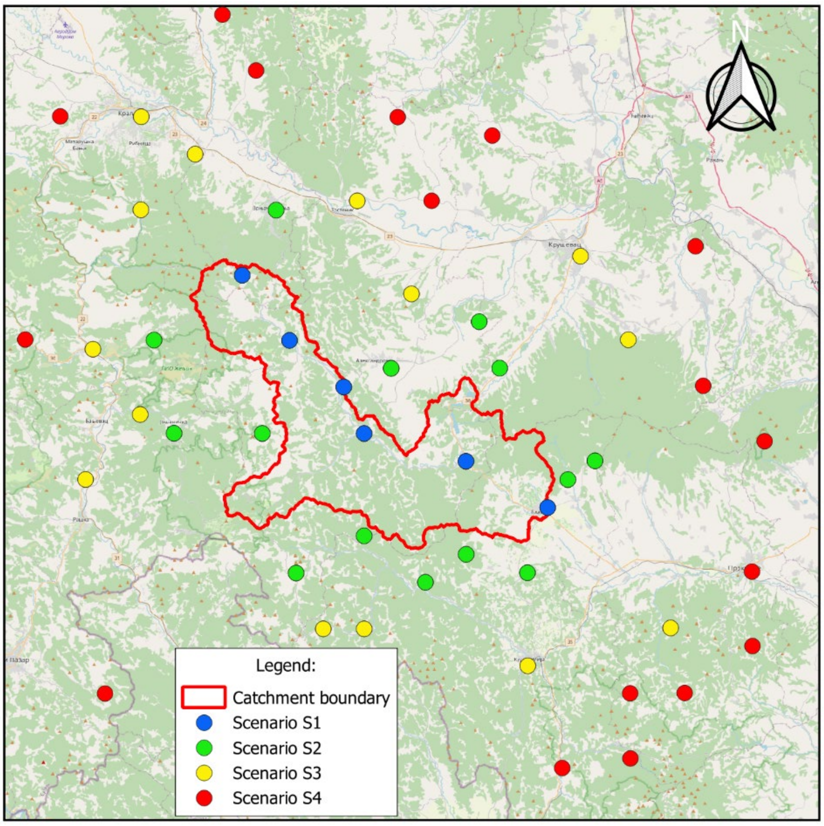

Figure 4: Rain gauge station on the Ćelije lake catchment acording to calculation scenarios

4. RESULTS AND DISCUSSION

As part of this research, spatial interpolation calculations of mean annual precipitation data were performed for four calculation scenarios that differ in the number of rain gauge stations included in the calculation. Spatial interpolation was performed using the Kriging method, more precisely Ordinary Kriging, which is widely used in the aforementioned area.

When adjusting the function to the data on the semivariogram, it was determined that the data on the mean annual precipitation from the measuring stations do not follow the Normal probability distribution. The normalization of the measured data was performed using a logarithmic transformation. For the approximation of the semivariogram, the linear approximation given by the equation was used:

$$\gamma(d) = a * d + b \tag{4}$$

where a and b are the calibration coefficients of the equation and d represents the Euclidean distance.

During the calibration of the semivariogram function, it was determined that the best agreement between the measured data and the function occurs for the maximum value of the distance of 10,000 m and the limitation of the minimum and maximum number of stations included in the calculation to 3 and 20, respectively.

By spatial interpolation of data on average annual precipitation, a 3D surface was formed in raster format, pixel size 100*100 m, where each pixel has an interpolated value of precipitation. The average value of precipitation in the analyzed basin of Ćelije Lake was determined as the average value of the sum of all pixels within the catchment boundary.

The problem of visual representation of interpolated precipitation values from the 3D surface was solved by drawing contour isolines of precipitation with an equidistance of 100 mm of annual precipitation. Plotting the isolines of precipitation allows insight into the change in the spatial distribution of precipitation for different calculation scenarios.

Figure 5 shows the results of spatial interpolation of annual precipitation for four calculation scenarios. The results of spatial interpolation for calculation scenario S1, which includes only rain gauge stations located in the analyzed watershed, are shown in Figure 5 - a. The irregular shape and sudden breaking of the precipitation isolines for the S1 scenario indicate that the chosen spatial interpolation method requires a larger number of rain gauge stations for successful application. From the results shown, it can be concluded that the method of ordinary Kriging requires more than 6 measuring stations, as used in the calculation for scenario S1.

The results of spatial interpolation of rainfall for scenarios S2, S3 and S4, shown in Figure 5 - b, c and d, show that the Ordinary Kriging method gives significantly better results when the number of measuring stations is larger. Regular shapes of precipitation isolines without sudden breaks confirm the previously stated conclusion.

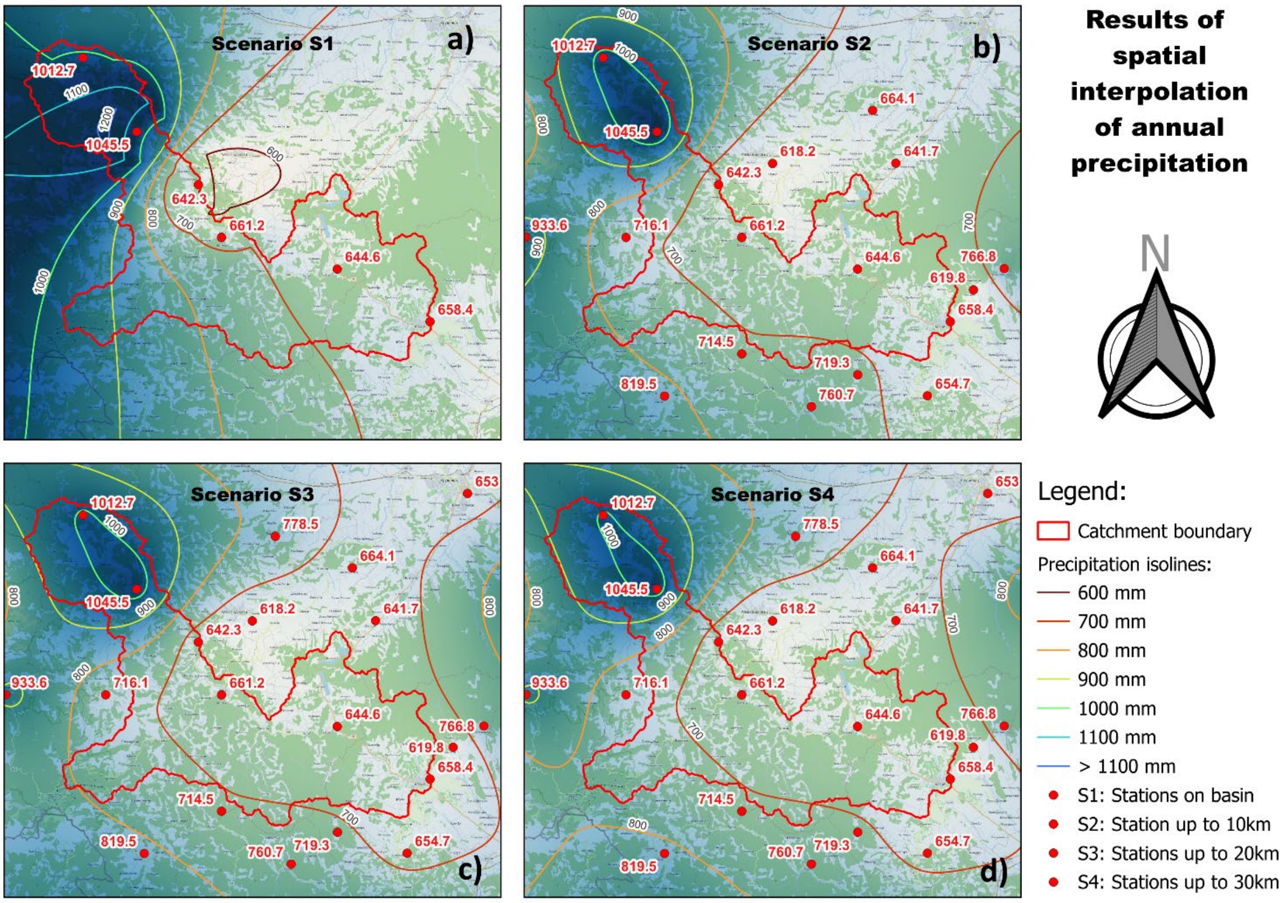

Figure 5: Results of spatial interpolation of annual precipitation for four calculation scenarios

It can be clearly concluded from Figure 5 that scenario S1 does not give good calculation results due to the small number of measuring stations, but from the shown figure it is not possible to clearly conclude how much the differences in annual precipitation interpolation values are for the remaining three calculation scenarios for the analyzed Ćelije lake catchment. The values of average annual precipitation for the analyzed catchment for all four calculation scenarios are shown in table 1.

Table 1: Annual precipitation for four calculation scenarios

Scenario:	Distance from catchment boundary: [km]	Number of stations: [/]	Average annual precipitation: [mm]
S1	0	6	799
S2	10	20	745
S3	20	34	744
S4	30	51	743

Based on the data shown in Table 1, it can be concluded that the mean annual precipitation values for the analyzed Čelije lake catchment differ slightly for calculation scenarios 2-4. It can also be concluded that the results of spatial interpolation using the Ordinary Kriging method change slightly with the increase in the number of rain gauge stations over 20.

In order to determine the reasons for such similar results, it is necessary to perform a comparative analysis of the rainfall isolines for the analyzed watershed. Figure 6 shows a comparative analysis of isolines for all four calculation scenarios.

From Figure 6, it can be clearly concluded that, except for the precipitation isolines for scenario S1, the precipitation isolines for the other three calculation scenarios are spatially quite close, even to the extent that they overlap in some cases. The matching of precipitation isolines is manifested by very similar values of average precipitation in the analyzed Lake Ćelije catchment.

At the end of the analysis, it can be concluded that the Ordinary Kriging method does not provide satisfactory results of spatial interpolation of precipitation when the number of rain gauge stations is small. With the increase in the number of rain gauge stations over 20, the spatial interpolation results converge to a constant value very quickly.

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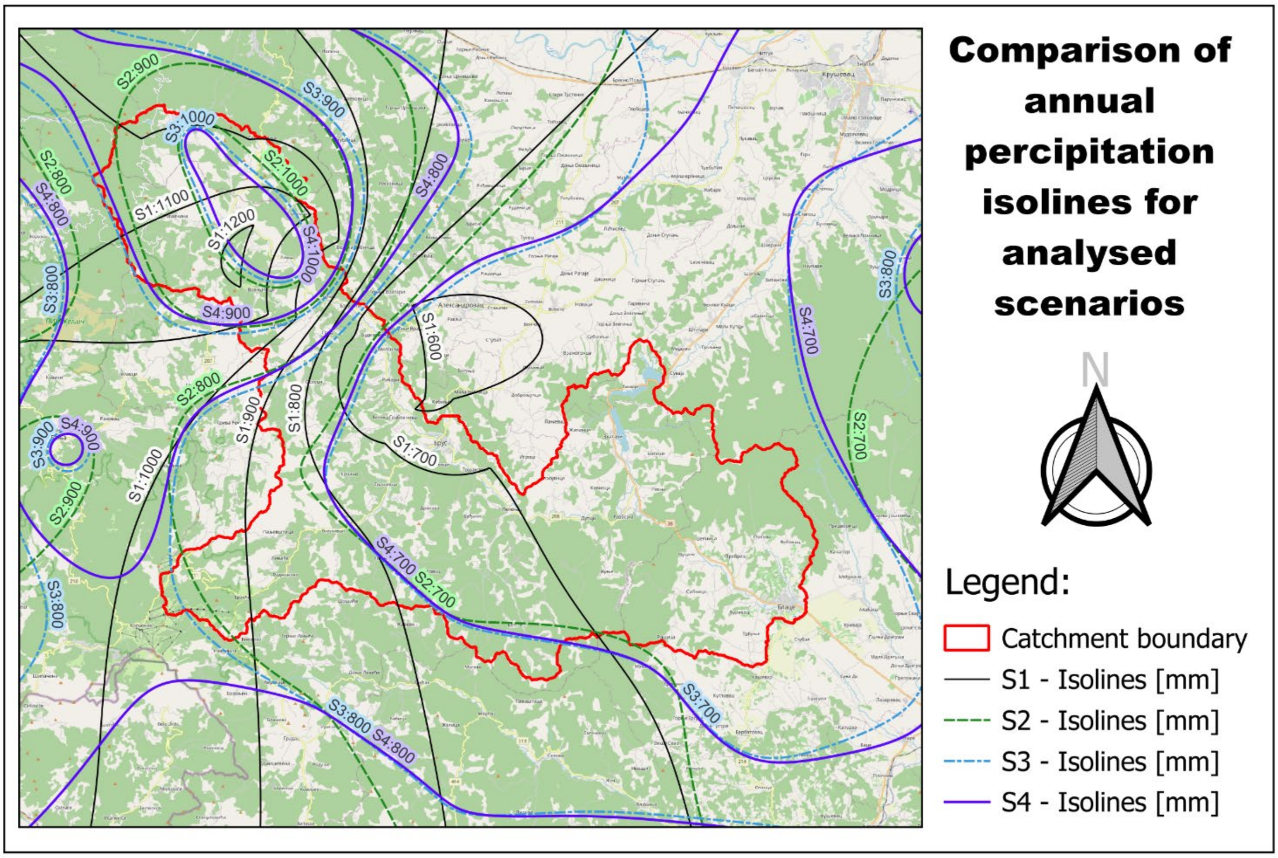

Figure 6: Comparative analysis of precipitation isolines for all four calculation scenarios

5. CONCLUSIONS

As part of this research, an analysis of the influence of the number of rain gauge stations on the results of spatial interpolation of mean annual precipitation for the surface of the experimental catchment, Lake Ćelije, was carried out, and the following conclusions were determined:

- when making hydrological studies, it is very important to include the surrounding rain gauge stations in the analysis,
- the results of hydrological analyzes based on a small number of rain gauge stations in the catchment are not reliable,
- The Ordinary Kriging method of spatial interpolation is very sensitive to a small number of rain gauge stations, as a result of which it does not give satisfactory results,
- with an increase in the number of rain gauge stations over 20, the Kriging method very quickly converges to a constant value of average annual precipitation in the analyzed basin.

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