Environmental Engineering and Management Journal

August 2021, Vol.20, No. 8, 1383-1394
http://www.eemj.icpm.tuiasi.ro/; http://www.eemj.eu

"Gheorghe Asachi" Technical University of Iasi, Romania

A RADIAL BASIS FUNCTION APPROACH TO ESTIMATE PRECIPITATIONS IN BRASOV COUNTY, ROMANIA

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Abstract

This research tackles the problems of spatial distribution of precipitation using five deterministic sub methods related to the radial basis function (RBF) group: thin-plate spline (TPS), spline with tension (ST), multiquadric (MQ), inverse multiquadric (IMQ) and completely regularized spline (CRS). The study is used for retrieving annual precipitation over Brasov County, Romania for a period of two decades (2000-2019) using data from the fifth-generation reanalysis dataset (ERA5) provided by the European Centre for Medium-range Weather Forecasts (ECMWF). Each method was tested for 10 and 60 neighbours, and the results were evaluated through cross-validation, Taylor diagram and six statistical indicators: root mean square error (RMSE), mean error (ME), correlation coefficient (R), determination coefficient (R^2), average absolute percent relative error (AAPRE) and average percent relative error (APRE). The result of the study shows a similar pattern between all methods, where the predicted precipitation increases from south to north. The southern part of Brasov County recorded in two decades 1547.7 mm precipitation, and the northern part 2149.5 mm. From all the methods analysed, the most accurate method of predicting precipitation in Brasov County is ST60. The study reveals that the number of neighbours influence the accuracy of prediction. As a result, the best prediction of precipitation was generated by ST60. Not for all methods the increase number of neighbours lead to better results. From all outputs, 66.6% have better results when is used 60 neighbours and 34.4% with 10 neighbours.

Keywords: cross-validation, deterministic, precipitation, prediction

Received: June, 2020; Revised final: December, 2020; Accepted: January, 2021; Published in final edited form: August, 2021

1. Introduction

Precipitation is one of the most important climatic factors which affects all ecosystems (Huang et al., 2009). Knowing the amount of water from precipitation is a key factor in hydrological management, managing to predict extreme events. Soil erosion, floods and the destruction of agricultural crops are among the most negative consequences of intense precipitation (Nainggolan et al., 2012). Globally, floods rank first in natural disasters (Zaharia et al., 2015). Compared to temperature, precipitation involves a more complex process and is more difficult to predict (Fischer and Knutti, 2015). According to the Intergovernmental Panel on Climate Change (IPCC) report, between 1981-2010, global warming caused a 12% increase of precipitation at global scale (Shukla, et al., 2019). As a result, floods with a strong impact on the environment have occurred in recent years. The European Environment Agency report on floods states that between 1980 to 2010, 3.563 floods were reported across Europe resulting in a significant increase of floods (Jacobs, 2016). In Romania, 48% of the total natural disasters recorded between 1900-2013 were caused by floods (Zaharia et al., 2015). One of the areas that has often been affected by floods is Brasov County, Romania (Romanescu et al., 2017). Such a case occurred on March 14th, 2018 at Sercaia and Mândra, localities from Brasov County, where 12 houses were affected and approximately 400 people

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needed assistance (Jacobs, 2016). In this context, knowing the spatial distribution of precipitation in the study area is very important.

Almost six decades ago (1960), geographic information systems (GIS) emerged as a means of solving complex geographical problems (Goodchild, 2018). Since then, GIS are in a continuous development and have applicability in various fields, such as: tourism (Wei, 2012), hydrology (Wolock et al., 2004) and health (Fradelos et al., 2014). The widespread use of GIS is due to the ability and capability to analyse, store and model data. A major contribution in the development of these systems is due to the advanced development of artificial intelligence (AI) in various field (Mahdaviara et al., 2020a; Mahdaviara et al., 2020b; Rostami et al., 2016, Rostami et al., 2017a; Rostami et al. , 2017b; Rostami et al., 2017c; Rostami et al., 2017d; Rostami and Shokrollahi, 2017; Rostami et al., 2018d; Rostami et al., 2019a; Rostami et al., 2020) as well as neural network technique (Karkevandi-Talkhooncheh et al., 2018; Rostami et al., 2018a; Rostami et al., 2018b; Rostami et al., 2018c). The development of AI added a spatial-temporal dimension in the representation of natural phenomena, managing to capture their magnitude and the relationships that govern them, changing the way we are understanding different processes, such as geology (Rostami et al., 2019b; Rostami et al., 2019c; Mahdaviara et al., 2020c; Farahani et al., 2018).

One of the many capabilities of GIS are the spatial interpolation methods. Interpolation represents the process of estimating a new value based on the measured ones from data set (Gunarathna et al., 2016). There are two types of spatial interpolations, deterministic and geostatistical (Childs, 2004). Deterministic methods (global polynomial interpolation (GPI), inverse distance weighted (IDW)) are based on mathematical formulas, while geostatistical methods (simple kriging, indicator kriging) use probabilistic models to make predictions. Interpolation methods have been used in various precipitation research (Arslan, 2014; Basconcillo et al., 2017; Borges et al., 2015; Bostan and Akyürek, 2009; Chen and Sun, 2009; Dobesch et al., 2013; Hutchinson, 1995; Sun et al., 2014; Ye et al., 2015). Although there are many interpolation methods, there is no method that can be applied in all areas and data sets. Therefore, a comparison of interpolation methods is needed to highlight the prediction accuracy of each method (Basconcillo et al., 2017). Moreover, in the literature there is a lack of studies on the evaluation of the five sub methods belonging to radial basis function (RBF) to determine the prediction of precipitation in Brasov County.

The main objective of this study is to test five interpolation sub methods (thin-plate spline (TPS), spline with tension (ST), multiquadric (MQ), inverse multiquadric (IMQ), completely regularized spline (CRS)) existing in the RBF group and to determine which method generate the most accurate precipitation over Brasov County. Each method was tested for 10 and 60 neighbours, respectively. The performance of the interpolation sub methods was evaluated using cross-validation principle and six statistical indicators: correlation coefficient (R), determination coefficient (R^2), root mean square error (RMSE), mean error (ME), average absolute percent relative error (AAPRE) and average percent relative error (APRE). Also, we highlighted the results using Taylor diagram. The precipitation data retrieved from the ERA5 dataset were analysed over two decades (2000-2019) in 69 locations from Brasov County. The location of ERA5 where choose randomly (Fig.1).

The article is structured in 6 sections, as follows: after the introduction (section 1), study area and the data used are described in section 2. Section 3 presents the interpolation sub methods related to the RBF group. In Section 4 the methods for evaluating the performance of the interpolation results are presented. Results are described and displayed in section 5 followed by section 6 where the conclusions and future research directions are presented.

2. Study area

Brasov County is located in the central part of Romania with a total area of 5.363 km, representing 2.2% of the total area of the country, and is one of the 41 counties of Romania (Fig.1). It is geographically delimited by the coordinates 45º45’00 N (latitude) and 25º30’00 E (longitude), with an average altitude of 1071 m (altitude increases from north to south) (Micu et al., 2016). According to the Köppen-Geiger Climate Classification, the climate in Brașov County is moderately cold, temperate-continental, with no dry seasons and hot summers (Dfb) (Kottek et al., 2006; Peel et al., 2007), being dependent on the characteristics specific of the relief, Romanian Carpathians and oceanic influences (Grecu et al., 2008). According to Grecu et al. (2008), the average annual precipitation in Brasov County varies between 500 mm and 1400 mm. Higher precipitation are found in hilly areas, while lower values are recorded in highlands. The distribution of precipitation differs in both time and space and is strongly influenced by the Romanian Carpathians mountains (Micu et al., 2016).

ERA5 reanalysis data

The latest reanalysis dataset is the fifth generation of the ECMWF climate reanalysis and replaces the ERA-Interim reanalysis (Wang et al., 2019). ERA5 reanalysis has a global coverage and provides hourly data for several atmospheric parameters by combining observations made in the past with climate models (Copernicus Climate Change Service, 2017). Currently, ERA5 data is available through the C3S Climate Data Store, from January 1950 to present (Copernicus Climate Change Service, 2017; Cucchi et al., 2020).

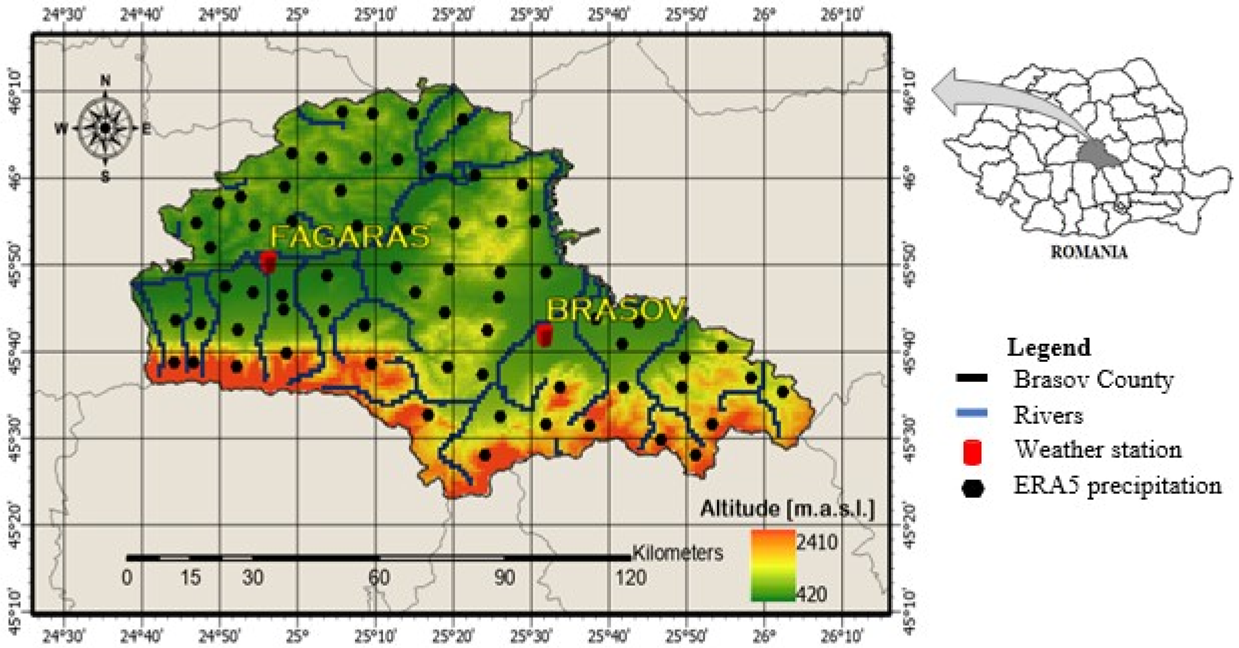

Fig. 1. Location and the topography of the study area

Unlike the former reanalysis, ERA5 reanalysis has more advantages, including higher temporal (one hour), spatial resolution (0.25º), uncertainty estimation and advanced Integrated Forecasting System Cycle 41r2 (Cucchi et al., 2020). ERA5 has been applied in various research studies on different areas of the Earth's surface (Mahto and Mishra, 2019; Tarek et al., 2019; Tetzner et al., 2019). In Romania, research was conducted using ERA5 data (Andrei et al., 2019; Dumitrescu et al., 2020; Ganea et al., 2019), but it was not used as a database to test certain interpolation methods. The precipitation provided by ERA5 reanalysis is widely available over a 0.25ºx0.25º grid. The ERA5 data used in the 69 geographic locations of the study area (Fig.1), for two decades (2000-2019), were interpolated from a regular grid using a bilinear function from NCAR Command Language (NCL). In order to identify the extreme values (outliers), which are different from the normal ones, we used summary function from R. The results show normal values (Table 1).

Table 1. Summary statistics of total annual precipitation in Brasov County

Min	*1st Qu.*	*Median*	*Mean*	*3rd Qu.*	*Max.*	*Skewness*	*Kurtosis*
1547.7	1603.3	1689.9	1754.6	1872.5	2149.5	0.754	2.25

3. RBF and sub methods

Also known as Spline, RBF represents a series of deterministic and multivariate methods, being intended specially to analyse phenomena in a continuous space (Borges et al., 2015; Gunarathna et al., 2016; Halos et al., 2016). The method is based on an equation that is dependent on the distance between the place where precipitation was measured and the position to be interpolated (Xie et al., 2011). According to Giang et al. (2013) interpolations performed with RBF are fast and accurate as the method goes through each measured value (Ye et al., 2015). Also, RBF has the possibility to make prediction of precipitation above the maximum and minimum value measured at weather stations.

Among the most popular radial functions included in RBF are: TPS, ST, MQ, IMQ and CRS (Arslan, 2014; Chen et al., 2017). For each method, the surface smoothness is controlled by a smoothing factor (c-kernel parameter), which is different for each method (Ding et al., 2018). The smaller the smoothing factor, the smoother will be the output, except for the IMQ function, where the surface becomes smoother if the smoothing factor is higher (Garnero and Godone, 2013). The RBF method does not provide satisfactory results if the precipitation values are very different from one location to another (Diaconu et al., 2019; Johnston et al., 2001). Table 2 shows the five-function included in the RBF used in this study and found in most GIS spatial analysis programs (ArcGIS, QGIS). Chen et al. (2017) and Garnero and Godone (2013) define the calculation formula of the RBF, as follows (Eq. 1):

$$\hat{Z}(a_0) = \sum_{i=1}^{n} \omega i \, \phi\,(\|s_i - s_0\|) + \omega n + 1 \tag{1}$$

where: $\phi(r)$ - general interpolation function of the RBF; ωi-weights; $\|s_i - s_0\|$ - Euclidean distance (r) between measured precipitation (s_i) and predicted (s_0).

TPS were developed by Wahba Grace and Wendelberger James to investigate a problem that occurs frequently in geoscience, the modelling of scattered data.

Table 2. The main radial functions of the RBF

RBF	***General interpolation function of the RBF*** $[\phi(r)]$
TPS	$(c \cdot r)^2 \cdot ln(c \cdot r)$
ST	$ln(c \cdot r)/2 + K_0(c \cdot r)^2 + C_E$
MQ	$\sqrt{r^2 + c^2}$
IM	$\frac{1}{\sqrt{r^2 + c^2}}$
CRS	$\sum_{n=1}^{\infty} \frac{(-1)^n \cdot r^{2n}}{n!\,n} = ln\left[\frac{c \cdot r}{2}\right]^2 + E_l\left[\frac{c \cdot r}{2}\right]^2 + C_E$

where: c – smoothing factor; r – distance between point and sample; E_l – exponential integration function; C_E – Euler's constant (0.577215); K_0 – modified Bessel function.

TPS is a special case of polyharmony spleen (Keller and Borkowski, 2019). The smoothing parameter (c) is calculated by minimizing the GCV (Generalized Cross Validation) function (Li and Heap, 2008).

ST were proposed by Schweikert in 1966 and implemented by Cline in 1974 (Wessel and Bercovici, 1998). ST represents a generalization of the cubic spleen, where a positive voltage parameter is associated with each interval. They can be used to preserve the properties of the shape and avoid inflection points (such as monotonicity or convexity) in the data set. It is a method that fails to achieve very smooth surfaces when smaller data are used (Garnero and Godone, 2013).

MQ was developed in 1971 by Hardy in order to make topographic maps based on the heights of points located randomly in the plan (Carlson and Foley, 1991). The accuracy of the method depends on the value of R^2, which represents the number of points together with the shape and size of the field containing data.

Developed by Mitasova and Mitas in 1993, CRS contains a tension parameter, which adapts the surface characteristics of the membrane spleen (Mitasova and Mitas, 1993). In the case of large values, tension parameter can reduce the exceedances that occur on surfaces, where there are large differences between values. According to Ali et al. (2012), CRS is suitable for climate data.

4. Performance assessment

4.1. Cross-validation

The performance of the five RBF sub methods was assessed and compared using one of the most common methods in climatology, the cross-validation method (Goovaerts, 2000; Wang, 2014). According to Apaydin et al. (2004), cross-validation involves a three-step process. In the first step, a location where precipitation was measured is temporarily removed from the data set. In the second step, the removed location is estimated based on the other locations where recordings were made. The last step involves a comparison of the estimated value with what was measured. This process is applied successively to the entire data set (Johnston et al., 2001).

4.2. Taylor diagram

Usually, the search of the best method that explains a certain phenomenon using traditional visualization tools, restrict the analysis to pair comparisons of data (semi variogram) (Correa and Lindstrom, 2013). An alternative to traditional tools is the Taylor diagram. Developed by Karl E. Taylor, the diagram is a unique way to graphically highlight the spatial correlation of two variables (measured and predicted), from a statistical point of view (Taylor, 2001). The diagram depicts three statistical coefficients: R, RMSE and standard deviation (STD) (Abbasian et al., 2019; Hu et al., 2018). Due to the geometric relationship between the three statistical coefficients and law of cosines, the diagram can be graphically represented (Lo Conti et al., 2014).

There are two types of Taylor diagram. The first diagram is the originally proposed by Taylor (2001), and the second is called Taylor modified in which data are normalized (Elvidge et al., 2014). The method is widely used in various research (Deng et al., 2013; Torma et al., 2015; Wu et al., 2013; Yin et al., 2012; You et al., 2014). It is suitable to use where there is a considerable difference between all methods to be compared in terms of all three statistical coefficients (R, RMSE, STD). In this study, Taylor diagram is used to highlight the difference between the methods with best and lowest result.

In a Taylor diagram (Fig. 2), measured and predicted precipitation are displayed as points (Ghajarnia et al., 2015; Taylor, 2001). The position of the points expresses the similarity between estimated precipitation and measured ones. In Fig. 2, the three coefficients are displayed as follows: R is represented as an azimuthal angle (black colour); RMSE is proportional to the distance from the point on the x-axis being marked as “measured” (green colour); STD is proportional to the radial distance from the origin of the x-axis (blue colour). The predicted values that are displayed closest to the measured point are the most appropriate to describe the phenomenon (Warrach-Sagi et al., 2013).

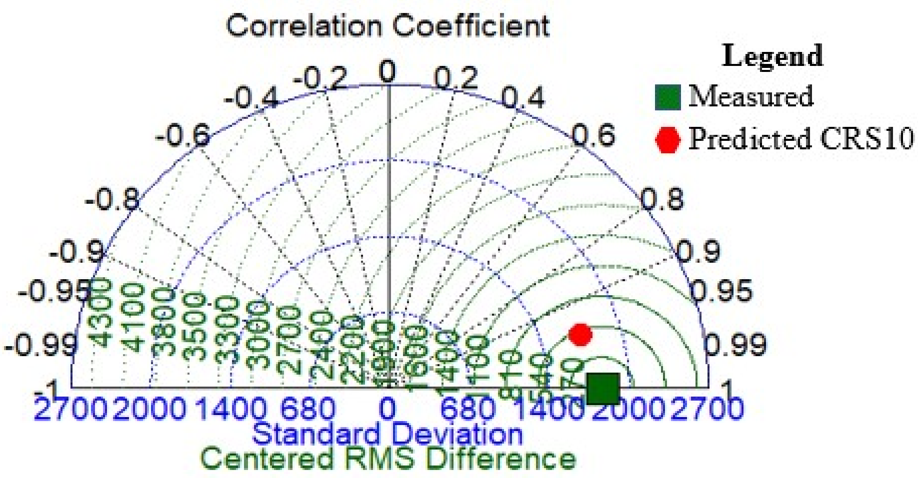

Fig. 2. Taylor diagram of measured and predicted CRS10

4.3. Statistical indicators

To highlight the performance of the interpolation methods, we used, in addition to Taylor diagram, a series of individual indicators for each interpolation method: R, RMSE, ME, APRE and AAPRE. In numerous research studies (Ahlgren et al., 2003; Asuero et al., 2006; Huang et al., 2009; Schober et al., 2018), R is defined as an instrument that measures the degree of linear association between measured and predicted values. According to Borges et al. (2015) and Sheugh and Alizadeh (2015), R can be computed as follows (Eq.2):

$$R = \frac{(\sum_{i=1}^{N} EM) - (\sum_{i=1}^{N} E \sum_{i=1}^{N} M)}{\sqrt{[\sum_{i=1}^{N} E^2 - (\sum_{i=1}^{N} E)^2][\sum_{i=1}^{N} M^2 - (\sum_{i=1}^{N} M)^2]}} \quad (2)$$

Determination coefficient (R^2) represents a viable error indicator often used to quantify the linear regression between measured and predicted precipitation. More precise, the R^2 shows how much of predicted precipitation represents the measured ones (Okpara et al., 2020).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(M-E)^2}{\sum_{i=1}^{N}(M-E)^2} \quad (3)$$

RMSE is another indicator often used in climatology. RMSE allows the STD measurement of the residues between two variables (Asa et al., 2012; Willmott and Matsuura, 2005). RMSE can be computed as follows (Xie et al., 2011) (Eq.4):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[E(s_i) - M(s_i)]^2} \quad (4)$$

ME calculates the arithmetic mean of the residue based on which we conclude whether the interpolation method underestimates or overestimates the precipitation, in the study area (Wise, 2011). ME is calculated as follows (Mardikis et al., 2005) (Eq.5):

$$E = \frac{1}{N}\sum_{i=1}^{N}[E_{(si)} - M_{(si)}] \quad (5)$$

Average Absolute Percent Relative Error (AAPRE) and Average Percent Relative Error (APRE) represents one of the most used method to compare the prediction values of a model (Tofallis, 2013). The methods have the advantage of scale-independency and interpretability (Kim and Kim, 2016). AAPRE (Eq.6) and APRE (Eq. 7) can be computed as (Attia et al., 2020; Hashemifard et al., 2010; Mazloom et al., 2020):

$$AAPRE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{M_i - E_i}{E_i}\right| \quad (6)$$

$$APRE = \frac{100}{N}\sum_{i=1}^{N}\left(\frac{M_i - E_i}{E_i}\right) \quad (7)$$

5. Results

The RBF sub methods: TPS, ST, MQ, IMQ and CRS were used in this study to test the accuracy of annual precipitation prediction, over Brasov County. At first glance, all results show the same pattern of precipitation. The spatial distribution of precipitation over Brasov County of each method shows that precipitation increases from south to north (Fig. 4; Fig. 5). Thus, the southern part recorded 1547.7 mm, and the northern part 2149.5 mm, in the analysed period. Also, another finding in all maps generated by the methods is the so-called bull's eye. Bull's eye are concentric areas of equal value around stations where precipitation has been recorded (Johnston et al., 2001). This is due to the large differences in precipitation records between places (Diaconu et al., 2019). These have been reported in various research studies (Irmak et al., 2010; Zhang et al., 2014), being found especially at IDW.

Once the spatial distribution of precipitation was generated, the result of each method was compared through cross-validation, Taylor diagram and six statistical indicators (RMSE, ME, R, R^2, APRE and AAPRE). The results show a similarity between all methods, with one exception. TPS 10 and TPS 60 indicate the largest errors in estimating precipitation compared to measured ones (Table 3). From all the methods, the most accurate surface was generated by ST 60 neighbours, having the smallest RMSE, ME, APRE and highest R and R^2. The Taylor diagram (Fig.3) presents the method that generated the best results (ST60) and the largest errors (TPS60). Thus, as can be seen from the Fig. 3, the blue dot (ST60) is closer to the green square (measured) than the red dot (TPS60).

To highlight the influence of the neighbours in the precipitation accuracy, each method was tested with 10 and 60 neighbours, respectively. The Table 3 shows how the number of neighbours influence the precipitation accuracy. As a result, the best surface was generated by ST60.

For some methods, the increase number of neighbours lead to better results. From all outputs, 66.6% have better results when is used 60 neighbours and 34.4% with 10 neighbours. The methods tested with 60 neighbours that provided better results are the following: CRS (lowest RMSE, highest R, R^2), ST (lowest RMSE, ME, APRE, highest R, R^2), MQ (lowest ME, APRE, AAPRE, highest R, R^2), IMQ (lowest RMSE, ME, highest R, R^2), TPS (lowest RMSE, AAPRE, highest R, R^2). And for 10 neighbours: CRS (lowest ME, APRE, APPRE), ST (lowest AAPRE), MQ (lowest RMSE), IMQ (lowest APRE, APPRE), TPS (lowest ME, APRE).

The measured vs. predicted precipitation (Fig. 6, Fig. 7) generally shows a strong homoscedasticity in all methods, being the lowest generated by TPS. All interpolations were performed using ArcGIS Pro from ESRI, and all the statistical analyses were obtained through the statistical programming language R in the integrated development environment R Studio.

6. Conclusions

In this study, we tested the accuracy of precipitation prediction of five sub methods (TPS, ST, MQ, IMQ and CRS) related to the RBF group, in Brasov County, Romania. All methods were evaluated using the cross-validation principle, Taylor diagram and six statistical indicators (RMSE, ME, R, R^2, APRE and AAPRE).

The research was performed over a period of two decades (2000-2019) using the latest ECMWF reanalysis dataset ERA5. The result of the study shows a similar pattern between all methods, where the estimated precipitation increases from south to north. In the period of analysis, the southern part of Brasov County recorded 1547.7 mm, and the northern part 2149.5 mm.

From all the methods analysed and tested by the methods mentioned above, the most accurate method of estimating precipitation in Brasov County is ST, when 60 neighbours are used. ST60 overestimates precipitation by an average of 1.75 mm (ME), with a standard residual deviation of 496.53 mm (RMSE). From Taylor diagrams it can be seen how ST60 is closer to the point where precipitation was measured, which indicates a higher accuracy than the other analysed methods.

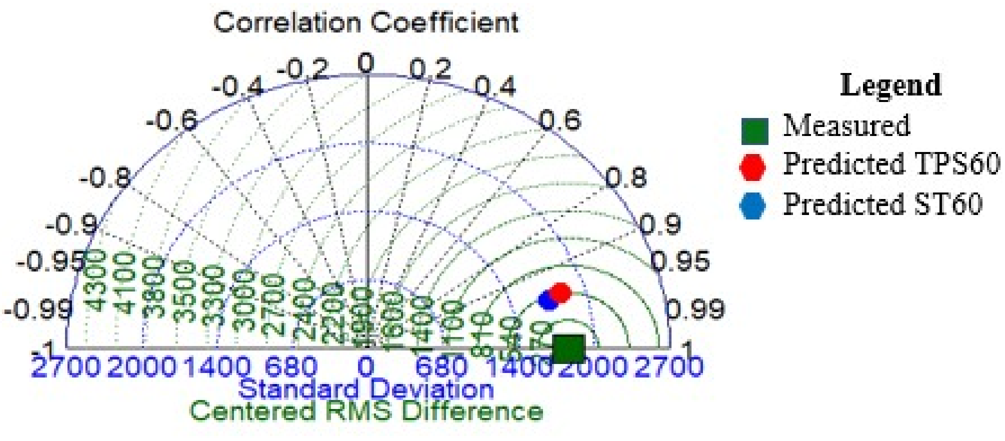

Fig. 3. Taylor diagram of measured vs estimated (ST60 and TPS60)

Table 3. Results of statistical indicators for predicting the spatial distribution of precipitation in Brasov County using RBF for different neighbours

RBF	***RMSE***		***ME***		***R***		***R^2***		***APRE [%]***		***AAPRE [%]***	
	Number of neighbours											
	10	***60***	***10***	***60***	***10***	***60***	***10***	***60***	***10***	***60***	***10***	***60***
CRS	498.84	497.18	**1.90**	1.94	**0.960**	**0.961**	**0.924**	**0.925**	-0.101	-0.109	1.507	1.519
ST	**498.63**	**496.53**	2.17	**1.75**	**0.960**	**0.961**	**0.924**	**0.925**	**-0.002**	**-0.001**	1.506	1.510
MQ	499.21	501.19	13.44	10.07	0.959	0.960	0.922	0.923	-0.155	-0.151	1.394	1.349
IMQ	505.03	503.06	1.95	1.80	0.959	0.960	0.922	0.923	-0.081	-0.084	1.508	1.510
TPS	553.16	544.29	25.62	28.38	0.953	0.955	0.909	0.912	-0.188	-0.202	**1.357**	**1.309**

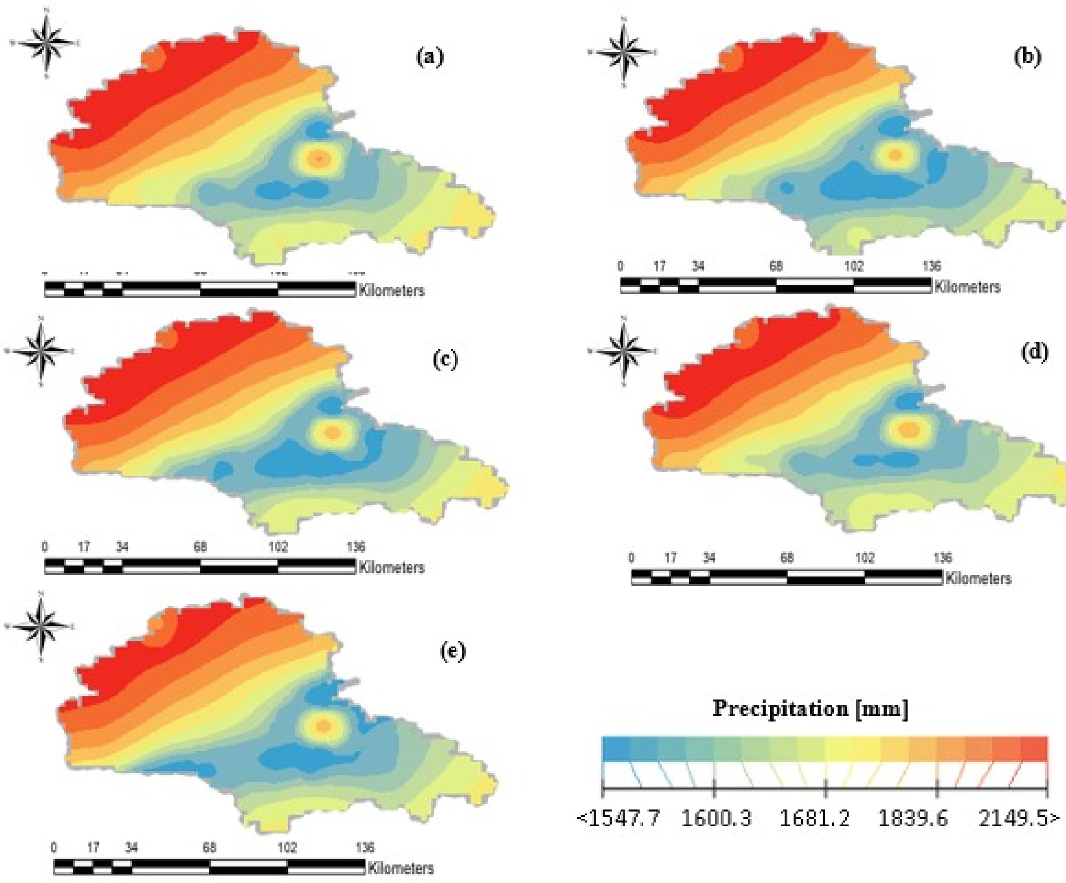

Fig. 4. Spatial distribution of annual precipitation of the last two decades (2000-2019) in Brasov county using RBF for 10 neighbours: (a) CRS, (b) ST, (c) MQ, (d) IMQ and (e) TPS

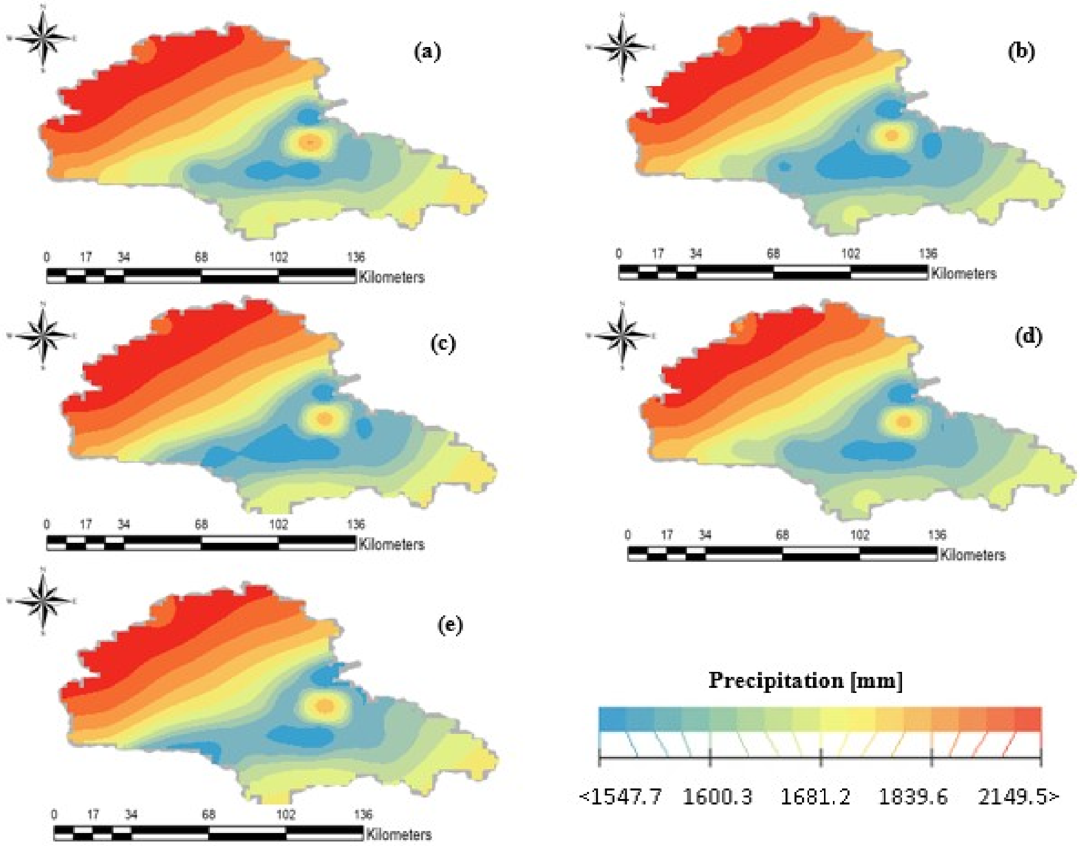

Fig. 5. Spatial distribution of annual precipitation of the last two decades (2000-2019) in Brasov county using RBF for 60 neighbours: (a) CRS, (b) ST, (c) MQ, (d) IMQ and (e) TPS

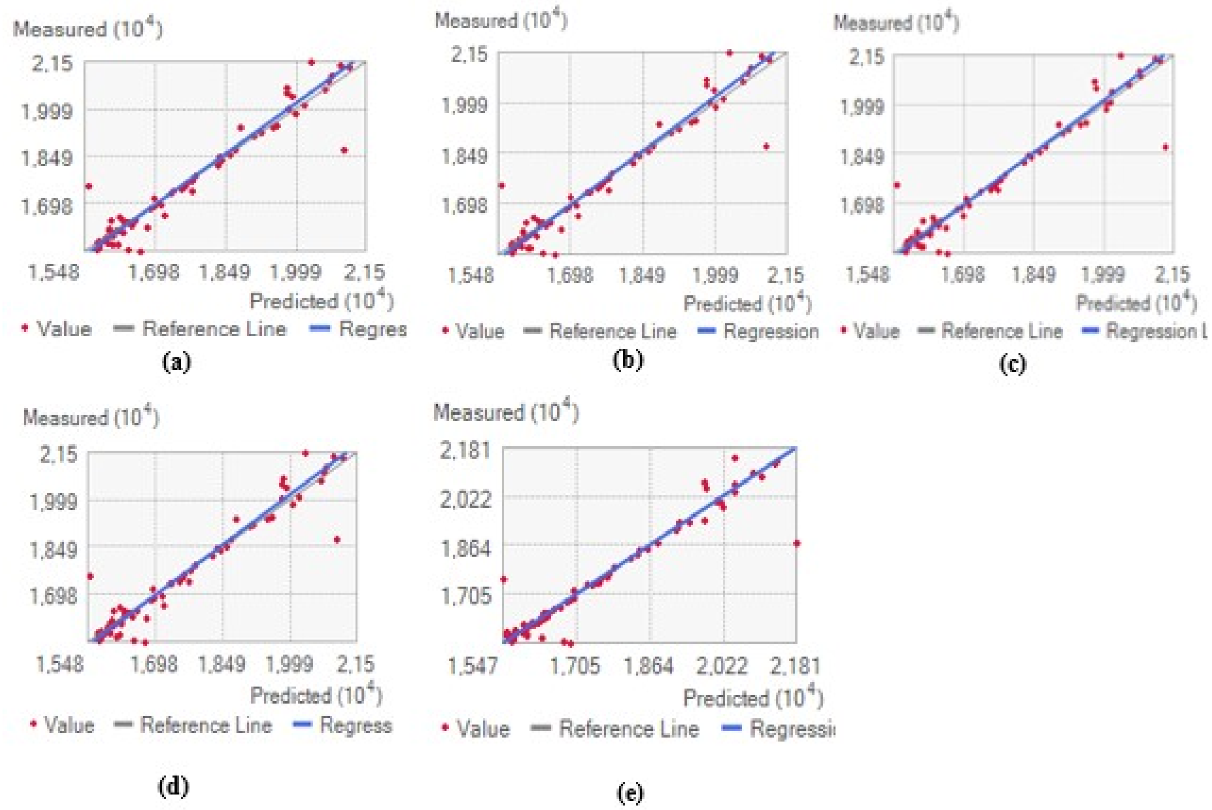

Fig. 6. Measured vs predicted values of the RBF for 10 neighbours: (a) CRS, (b) ST, (c) MQ, (d) IMQ and (e) TPS

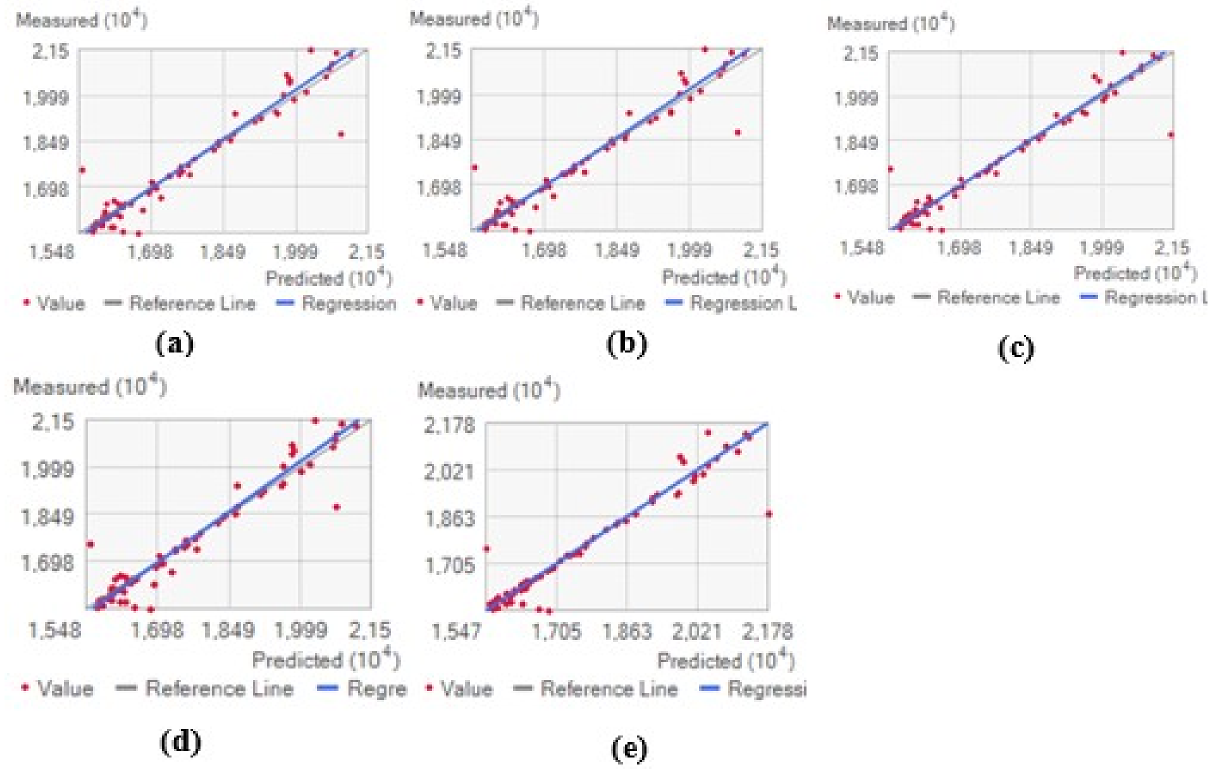

Fig. 7. Measured vs predicted values of the RBF for 60 neighbours: (a) CRS, (b) ST, (c) MQ, (d) IMQ and (e) TPS

To highlight the influence of neighbours in the accuracy of the prediction, each method was tested for 10 and 60 neighbours, respectively. The results show that the number of neighbours influence the accuracy of prediction. As a result, the best prediction of precipitation was generated by ST60. Not in all methods the increase number of neighbours lead to better results. From all outputs, 66.6% have better results when is used 60 neighbours and 34.4% with 10 neighbours.

This study shows promising results for future research on secondary variables (altitude, slope, latitude, longitude) in estimating precipitation and testing the smoothing factor at different values. Also, the output of interpolation methods can be used for further investigation on revealing the higher risk flood.

Acknowledgements

We hereby express our gratitude to the Research Centre of the Portuguese Air Force Academy and to ECMWF for ERA5 reanalysis data. Also, we thank to the anonymous reviewers for the constructive and valuable comments.

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