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Regional mapping of climate variables in Galicia from point samples

Mapeo regional de variables climáticas en Galicia a partir de datos puntuales

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Abstract

Galicia's (NW Spain) diverse climate, driven by various factors, exhibits significant spatial and temporal variability, directly affecting the region's economy and society. Taking this into account, it is of great importance to have climate observation networks that cover most of the territory, and in the case of not having them, to have tools that allow the estimation of climate parameters.

The main tools used for the estimation of parameters in unmeasured locations are climate database and the interpolation of data from climate stations, with kriging being one of the most widely used interpolation methods.

The evaluation of climatic database is very important to establish how well they estimate the parameters and to ensure that they result in a homogeneous data series. For this purpose, in the present study a comparison was made of point data from the MeteoGalicia weather station network with data extracted from the SIMPA, AEMET and ERA5 databases and with data resulting from interpolation using regression kriging methods. The climatic parameters for which data were used for the study are: mean temperature, precipitation and reference potential evapotranspiration (Eto).

To extract the data from SIMPA, ERA5 and AEMET and to interpolate point data from MeteoGalicia, we worked with the statistical programming environment R. After extracting the data or interpolating them, they were compared with the data measured in the MeteoGalicia network of climatological stations using the Nash-Sutcliffe index.

The results of this study seek to conclude which method is more effective for estimating each of the parameters studied. In general, the predictions based on interpolation (AEMET and regression kriging) presented the best goodness of fit, while SIMPA also presented good results for some parameters. In general, the parameters with the best estimation results were mean temperature, followed by precipitation and finally potential evapotranspiration.

Keywords: Galicia climate, spatial interpolation, spatial variability, geostatistics, climatological databases

Resumen

Debido a los múltiples factores que influyen en el clima en Galicia (NO España), éste presenta una alta variabilidad espacial y temporal, lo que afecta directamente a muchas actividades económicas y sociales. Es de gran importancia disponer de redes de observación climática que cubran la mayor parte del territorio, y en el caso de no tenerlas, contar con herramientas que permitan predecir parámetros climáticos.

Las principales herramientas utilizadas para la estimación de parámetros en localizaciones no medidas son las bases de datos climáticos y la interpolación de datos de las estaciones climáticas, siendo el krigeado uno de los métodos de interpolación más usado.

La evaluación de las bases de datos climáticos es muy importante para establecer cuan bien estiman los parámetros y asegurar que resulten en una serie de datos homogénea. Para esto, en el presente estudio se hizo una comparación de datos puntuales de la red de estaciones meteorológicas de MeteoGalicia con datos extraídos de las bases de datos de SIMPA, AEMET y ERA 5 y con datos resultados de la interpolación mediante krigeado de regresión. Los parámetros climáticos usados para el estudio son: temperatura media, precipitación y evapotranspiración potencial de referencia.

Para extraer los datos de SIMPA, ERA5 y AEMET y también para interpolar datos puntales de MeteoGalicia, se trabajó con el entorno de programación estadística R. Después de extraer los datos o de interpolarlos, se compararon con los datos medidos en la red de estaciones climatológicas de MeteoGalicia mediante el índice de Nash-Sutcliffe.

El objetivo de este trabajo es la determinación de que metodología es más efectiva para estimar cada uno de los parámetros estudiados. De manera general, las predicciones basadas en interpolación (AEMET y krigeado de regresión) son las que presentaron una mejor bondad de ajuste, SIMPA presentó también buenos resultados para algunos parámetros. Los parámetros en general con mejores resultados de estimación fueron temperatura media, seguida de precipitación y por último evapotranspiración potencial de referencia.

Palabras clave: clima de Galicia, interpolación espacial, variabilidad espacial, geoestadística, bases de datos climatológicos

1. INTRODUCTION

Galicia, in northwest Spain, presents an extraordinarily varied succession of weather types (CASTILLO et al., 2006), this is due to the many factors that influence the Galician climate, both the fixed characteristics due to its location and the characteristics imported through the air masses that transport the conditions of their places of origin.

Galicia's unique location in northwestern Europe, at the confluence of various air masses (maritime, maritime polar, maritime tropical, and continental) and ocean currents, results in a highly variable climate. Situated within the influence of major atmospheric features like the Azores High, the Icelandic Low, and central European anticyclones, as well as the circumpolar vortex, Galicia experiences significant spatial and temporal variations in weather patterns, as highlighted by CASTILLO et al. (2006).

Regarding precipitation in Galicia, according to CASTILLO et al. (2006), the annual precipitation is 1180 mm (varying from a minimum of 500 to 600 mm in the driest areas to 1800 to 2000 mm in the coastal areas), distributed annually in 337 mm in winter, 280 mm in spring, 156 mm in summer and 407 mm in autumn.

The spatial distribution of precipitation in Galicia is quite complex and presents much spatial and temporal variability, which cannot be explained only by atmospheric dynamics. The relief factor is essential to understand and explain the variability of precipitation, the orographic factor works as an intensifier of precipitation due to frontal systems, and acts by increasing the altimetry variability and orientations, which are determinants of the inequality in the distribution of rainfall throughout the Galician territory (CASTILLO et al., 2006). Depending on the area, the relief factor may explain the variations in precipitation to a greater or lesser extent.

In Galicia, temperature and reference potential evapotranspiration, like precipitation, demonstrate significant spatial variability, closely linked to the region's topography.

Given the significant spatial and temporal variability of Galicia's climate, the strong climate-society relationship, and the crucial role of climate in determining viable economic activities (e.g., agriculture, forestry), and water resource availability, it is essential to have a robust network of meteorological observations across the region. Where observational data is lacking, reliable tools are necessary to extrapolate climate data while accounting for the full extent of spatial and temporal variability within the region. This ensures accurate climate variable estimations for all locations.

Even though in recent years meteorological observation networks have become increasingly dense (partly due to automatic weather stations), on many occasions the climatic series lack the desirable continuity and homogeneity (TERRADELLAS, 2008), both because of missing data at the station itself, measurement errors, and because of lack of data at unmeasured locations.

Parameter estimation in unmeasured locations is a very common problem in engineering. One of the most widely used tools to estimate parameters at unmeasured locations based on point observations are climate models with reanalyses, which try to represent the climate system as completely as possible. Climate reanalyses combine past observations with models to generate consistent time series of multiple climate variables (MUÑOZ-SABATER et al., 2021).

Despite the evolution and adaptation of models according to the needs, numerical models should be evaluated to establish how well they represent reality (ANDRADE & BLACUTT, 2010) and ensure that they result in a homogeneous data series. The validation of the models is done through comparison of data from weather stations (observations) and model data over long periods, the Nash-Sutcliffe efficiency index can assess the predictive skill of the models.

Another tool used to estimate climate parameters in unmeasured locations is the interpolation of data from weather stations, one of the most used methods is kriging, which considers the spatial correlation of the data and attributes higher weights to the values closer to the location we are looking for the parameter. For many decades, kriging and deterministic interpolation techniques, such as inverse distance weighting and nearest neighbour interpolation, have been the most popular spatial interpolation techniques. Kriging with external drift and regression kriging have become basic techniques that benefit both from spatial autocorrelation and covariate information (SEKULIĆ et al., 2020).

In this study, the values of the climatic parameters: monthly mean temperature, monthly reference potential evapotranspiration and monthly precipitation, from January 2010 to December 2022, extracted from the AEMET spatial climatological databases ROCIO IBEB 5km (daily maximum temperature, minimum temperature and precipitation data), ERA5 and SIMPA (monthly mean temperature, monthly reference potential evapotranspiration and monthly precipitation) were compared with monthly point data obtained from meteorological stations of the MeteoGalicia network. Data for the same climatic parameters were also interpolated by residual kriging using data from the MeteoGalicia network of stations, and the four methodologies used were evaluated with respect to the data measured at the stations of the MeteoGalicia network.

2. MATERIAL AND METHODS

The initial phase involved downloading data from each climatological model and MeteoGalicia observations. Data for the period January 2010 to December 2022 was obtained from the respective websites of each model and MeteoGalicia by selecting the desired variables. An exception was SIMPA input data, for which data was only available until September 2019.

Data extraction utilized the raster library (HIJMANS, 2023), employing bilinear interpolation to determine values at specific coordinates. This method involves calculating a weighted average of the four nearest raster cells. Bilinear interpolation, suitable for interpolating two-dimensional scalar fields, was applied to data from all databases (ROCIO_IBEB, ERA5, and SIMPA). The extraction process initially obtained parameter values at the cell centers and subsequently used bilinear interpolation to estimate values at the precise locations, which typically do not coincide with cell centers.

In all cases R scripts were used to extract the data at the MeteoGalicia station locations.

As a reliable and widely applied statistic, the Nash-Sutcliffe Efficiency (NSE) is used to assess how well the data from different methodologies align with measured observations (McCUEN et al., 2006).

2.1 ROCIO_IBEB AEMET

ROCIO_IBEB AEMET is a grid generated using a selected set of pluviometric observations from AEMET's National Climatological Data Bank, specifically, the 24-hour accumulated precipitation series from selected stations. It covers the period from 1951 to 2022 and is updated periodically (AEMET, n.a.).

The precipitation grid was generated using Optimal Interpolation (OI), a statistical method well-suited for handling irregularly distributed observations. OI aims to produce the best estimate by combining a set of observations with an initial field estimate, while considering the error associated with each data source. This involves starting with an initial estimate from a climatological model and refining it by incorporating weighted measurements from surrounding locations within the search area

The daily extreme temperature grid uses the total number of stations available in the national climatological data bank of AEMET. The methodology used is very similar to the one used in the regeneration of the precipitation grid, with the difference that for the generation of the temperature grid, data based on the historical analysis of the HIRLAM numerical weather prediction model operative in AEMET (short-range prediction) are used as starting information (first estimate), which is corrected by the observations coming from the AEMET climate database, consisting of an adaptation of the HIRLAM Surface Analysis code based on the Optimal Interpolation algorithm. The grid size is 5 km.

The R script to extract the data required the use of the CDO function (SCHULZWEIDA, 2023) and the Climate Operators package (PAYNE, 2023) CDO works on linux, so when working with windows OS, a linux emulation was installed. The extraction script is available on zenodo. The data extraction script in R from netCDF maps is available at zenodo https://doi.org/10.5281/zenodo.14011191

2.2 SIMPA

The SIMPA integrated hydrologic model is a conceptual, continuous basin simulation model designed to evaluate water resources and conceptually based on the aggregated Témez model (MTERD & CEDEX, 2020). Precipitation, mean temperature and monthly ETo data are from the input maps of the SIMPA hydrologic model.

In this model Spain has been gridded in a 0.5 km grid (spatial resolution), and monthly (temporal resolution), and water balances are performed in each of these cells. The meteorological data on precipitation and temperature come mainly from the climatic series of the observations of the State Meteorological Agency (AEMET).

After having the complete series, the maps are interpolated to obtain a continuous data network. For the interpolation of temperature values, a multivariate regression with altitude, distance to the coast, latitude and longitude is used, in addition to the residual component (inverse of the squared distance), since a similar regression methodology is applied for the interpolation of precipitation values, but the residual component is obtained by simple kriging.

Finally, in the atmospheric variables treatment stage, reference potential evapotranspiration is estimated by combining the Hargreaves and Penman-Monteith methods and applying to the result a seasonal coefficient according to land use (MINISTERIO PARA LA TRANSICIÓN ECOLÓGICA Y EL RETO DEMOGRÁFICO, 2020).

The maps of climatic variables can be download from https://www.miteco.gob.es/en/agua/temas/evaluacion-de-los-recursos-hidricos/evaluacion-recursos-hidricos-regimen-natural.html

The data extraction script in R from the geoTiff maps is available at zenodo https://doi.org/10.5281/zenodo.14011191.

2.3 ERA5

The format of the data downloaded from the Copernicus website (Climate Copernicus) is netCDF. These data can be downloaded from https://www.ecmwf.int/en/era5-land.

According to SILES (2022), ERA 5 is one of the products of the Copernicus Climate Change Service (C3S), which is a platform whose mission is to provide access to global climate data (past, present and future) to support climate change mitigation efforts. The C3S platform is implemented by the European Centre for Medium-Range Weather Forecast (ECMWF), which has a long history of climatological reanalyses (FGGE, ERA-15, ERA-40, ERA-Interim, ERA5), ERA5 being the most recent of them. We worked with ERA5-Land, which, according to SILES (2022), is a special set, only available for continental surfaces, covering the period from 1950 to date and was developed in order to deepen the study of hydrological and thermodynamic variables on these surfaces. The atmospheric parameters of this dataset have a spatial resolution of 9 km and are available monthly and hourly temporal resolutions data.

The data extraction script in R from the netCDF data is available at zenodo https://doi.org/10.5281/zenodo.14011191

2.4 Regression kriging

The objective of geostatistics, according to ZHANG (2011), is to predict the spatial distribution of a property under study, in this specific case, the climatic parameters. This prediction can take two forms: the estimation form, which is based on sample data (observed) and data from a model (variogram) representing the spatial correlation between the sample data, and the simulation form, which produces several maps of the distribution of the properties, using the same variograms. The most common procedure in geostatistical estimation analysis, according to ROSSITER (2022) is kriging, which basically consists of constructing a linear predictor for an unobserved parameter, the shape of the predictor is defined as a function of the covariance structure of the data using an analysis tool known as a variogram (it puts the variance between pairs of data as a function of the distance between the points in the pair).

There are different variations of kriging, such as ordinary, universal, external drift (KED) and regression (RK). According to HENGL (2009), theoretically they all describe the same technique, but in practice they present computational differences, in the RK the deterministic predictors (regression) and the stochastic (kriging) are calculated separately, while in the KDE the two components are predicted at the same time.

The whole kriging procedure explained above is from ordinary kriging, which is a technique in which the variable is only modelled from itself and its position, knowing the variogram model, and that the spatial mean is not known a priori and must be estimated from data (ROSSITER, 2024).

The main method used in this work to estimate the climatic parameters of mean temperature, precipitation and potential evapotranspiration at MeteoGalicia weather station locations was regression kriging. In this technique, as already explained above, the value of the target parameter at the same location is estimated by the sum of the deterministic (regression) and stochastic (residuals) components, using the following formula (MATHERON, 1971) (1).

$$\hat{z}(s_0) = \hat{m}(s_0) + \hat{e}(s_0) = \sum_{k=0}^{p} \widehat{\beta_k} * q_k(s_0) + \sum_{i=i}^{n} \lambda_i * e(s_i) \,\#(1)$$

Where is the deterministic part (regression), is the residual part, are the coefficients of the deterministic model, which are estimated using generalized least squares (GLS), are the weights of the kriging determined previously and are the residuals at the location (HENGL, 2009).

The code used follows the steps described above, if when adjusting the variogram of the residuals any error is obtained, it performs an ordinary kriging with the raw data, that is, without removing the trend, calculating directly the variogram of the variances between the parameter values of the pairs of points (as explained above). If it still gives an error, the code calculates the parameter by applying an IDW (inverse of the squared distance).

In the script developed for R (available on Zenodo https://doi.org/10.5281/zenodo.14011191), this code works mainly with the Gstat library (PEBESMA, 2004). The script estimates the values for each month and for each

MeteoGalicia station, without using the data from that station to construct the residual variogram or for the regression kriging.

MeteoGalicia climatic data using in regression kriging interpolation and methods validation can be downloaded from https://www.MeteoGalicia.gal/observacion/estacions/estacions.action?request_locale=es

3. RESULTS AND DISCUSSION

The estimation of all parameters, all locations and all months was performed using the regression kriging (RK) method, which means that for all parameters, months and locations a variogram model could be fitted to the residuals, once the estimated deterministic component was removed as a function of X, Y and elevation.

To calculate the total NSE index of the parameter for each method, the index was calculated with all the data of the different climatic parameters estimated and all the months by the different methodologies used and the data measured at the MeteoGalicia stations for the same months and parameters studied (Table 1). In the case of ROCIO_IBEB AEMET there is no NSE data for ETo, since this methodology does not give estimation data.

Table 1. NSE indices for climatic parameters calculated using the values of all climatological stations. Indices calculated with data from ERA 5, ROCIO_IBEB AEMET, SIMPA and regression kriging.

	ERA5	**ROCIO_IBEB AEMET**	**SIMPA**	**Regression kriging**
Precipitation	0.75	0.87	0.87	0.85
Mean temperature	0.90	0.93	0.96	0.99
ETo	0.70	-	0.60	0.97

Table 1 shows that the method that best fits the measured precipitation data are the SIMPA input maps, followed by ROCIO_IBEB AEMET and regression kriging, with very similar indexes among the three, and finally ERA 5 with a lower NSE value. It is observed that both SIMPA, AEMET and kriging present very good indices according to MORIASI et al. (2007), while ERA 5 is in the limit between good and very good.

The best method to predict the mean temperature is the regression kriging, but with very little difference with the estimates of SIMPA, followed by AEMET and finally ERA5, but highlighting that the NSE value in all cases is equal or higher than 0.9, and in the case of regression kriging reaches 0.99, due to the improvement in the estimation provided by the secondary variables used: X, Y and elevation.

It can be observed that the most effective method (with less error) to predict ETo in unmeasured locations is kriging, followed by ERA 5 and finally SIMPA. A significant difference is shown between the NSE values in kriging, ERA5 and SIMPA, for RK the index is very close to 1, which according to MORIASI et al. (2007) is a very good NSE value, the NSE value of ERA is already classified as good and that of SIMPA as satisfactory.

For ETo, with the indexes calculated for the predictions at each of the stations, the following maps were obtained for each database (Figure 1).

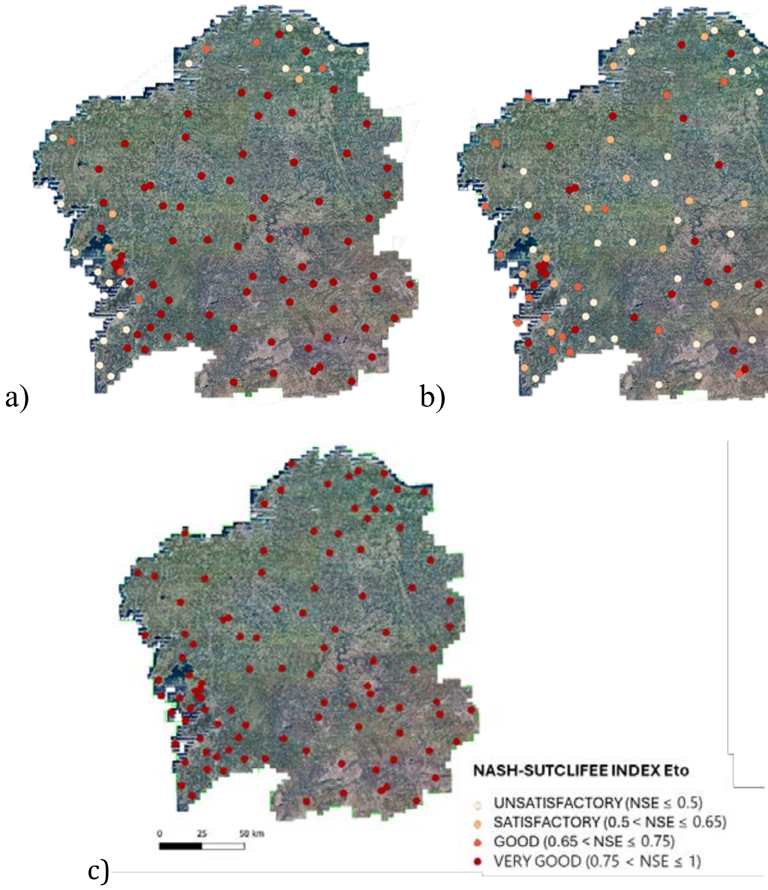

Figure 1. Maps of the NSE indices calculated for ETo parameter at the locations of the meteorological stations with data from: a) ERA5; b) SIMPA; c) RK.

In these maps was used the classification of MORIASI et al. (2007), which classifies as very good indices those above 0.75, as good those between 0.65 and 0.75, as satisfactory those between 0.5 and 0.65 and as unsatisfactory those below 0.5.

As already observed with the tables, the kriged predictions stand out as much more accurate than those of ERA 5 and SIMPA. With kriging, as seen in the map, the predictions for all stations are very good.

Analysis of the kriging data reveals that while ERA5 predictions exhibit a high percentage of very good results, a significant number of good, satisfactory, and unsatisfactory predictions also exist. A spatial analysis of the unsatisfactory predictions demonstrates a notable concentration along the southwest and northwest coasts, indicating potential challenges in coastal regions.

Finally, in the map with the SIMPA indices we observe many unsatisfactory and satisfactory indices distributed all over the map.

For precipitation, with the indices calculated for the predictions in each of the locations, the following maps were obtained (Figure 2).

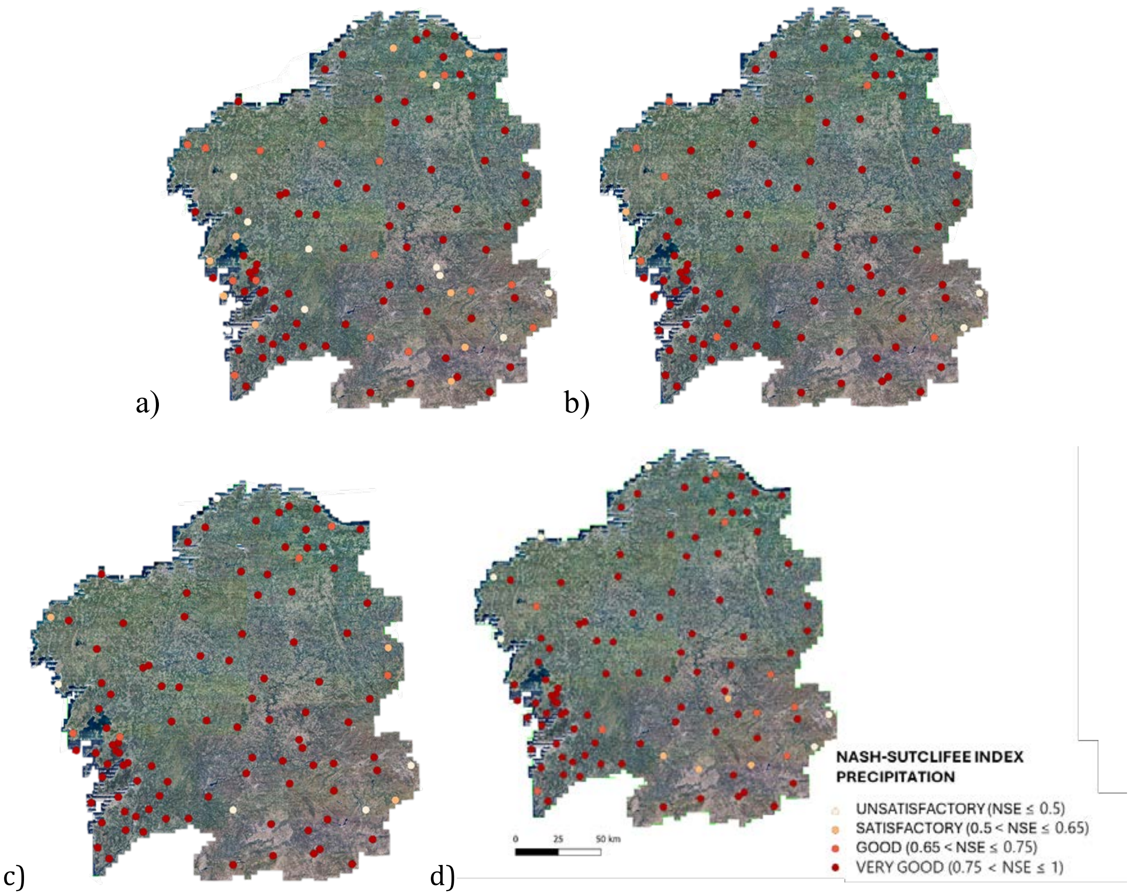

Figure 2. Maps of the NSE indices calculated for Precipitation parameter at the locations of the meteorological stations with data from: a) ERA5; b) SIMPA; c) ROCIO_IBEB; d) RK.

In this case, as previously mentioned with the table, very similar maps are observed for regression kriging, ROCIO_IBEB and SIMPA, with most of the locations with very good, some good, satisfactory and very few unsatisfactory predictions. While ERA 5 map shows a higher number of good, satisfactory and unsatisfactory predictions.

As with the potential evapotranspiration, it can be observed (mainly in the case of ERA 5) that the unsatisfactory predictions are concentrated in the southwest coast, northeast coast and a few in the southeast area of Galicia.

Finally, with the NSE indices calculated for the mean temperature prediction in each of the locations, the following maps were obtained (Figure 3).

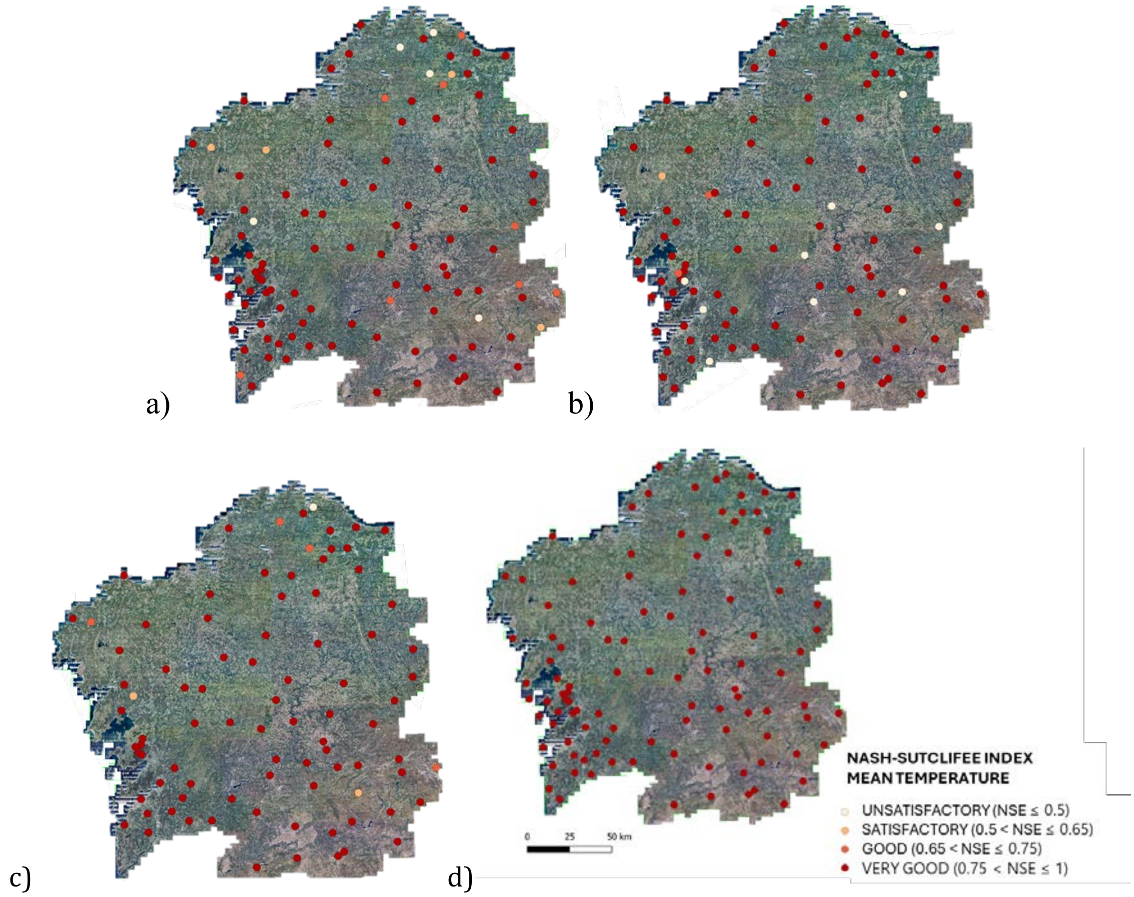

Figure 3. Maps of the NSE indices calculated for the ETo parameter at the locations of the meteorological stations with data from: a) ERA5; b) SIMPA; c) ROCIO_IBEB; d) RK.

It is observed that RK and SIMPA maps do not show any location with predictions below very good, then, the ROCIO_IBEB map shows most of the locations with very good predictions, some few with good and satisfactory predictions, most of them in coastal areas. Finally, ERA5 shows most of the locations with very good predictions, some with good and satisfactory predictions and very few with unsatisfactory predictions.

Finally, it is noteworthy that the maps reveal a concentration of the lowest indices in coastal regions, particularly in the southwest and northeast, as well as in southeastern areas. This spatial pattern may be attributed to the influence of the region's topography (Figure 4).

It can be noted that these are areas with a lot of change in altitude, which could affect the estimates since it can be observed nearby areas that do not always correspond to the area, we want to predict due to altitude jumps. More detailed studies would be interesting to establish a concrete statistical relationship between the NSE indices and the relief of Galicia.

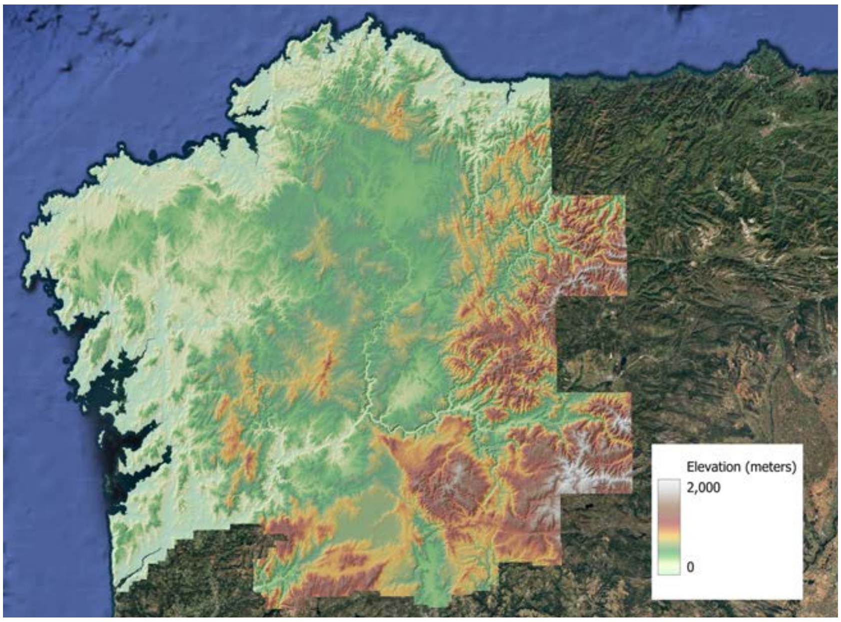

Figure 4. Galicia DEM from IGN dataset describes the ground elevation of Galicia with a spatial resolution of 25x25m.

4. CONCLUSIONS

The following conclusions can be drawn from this study:

- Regression kriging is the best prediction technique for the ETo and mean temperature parameters, and the third best prediction technique for the precipitation parameter, but with an NSE index value very close to the two best methods.

- The ROCIO_IBEB database is the best prediction technique for the precipitation parameter (next to SIMPA), and the third best for the mean temperature parameter.

- SIMPA database is the best prediction technique for precipitation (next to ROCIO_IBEB), the second-best technique for mean temperature prediction, and the worst technique for ETo prediction.

- ERA5 is the second-best prediction technique for ETo and the worst for precipitation and mean temperature prediction.

In general, the predictions based on interpolation (regression kriging, SIMPA and ROCIO_IBEB) show the best results. In the three cases (ROCIO_IBEB, SIMPA and regression kriging) the indexes are lower for the precipitation parameter, that may be due to the fact that, the pattern of precipitation is not as stable as that of temperature, and in the specific case of ROCIO_IBEB it may be related to the very irregular and time-varying distribution presented by the rainfall stations, besides the fact that in Galicia the number of rainfall stations is scarce and the density is low.

In the case of ERA5, which combines results from meteorological models with observations to correct the models, it presents, in general, the lowest NSE indices, which may be because in these cases the errors of the models and the observations are combined and may generate some uncertainty in the data.

Finally, in the case of SIMPA, the lower value of ETo when compared to precipitation and temperature may be related to the fact that temperature-based prediction models (Hargreaves) corrected based on the Penman-Monteith model are used to define ETo, so that even more errors are carried over.

DATA AVAILABILITY STATEMENT

The R scripts are available on https://doi.org/10.5281/zenodo.14011191 and the dataset used in this research is available upon reasonable request to any of the authors of this research article.

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