

Spatial interpolation methods for distribution of Regional Climate Models' daily precipitation at basin scale

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Abstract: The object of this research is to evaluate well-known spatial interpolation methods on hindcast precipitation data derived from up-to-date Regional Climate Models. The proposed climate models are the CMCC-CCLM4-8-19 v.1, CNRM-ALADIN52 v.1 and GUF-CCLM-NEMO4-8-18 v.1 with a spatial resolution of 0.44°. The Inverse Distance Weighting, Spline, Ordinary Kriging attributed by the Spherical, Exponential, Gaussian and Linear models, as well as Thiessen polygons spatial distribution methods are implemented into the climate model derivatives. The methodology is applied in a watershed in Northern Greece, with the outputs of the interpolation techniques to be compared against gauged precipitation records. The reliability of the spatial interpolation results is estimated by using statistic metrics and the results indicate that Ordinary Kriging is slightly superior to the other methods. By applying the latter interpolation method, future precipitation could be properly distributed at basin scales and hydrological modelling grids. Hence, the coupling of climate with rainfall-runoff models could improve the accuracy of the simulation of river discharges under climate change, especially when large scale development projects are envisioned within the watershed.

Keywords: Spatial interpolation, Regional Climate Models, Hindcasts, Precipitation, River basin

1 Introduction

Precipitation is recognized as the most important parameter in hydrologic modelling processes of surface water bodies, with precipitation's spatial and temporal variability to have a crucial role on rainfall-runoff models' performance and on the accuracy of the simulated discharges (Lobligeois et al. 2014). Beside the recent advancements in telemetric monitoring technologies, such as high reliable sensors at low cost, energy autonomy, and communication and transmission networks with worldwide coverage (Skoulikaris et al. 2018), the lack of densely precipitation gauges covering the globe is apparent (Kidd et al. 2017). In Greece for example, during the last two decades a modern network of about 350 automated weather stations have been established (Lagouvardos et al. 2017). However, isolated mountainous areas are poorly covered. Nevertheless, the rainfall intensity and duration on these areas, where the headwaters are generated, is of high importance in runoff simulations, even in case of sparse rain gauge networks, which do not probably offer a representative sampling of the precipitation distribution.

To overcame the lack of densely gauging networks, spatial interpolation techniques, such as the Inverse Distance Weighting (IDW), Spline, Kriging and Thiessen polygons techniques, are routinely been used in hydrologic simulations (Cheng et al. 2017), with their accuracy to be thoroughly investigated in the literature (Yang et al. 2015, Boucouvala et al. 2017). The applicability of these methods is also met, when coarser gridded climatic parameters need to be nested in more refine grids of spatial distributed hydrologic models to assess climate change impacts on hydrological processes (Skoulikaris and Ganoulis 2011, Gofa et al 2019).

In terms of climate change, the Mediterranean basin is considered a hotspot, since the outputs of the latest IPCC's Assessment Report (AR5) are consistent in projecting monthly net rainfall decrease during winter (Allen et al. 2014). On the other hand, summer periods, and not only, will be characterized by an increase in frequency of extreme precipitation intensity, i.e. a tendency that could enhance the risk of floods.

The present research aims at evaluating four well known spatial interpolation methods, namely IDW, Spline, Ordinary Kriging and attributed models as well as Thiessen polygons, on daily hindcast precipitation data coming from three up-to-date Regional Climate Models (RCMs). Case study area is a mountainous Mediterranean basin located in Greece, where precipitation gauged data were available. The output of the research is believed to improve the distribution of gridded climate data at higher resolution grids used by hydrologic models and thus contribute to the accuracy of the runoff simulations when climate change forms part of the objective.

2 Data and Methodology

2.1 Case study area

The area under investigation is the downstream part of the Nestos river basin, and particularly the watersheds that are located downstream of a large hydropower plant (HPP) (Fig. 2). The case area is a mountainous one with a mean elevation of 981.0 m above sea level and an extent of 1,235 km², i.e. covering 41.6% of the whole basin. The waters of these natural watersheds, i.e. no mankind intervention have been conducted within it, are drained in the river's main course and together with the HPP's water outflows are accumulated to the lower deltaic area for covering the irrigation demands and preserving the identified important ecosystems. The research importance of the specific case area coincides to the development plans related to the construction of a new large HPP at the near future, which will drain the waters of the watersheds within its reservoir. The specific development project is clearly mentioned in the Program of Measures of the River Basin Management Plan of the river (Special Secretariat for Water 2013).

2.2 Climate models and concentration pathways

The climate variable of precipitation utilized in the research was obtained by three high-resolution Regional Climate Models (RCMs) with a spatial resolution of 0.44° in a rotated pole projected geographic system. Particularly, hindcast precipitation for the period 1981-2000 was retrieved by the CMCC-CCLM4-8-19 v.1, CNRM-ALADIN52 v.1, and GUF-CCLM-NEMO4-8-18 v.1 climate models, hereinafter CMCC, CNRM and GUF respectively. The RCMs have been developed and implemented in the framework of the MEDiterranean COordinated Regional climate Downscaling EXperiment (MED-CORDEX) initiative (Ruti et al. 2016).

3.3 Spatial interpolation methods

In this research, spatial interpolation geostatistical and deterministic approaches were applied to produce spatially continuous precipitation data from three climate models. For this purpose, the IDW, Spline, Ordinary Kriging and Thiessen polygons methods were selected as the most appropriate methods (Ly et al. 2013, Hofstra et al. 2008). In the case of the Ordinary Kriging, the Spherical, Exponential, Gaussian and Linear variogram models were applied to investigate the best fit model to the theoretical (sample) variogram. Detailed description of the abovementioned interpolation methods is thoroughly provided in the literature (Goovartes 2000, Hofstra et al. 2008). The implementation of the methods over the case study area was realized with the use of geographic information systems.

The climate models' interpolated precipitation was evaluated using statistic meters, i.e. root mean square error (RMSE), standard deviation and correlation coefficient, as well as scatter plots in R computing environment (Hothorn and Everitt 2014), in relation to observation data. The latter are coming from 4 gauge stations located within the basin, namely Toxotes (1), Paranesti (2), Ptelea (3), Prasinada (4), i.e. stations 1-4 of Figure 2, covering a period of five years, i.e. 1990-1994. A fifth station, namely Mesochori (5), i.e station 5 in Figure 2, was used to assess the accuracy of the proposed methods in distributing the observed rainfall derived from the 4 stations within the watershed's scale. Then, after having identify the most accurate method in representing the observed precipitation, the same procedure i.e. the implementation of the IDW (M1), Spline (M2), Ordinary Kriging Spherical model (M3), Ordinary Kriging Exponential model (M4), Ordinary Kriging Gaussian model (M5), Ordinary Kriging Linear model (M6) and Thiessen polygons (M7) methods on the RCMs precipitation and theirs' correlation analysis to the observed data of the 4 stations was performed.

3 Results and discussion

The results of the linear correlation analysis are exposed in the form of scatter plots (Figure 1), with the figures around each scatter plot to represent the precipitation in mm. Starting with the observation datasets of the 4 gauge station, i.e. stations 1-4, and their validation against the additional utilized station, i.e. station 5, the results demonstrated that the Ordinary Kriging applying the Gaussian model (M5) depicted the best performance compared to the other spatial interpolation methods (Figure 1a). The specific method presented the lowest RMSE and standard deviation (~50) and the highest correlation coefficient (0.85). On the other hand, the Thiessen polygons method performed the lowest correlation (0.1) and the largest RMSE and standard deviation.

Regarding the interpolated CMCC, CNRM and GUF climate models' hindcast precipitation data against the observed precipitation data for the period 1990-1994, in the case of the CMCC climate model the Ordinary Kriging applying the Exponential variogram model (M4) proved the lowest RMSE and standard deviation and satisfactory correlation coefficient (Figure 1b). In contrast the Ordinary Kriging applying the Spherical model performed insignificant negative correlation coefficient (-0.02). The largest RMSE (594) was exhibited by the Spline method (M2).

As the CNRM precipitation is concerned, the Ordinary Kriging applying the Gaussian Model (M5) was superior to the other spatial interpolation methods as shown in Fig. 1c. The least satisfactory results (large RMSE and standard devia-





tion as well as low correlation) were displayed by the Spline method. In contrast, the IDW presented more satisfactory results.

Finally, concerning the GUF climate model and its outputs (Figure 1d), the best performance was exhibited by the Ordinary Kriging applying the Gaussian model (M5). The specific method presented the highest correlation coefficient (0.87) and the lowest RMSE and standard deviation. On the other hand, the Thiessen polygons performed the largest RMSE (680) and slightly negative correlation coefficient (-0.2).

Overall, both the models' and stations' data present a small statistically insignificant correlation since the data points in the scatter plot are randomly distributed (first column and first row at each scatter plot box). The correlation between the models can be considered as positive. Moreover, the analysis showed that in all cases the Ordinary Kriging method performed better than the other methods. The specific method was superior when the Gaussian model was applied in the 3 out of 4 simulated cases. Similar evaluation results are also presented in a different case study basin in the Mediterranean, where the Kriging with external model's drifts method showed the smallest error of prediction of rainfall distribution (Pellicone et al. 2018).

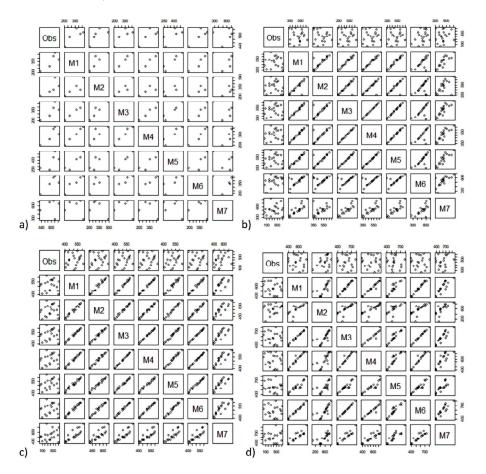


Fig.1. Scatter plots for the best-fit interpolation method for the cases of a) the observed precipitation (mm) of 4 stations (stations 1-4 of Figure 2) against the validation station (station 5 in Figure 2), b) the CMCC precipitation, c) the CNRM precipitation, d) the GUF precipitation against the observed data (mm) respectively for the same time period, where M1=IDW, M2=Spline, M3= Ordinary Kriging Spherical model, M4= Ordinary Kriging Exponential model, M5= Ordinary Kriging Gaussian model, M6= Ordinary Kriging Linear model and M7=Thiessen polygon methods.

The graphical illustration of the best-fit interpolation method for each of the climate models is depicted in Figure 2. The CMCC and CNRM models' precipitation, although interpolated by different models such as the Exponential (M4) and Gaussian (M5) models respectively of the Ordinary Kriging method, demonstrate a similar spatial distribution over the basin. Additionally, the maximum interannual precipitation of these two models is almost identical. The GUF precipitation distribution is also based on the Ordinary Kriging but attributed by the Gaussian model, with the specific dataset to present increased precipitation amounts in the eastern part of the basin in comparison with the two other climate models' datasets. The maximum precipitation is also slightly, i.e. 9.1%, overestimated.

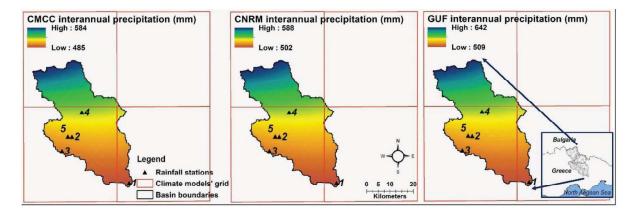


Fig.2. Climate models' precipitation distribution over the case study basin based on the best interpolation method, i.e. the Ordinary Kriging applying the Exponential model (M4) for the CMCC and the Ordinary Kriging applying the Gaussian model (M5) for the CNRM and GUF models.

4 Conclusions

In the present paper, the IDW, Spline, Ordinary Kriging using the Spherical, Exponential, Gaussian and Linear Models and Thiessen polygons were applied to CMCC, CNRM and GUF regional climate models hindcast precipitation data. The interpolated climate model precipitation outputs were evaluated in comparison to observed precipitation data for a specific, rather small, historical period. The statistical analysis showed that Ordinary Kriging was superior to the other interpolation methods. More specifically, regarding the CMCC model, the spatial precipitation distribution of the river basin was satisfactorily simulated by the Ordinary Kriging applying the Exponential model. In the case of the CNRM and GUF models, the Ordinary using the Gaussian model reasonable represented the rainfall regime over the catchment for the historical period.

As a follow up of the present research, the same methodology is planned to be implemented with the use of longer time series, such as ERA5 reanalysis data, serving the role of the observation datasets in order to re-validate the outputs. The best-fit interpolation methods could be used for distributing the future precipitation of the proposed RCMs in densely hydrologic model grids for the simulation of the basin's runoff under climate change conditions and thus the rational use of the water resources particularly when large scale projects are foreseen to be developed.

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