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DOES THE GAP-FILLING METHOD INFLUENCE LONG-TERM (1950–2019) TEMPERATURE AND PRECIPITATION TREND ANALYSES?

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ABSTRACT

Incomplete climatic series require gap-filling approaches so they can be used in homogeneous long-term spatiotemporal trend analyses. Monthly mean Temperature (MT) and Precipitation (PR) databases from the meteorological stations of the Iberian Peninsula have a high percentage of data gaps: 80.21 % and 73.25 % for the period 1950–1979 (P1), and 61.82 % and 58.03 % for the period 1980–2019 (P2). The different gap-filling methods of the *Emmental* software were tested to determine their performance and whether the gap-filling method influences these trend analyses. The nonparametric Theil-Sen approach and the Mann-Kendall test were used to assess the trend magnitude and its significance. The results showed (i) similar patterns between the evaluated methods, but with (ii) spatial differences, especially during P1. (iii) The comparison between standardized gap-filled and unfilled series did not show significant differences for MT and PR, although a reduction in the trend variability occurred in the first case (filled). (iv) Summer mean temperatures showed the largest warming trend (0.27 °C/decade), while autumn showed the smallest (0.21 °C/decade) (median data for P1 and P2). Overall, an increase of 1.45 °C occurred in the entire period (annual median). (v) PR did not show any clear trend in any month in the entire period. This research has shown how climate trends can be affected by a reduction in data variability due to the application of gap filling methods. Although accounting for variability is of crucial importance for climate analysis, ignoring discontinuities in derived climatic surfaces causes greater spatiotemporal inconsistencies in derived climate products.

Keywords: gap-filling; time series; meteorological stations; long-term climate trend analysis; mean temperature; precipitation; Iberian Peninsula.

Recepción: 08/04/2022 Aceptación definitiva: 19/05/2022

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¿INFLUYE EL MÉTODO DE RELLENO DE DATOS FALTANTES EN LOS ANÁLISIS DE TENDENCIAS DE TEMPERATURA Y PRECIPITACIÓN A LARGO PLAZO (1950–2019)?

RESUMEN

Las series climáticas incompletas requieren de enfoques de relleno de lagunas de información para que puedan ser usados en el análisis homogéneo de tendencias espaciotemporales a largo plazo. La base de datos mensual de Temperatura Media (MT) y Precipitación (PR) de las estaciones meteorológicas de la Península Ibérica presenta un alto porcentaje de datos ausentes: 80.21 % y 73.25 % para el periodo 1950–1979 (P1), y 61.82 % y 58.03 % para el periodo 1980–2019 (P2). Se emplearon los diferentes métodos de relleno de datos faltantes del software *Emmental* para determinar su rendimiento y si el método de relleno influye en el análisis de las tendencias. El enfoque no paramétrico de Theil-Sen y la prueba de Mann-Kendall evaluaron la magnitud de la tendencia y su significación. Los resultados mostraron (i) patrones similares entre los métodos evaluados, pero con (ii) diferencias espaciales, especialmente durante P1. (iii) La comparación entre las series normalizadas completadas y no completadas no mostró diferencias significativas para la MT y la PR, aunque en el primer caso (completadas) se produjo una reducción de la variabilidad de las tendencias. (iv) La temperatura media de verano mostró la mayor tendencia al calentamiento (0.27 °C/década), mientras que la menor tuvo lugar en otoño (0.21 °C/década) (datos medios para P1 y P2). En general, se produjo un incremento de 1.45 °C en todo el período (mediana anual). (v) La PR no mostró una tendencia clara en ningún mes considerando todo el período. Esta investigación ha demostrado cómo las tendencias climáticas pueden verse afectadas por la reducción de variabilidad de los datos debida a la aplicación de métodos de relleno de datos ausentes. Tener en cuenta la variabilidad de los datos es de crucial importancia para análisis climáticos, pero ignorar las discontinuidades en las superficies climáticas derivadas causa mayores inconsistencias espaciotemporales en los productos climáticos derivados.

Palabras clave: Relleno de datos faltantes; series temporales; estaciones meteorológicas; análisis de las tendencias climáticas a largo plazo, temperatura media, precipitación, Península Ibérica.

1. Introduction

Monitoring climate change requires observational datasets of long-time periods, which should be as complete as possible to ensure a consistent time series analysis, the comparison between different series, the detection of breakpoints, and the generation of multitemporal surfaces to derive climate change metrics, such as the climate velocity (Loarie *et al.*, 2009; Dobrowski and Parks, 2016; Brito-Morales *et al.*, 2018). Furthermore, the development of societal and environmental climate change mitigation and adaptation strategies depends on the quality of the climate data. However, missing values (data gaps) in the series are common, and there are very few stations with a complete long-term series, which is a big problem when the geographical variability of the climate is a major feature. For instance, the number of observatories recording meteorological variables has increased gradually in the Iberian Peninsula between 1860 and 2019; however, the number of stations has increased significantly since 1975. The sudden installation of new stations and the increasing number of professional staff to make the observations were administrative responses to the need for a more densely distributed climatic network for climate monitoring. Thus, the time series dataset structure differs in spatiotemporal coverage, with scarce and spatially distanced stations in the first decades and more densely distributed stations in the recent ones (Figure 1). In terms of the temporal structure of the datasets, the observations are more densely concentrated over the last four decades (Figure A1 in Appendix 1).

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There are diverse reasons for the gaps, ranging from human-induced errors caused by not reporting records or misinterpretation during data transcription (manual stations) or due to malfunctions of electronic/mechanic instruments (automatic stations), information transmission, or storage. Furthermore, meteorological instruments are occasionally replaced or renewed, introducing temporal discontinuities in the series. Frequently these changes are hardly reported in the metadata associated with the stations.

All these effects result in incomplete series with data gaps ubiquitously distributed throughout them. Thus, various studies have proposed different gap-filling approaches to identify an appropriate method that is adapted to a target variable. As a result, many gap-filling techniques have been developed, varying in complexity and ranging from simple to extremely complex approaches. The simplest methods are based on the imputation of data gaps according to the information contained in the same time series, assigning the data before or after the gap, or applying the local or the sample average of the series (Pappas *et al.*, 2014; Gil-Guirado and Pérez-Morales, 2019). Another technique widely used in the reconstruction of the precipitation datasets is the Normal Ratio (Paulhus and Kohler, 1952; Longman *et al.*, 2018;). Others, such as the kNN weighted averaging method, consist in generating reference series in a location formed by the weighted average of the data observed in neighboring stations (Beguería *et al.*, 2019). Yet other approaches consider multiple linear regression models (Mora *et al.*, 2014; Tardivo and Berti, 2014; Serrano-Notivoli *et al.*, 2017), the Inverse Distance Weighting algorithm (Bielenki Junior *et al.*, 2018; Lu and Wong, 2008; Armanuos *et al.*, 2020) and, more recently, strategies such as tree based methods and machine learning algorithms (Körner *et al.*, 2018; Bellido-Jiménez *et al.*, 2021), or the combination of several gap-filling methods (Armanuos *et al.*, 2020; Longman *et al.*, 2020).

Generally, gap-filling approaches focus on minimizing the error (*e.g.*, the Root Mean Square Error, RMSE) using a leave-one-out cross-validation method that allows observed and estimated values to be compared, or approaches maximizing the goodness of fit in regression models for example through the coefficient of determination, R^2 (Teegavarapu and Chandramouli, 2005; Vicente-Serrano et al., 2009; Singh and Xiaosheng, 2019).

Given the different available techniques and results, this study examines the effect of four gap-filling approaches on the long-term temperature and precipitation trends in the Iberian Peninsula. We assessed the trend magnitude and significance, and analyzed the spatiotemporal patterns, focusing on how the different gap-filling methods influence the completion of the climatic dataset, the long-term trend, and the spatiotemporal patterns. The research applies the *Emmental* program implemented in the MiraMon software (Pons, 2004) to large datasets of month-to-month records of these two major climatic variables in the Iberian Peninsula (Spain, Portugal, and Andorra), as described in the methodology section.

We hypothesize that (i) temperature and precipitation variables will exhibit different gap-filling method parametrizations according to their dataset structure and spatiotemporal irregularity (with a denser spatiotemporal network for precipitation). (ii) The gap-filling method will influence the magnitude and significance of long-term trends in temperature and precipitation according to the method itself and the spatiotemporal structure of the datasets. And (iii) the proportion of data gaps in the dataset may condition the performance of the gap-filling methods according to the structure of the dataset.

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2. Materials and methods

2.1. Study area

The study area is defined by the Iberian Peninsula, comprising Spain, Portugal, and Andorra, a context located in the border region between tropical and semi-tropical climates, which offers ideal conditions to evaluate climate change in the northern hemisphere. This context is characterized by a significant climatic variability, with dry conditions in the southeast Mediterranean, continental regimes towards the center, and humid conditions in the north-west Atlantic context. Furthermore, due to its location, global warming is expected to become especially evident in the peninsula due to its sensitivity to climate change. Therefore, climate monitoring is essential to adopt appropriate climate change adaptation measures.

2.2. Climatic datasets

Datasets of monthly mean temperature (MT) (in d°C) and precipitation (PR) (in dmm) were compiled from observations provided by the Spanish (Agencia Estatal de Meteorología (AEMET)) and the Andorran (Servei Meteorològic Nacional) meteorological services. Furthermore, additional stations were collected from the Sistema Nacional de Informação de Recursos Hídricos (SNIRH) of Portugal. As a result, large datasets were generated for each climatic variable. We selected stations with observations spanning from January 1950 to December 2019 for each climatic variable, a seventy-year period during which the number of observatories and observations significantly varied. Details about the spatial distribution are provided in Figure 1 while Figure A1 in Appendix 1 provides details of the temporal distribution of the observations. A higher proportion of gaps was concentrated in the first decades of the period.

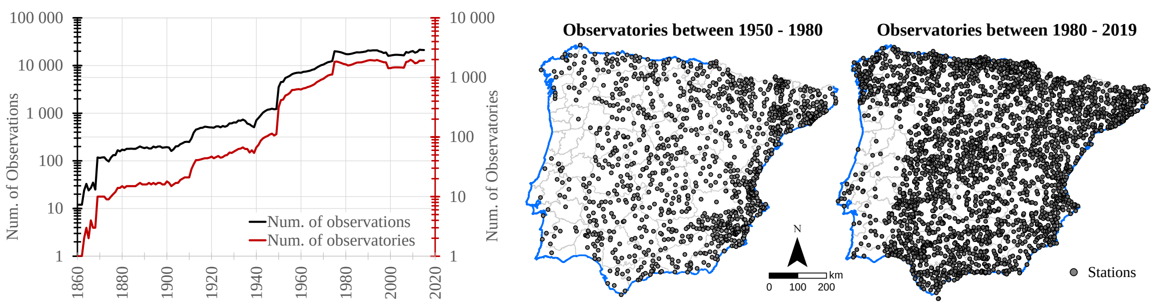

Figure 1. Mean temperature dataset structure: spatiotemporal distribution of observatories in the Iberian Peninsula

As shown in Table 1, almost 30 % of the MT dataset corresponds to observations, and 70 % are data gaps. Precipitation (PR) improves these proportions, with nearly 35 % observations and 65 % gaps. Furthermore, the table shows that if we divide the whole dataset into two periods, P1:1950–1979 and P2:1980–1979, the percentage of gaps in P1 (30 years of observations) was more prominent than in P2 (40 years of observations), with no differences between months.

The analysis periods could be established according to the year when new stations notably appeared (1975) or when the climatic trend was reported to change (1980). In this study we preferred to use the last of these to analyze the implications of the methods evaluated in this article, because the general interest in the scientific community is more focused on this aspect.

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Table 1. Structure of the climatic datasets (upper part) and gap distributions by month and aggregation of annual observations (lower part).

Var.	Period	Stations	No. Observ.	Completeness	No.Gaps	Gaps (%)
MT	(P1) 1950–1979	1889	256 845	19.59 %	1 054 275	80.41 %
	(P2) 1980–2019	3364	667 427	38.18 %	1 080 733	61.82 %
	(P3) 1950–2019	3642	924 272	30.21 %	2 135 008	69.79 %
PR	(P1) 1950–1979	5374	736 581	26.75 %	2 016 699	73.25 %
	(P2) 1980–2019	7158	1 540 808	41.97 %	2 130 232	58.03 %
	(P3) 1950–2019	7648	2 277 389	35.45 %	4 146 931	64.55 %

Var	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
MT	P1 [1]	6.71	6.72	6.70	6.69	6.69	6.69	6.72	6.73	6.70	6.70	6.68	6.69	7.20
	P2	5.14	5.12	5.15	5.14	5.14	5.15	5.15	5.19	5.16	5.16	5.13	5.19	6.23
	P3	5.81	5.80	5.81	5.80	5.80	5.81	5.82	5.85	5.82	5.82	5.80	5.83	6.65
PR	P1	6.12	6.11	6.09	6.08	6.08	6.10	6.15	6.14	6.10	6.10	6.07	6.10	6.90
	P2	4.81	4.78	4.80	4.78	4.78	4.85	4.90	4.94	4.85	4.81	4.85	4.87	6.37
	P3	5.37	5.35	5.36	5.34	5.34	5.39	5.44	5.45	5.39	5.36	5.37	5.40	6.59

[1] Values represent the split of percentages of gaps by months, while the annual percentage is estimated when all month values are available. All percentages in the table are referred to the maximum possible observations in each period.

2.3. Data preparation and filtering

In an initial exploratory phase, time series were quality controlled by testing data coherence within the series and with close neighbors, excluding outliers. During the filling stage, the stations with less than 240 observations (28.5% of a potential of 70 years x 12 months = 840 observations) only served as data providers and were not completed during the filling process (Figure 2). Therefore, we considered the stations with more than 20 years of monthly data to evaluate the choice of the filling method in the long-term spatiotemporal climatic trend analysis. This threshold was used based on the assumption of filling stations with a reasonable level of missing data to be reconstructed. However, further analysis would be required to evaluate the repercussions of considering a higher percentage of unfilled stations in the research. Other authors have excluded data series with less than 15 years for reconstruction (Vicente-Serrano *et al.*, 2009).

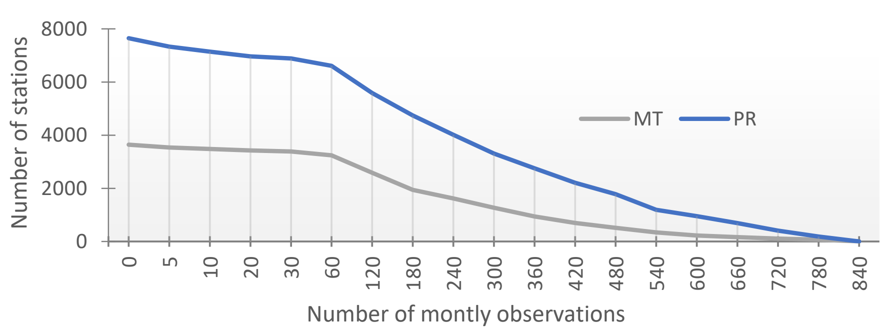

Figure 2. Frequency of stations with a number of monthly observations.

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2.4. *Emmental* gap-filling approaches

The *Emmental* gap filling program is implemented in the MiraMon Geographic Information System and Remote Sensing software (Pons, 2004), providing four strategies to fill time series with associated parametrization.

The **MONTH** method ('*M_*' suffix in parameters) considers other months of neighbor years of the same station. Thus, the main parameter to be set by the user is the maximum number of months of neighbor years to the gap—*i.e.*, as a temporal buffer—used to estimate the filling value (*M_YESTIM*). Then the average or the median of the neighbor years (as local approximates) can be used to approximate the gap value.

The **SIMILAR** method ('*S_*' suffix in parameters) explores the most similar series among spatially nearest stations. The similarity is computed between pairs of 'n' dates time series formed by the problem station and each station of a set of nearest neighbor stations. The main parameters to be set are the number of years—*i.e.*, a temporal buffer—from the gap and among the neighbor years (*S_YESTIM*) and the maximum number of nearest neighbor stations—*i.e.*, a spatial buffer—used in the similarity analysis (*S_N_NEARST*). The root-mean-square (RMS) and the R^2 can be used to perform the similarity analysis between series: in the first case, the station with the lower RMS provides the value for the gap in the problem station (*S_SUBMET=m*), with the possibility of applying a bias correction, computed as the mean of the differences between the common values for the years compared between stations (*S_SUBMET=o*). However, in the second case, the station with the strongest correlation, R^2 (assuming a minimum R^2 threshold of 0.6) provides the value after applying a linear model fitted with the common values for the years compared between the pair of stations (*S_SUBMET=r*).

In addition, for the MONTH and SIMILAR methods, an extra parameter controls the minimum number of years that will make the gap value estimation reliable (*M_MIN_YESTIM* and *S_MIN_YESTIM*), conditioning the presence of data gaps in the range of selected values, and hence the continuity and contiguity of the selected values around the gap. No gaps are allowed in the temporal selection when *S_YESTIM* = *S_MIN_YESTIM*.

The **REGRES** method ('*R_*' suffix in parameters) uses the nearest stations with data available in the gap year and month at the problem station. A multiple linear regression model is generated with the gap value as the dependent variable, regressed considering a set of independent variables. The user defines the covariates (*VAR_1*, *VAR_2*,...) and the maximum number of nearest neighbor stations (*R_N_NEARST*) included in the regression model. The covariates in this study were the Euclidean distance to the coast (as a measure of continentality), the potential solar radiation (evaluated as the annual average following Pons and Ninyerola, (2008)), the latitude, the longitude, and the altitude.

Finally, the **IDW** method ('*I_*' suffix in parameters) estimates the gap value by interpolating the available data from the nearest stations, considering the Inverse Distance Weighting algorithm. The importance of the data from the nearest stations for the interpolated gap is set by the IDW power parameter (*I_IDW*).

Emmental filling methods have the /TEST parameter, which makes it possible to assess the performance of filling methods in time series datasets and to approximate the parametrizations of the optimum filling method. In test mode, each real observation in a station is considered a gap and simulated according to the rest of the observations and the user's specified parametrizations. According to Table 1,

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about one-third of the whole dataset corresponded to available observations, which were used to derive the best filling parametrizations applied to fill the real gaps in the dataset, representing approximately two-thirds of the whole dataset (white spaces in Figure A1 in Appendix 1). Comparing estimated *vs.* real observations allows us to calculate evaluation statistics for each station and the global dataset: error statistics (*i.e.*, the minimum, maximum, and mean error, and the global RMSE), the goodness of fit of the residuals (the coefficient of determination, R^2, in the SIMILAR submethod), as well as the parametrization filling capacity performed. Nevertheless, there is a trade-off between minimizing RMSE and the filling capacity of the parametrizations, especially in the SIMILAR filling method, and parametrizations with the best performance (minimum RMSE) coincide with a relatively low percentage of gaps filled. It is important to note that SIMILAR uses parameters to control the temporal and spatial buffer, which can compromise the filling capacity according to the parametrizations. This particularity led us to explore an iterative gap-filling strategy, in which the best parametrizations obtained in the test mode were applied to fill the gaps iteratively, ordered by an increasing RMSE. Moreover, the percentage of gaps filled differed in the test mode (one-third of the dataset) from the filling mode (two-thirds of the dataset) due to the dataset structure. Thus, one-third of the real observations were used to fill two-thirds of the real gaps, using the parametrizations that minimize the RMSE estimated with around one-third of the data. Therefore, in the first stage, several testbeds were performed to estimate the optimal parametrizations (minimizing the RMSE) for each filling method, used in the second stage to fill the gaps in the climatic datasets.

2.5. Long-term trend assessment.

In this approach, the long-term trend was estimated in three temporal periods: two separated subperiods (P1: 1950–1979 and P2: 1980–2019), taking into account the splitting points found in previous research (Almarza and Luna, 2016; Carnicer et al., 2019), and the whole period (P3: 1950–2019). The magnitude and significance of the trend were evaluated monthly (*e.g.*, all January's observations, all February's observations), seasonally (*e.g.*, winter determined by averaging: December, January, and February), and annually (assessed averaging 12 months, when available for the year). Month-to-month linear regression was not considered due to the repercussions of the seasonal component for the magnitude and significance of the trend, and thus time series had to be previously de-seasonalized, as was tested. The nonparametric Theil-Sen (Sen, 1968; Theil, 1992) estimator was used to derive the trend magnitude, while the Mann-Kendall (Kendall, 1975; Mann, 1945) test was used to quantify the trend significance. These statistics have been used in several case studies (Alemu and Dioha, 2020; Beguería *et al.*, 2019; Gocic and Trajkovic, 2013; Teegavarapu and Nayak, 2017). The advantages of using nonparametric statistics are that they do not require data to be normally distributed, they have low sensitivity to breaks in inhomogeneous series, and there are abnormal values (Sayemuzzaman *et al.*, 2014). The Mann-Kendall test null hypothesis assumes that there is no trend in the data (random and independently ordered observations), which is tested against the alternative hypothesis, i.e., assuming there is a trend in the data.

The trend magnitude and significance were estimated for each climatic variable, period (*e.g.*, 1950–1979) and data aggregation (*e.g.*, January, spring, or Annual) for the original and filled series, considering at least five available observations. All station trends were considered when filling methods were compared without applying significance restrictions. However, before assessing the trends and significance, the time series were standardized to compare MT and PR patterns. Lastly, applying significance restrictions made it possible to analyze the climatic rate of change in the period. Gap-filling computations were performed with

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the *Emmental* program, and the statistics and trend analysis were programmed in R language, version 4.1.1 (R Core Team, 2022).

3. Results

3.1. Assessment of the Filling method parametrization

The testbeds performed in the test mode provided the best parametrizations, which minimized the overall RMSE and were used to fill the gaps. In the MONTH method, we tested the maximum number of years (*M_YESTIM*) from the year of the gap and among the neighbor years in the problem station, combined with the parameter (*M_MIN_YESTIM*) that sets the minimum number of years that makes the estimated value reliable. For instance, considering *M_YESTIM*=10 neighbor years from the year of the gap and *M_MIN_YESTIM*=6 years, means that at least six dates were available to approximate the gap value, while four or less were data gaps (*e.g.*, o–o–o–x–x–[simulated gap]–x–o–o–o–x, where 'o' denotes real observations and 'x' are gaps). The previous parameters ranged from 5 to 30 neighbor years, considering the mean and the median to approximate the gap. The results showed that the local average performed slightly better than the local median for MT and PR. Furthermore, the gap-filling capacity of the parametrization increased at the expense of degrading the overall RMSE when data gaps were allowed in the selected values through the *M_MIN_YESTIM* parameter (the lack of continuous and contiguous observations to approximate the simulated value increases the estimated error). For MT, a minimum RMSE of 14.5 d°C (*i.e.*, 1.45°C) was achieved with a *M_YESTIM* ranging between 10 and 18 years and filling between 72.13 and 86.81 % of gaps. For precipitation, a minimum RMSE of 477.7 dmm (*i.e.*, 47.77 mm) was achieved with a *M_YESTIM* of 30 years, filling 62.51% of gaps. This last result suggests that the larger the number of years, the lower the RMSE and the gap-filling capacity (Figure 3). It is essential to note that the RMSE corresponded to the overall evaluated dataset, with almost a million observations for MT and more than two million for PR (Table 1), which justified minimizing the overall dataset RMSE (see the RMSE spatial distribution in Figure 7).

The parametrizations were ordered by increasing RMSE and decreasing temporal buffer (Δ RMSE; ∇ YESTIM) and used to fill the real gaps iteratively. With this strategy, we preferentially used parametrizations providing the lower RMSE (long-length series), reducing the temporal buffer in the later iterations.

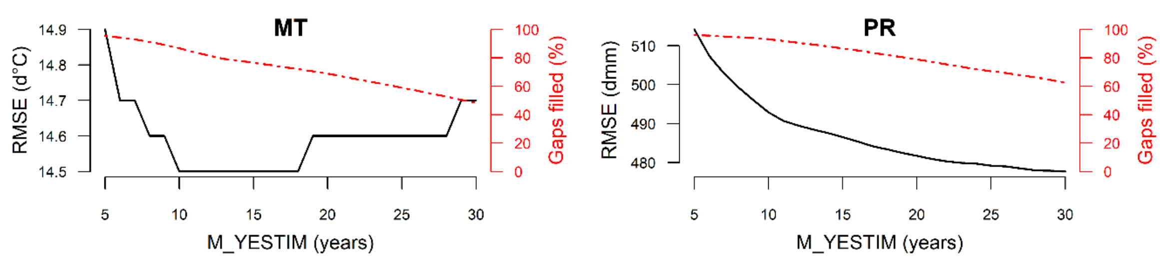

Figure 3. MONTH 'test' mode RMSE and gap-filling results, estimated considering 'n' neighbor years from the gap. The period 1950–2019 series is used.

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In the SIMILAR method, the following parameter combinations were evaluated: *S_YESTIM*, *S_MIN_YESTIM* (with the same definitions as for the MONTH method), and *S_N_NEARST*, which sets the number of the nearest neighbor stations used to estimate the similarity. We also used three submethods ('r', 'o' and 'm') to assign the gap value in the problem station. The results showed that the 'r' submethod obtained the lowest overall RMSE, followed by 'o' and 'm'. For MT, the lowest RMSE of 7.1 d°C was obtained when similarity was evaluated considering long-length series of between 25 and 30 years around the year of the gap and within 5 nearest neighbor stations, resolving between 11.51 and 18.23 % of the gaps. The maximum filling capacity, over 95.30 %, was achieved when similarity was evaluated considering a short-length series of 5 years within 150 nearest stations. For PR, analogous patterns were observed. With a long series of 23 years around the gap and 5 nearest stations, the overall RMSE was minimized to 207.2 dmm, resolving 34.72 % of the simulated gaps. The maximum filling capability of 95.47 % was achieved considering short-length series of 5 years evaluated within the 150 nearest stations. In the upper part of Figure 4, the *S_N_NEARST* is fixed to 5 nearest stations for MT and PR. The RMSE and gap-filling capacity decreased when the temporal buffer (*S_YESTIM*) was increased. In the lower part of the figure, the temporal buffer (*S_YESTIM*) was fixed to 25 years, increasing the RMSE and the gap-filling capacity when the number of nearest stations considered to evaluate similarity was increased.

Similarly to the previous MONTH method, parametrizations were ordered by increasing RMSE, decreasing the temporal buffer, and increasing the newly added spatial buffer (Δ RMSE; ∇ YESTIM; Δ NEARST). Thus, parametrizations with a long-length temporal buffer and near the problem station were preferentially used, reducing the temporal and increasing the spatial buffer in the later iterations. During the process, it is important to note that short-length stations, tagged as data providers, were iteratively restituted to their original form, thus avoiding data propagation through them.

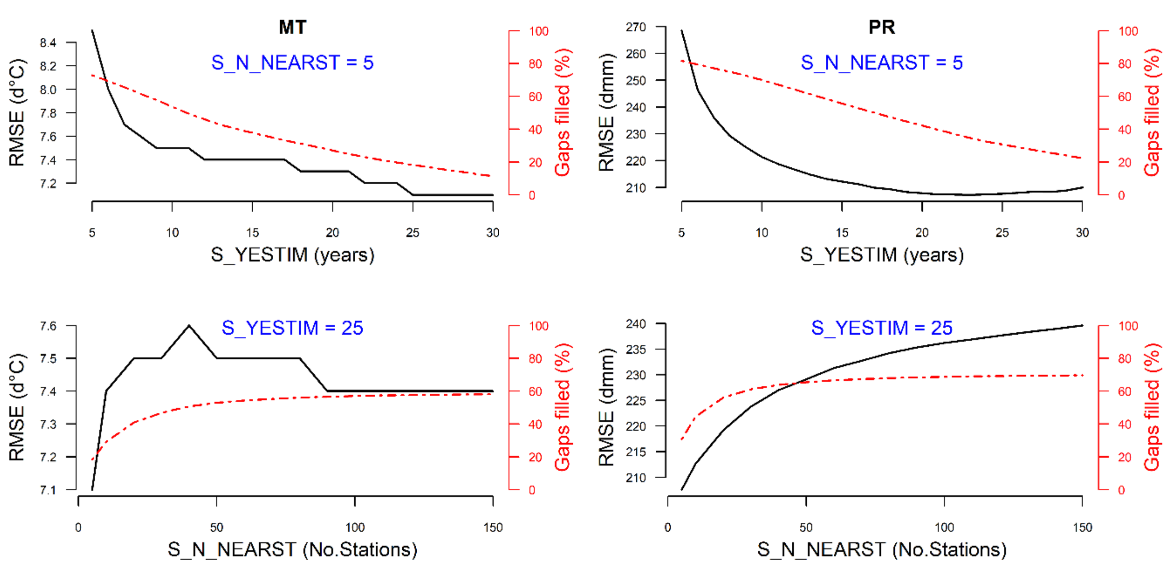

Figure 4. SIMILAR 'test' mode RMSE and gap-filling estimates, considering 'n' neighbor years from the gap and 'm' nearest stations. Results for the best submethod ('r') are shown.

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The REGRES method requires the stations to be intersected with a set of predictors to generate a multiple linear regression model (the Euclidean distance to the coast, the potential solar radiation, the latitude, the longitude, and the altitude, in our case). We tested the model performance considering the variables and the *R_N_NEARST* parameter (same definition as for the SIMILAR method). All variables were included in the model, and each predictor value was weighted according to its relative contribution to the overall prediction. The least-squares estimator ensures the maximal prediction of the gap to be filled from the set of variables used. The main difference with the previous methods was that the filling capacity was not compromised, and each parametrization filled 100 % of the gaps. Thus, the method showed an asymptotical RMSE decrease, achieving a minimum RMSE of 10.5 d°C for the 45 nearest stations in the case of temperature and a RMSE of 236.3 dmm for the 35 nearest stations in the case of PR (Figure 5).

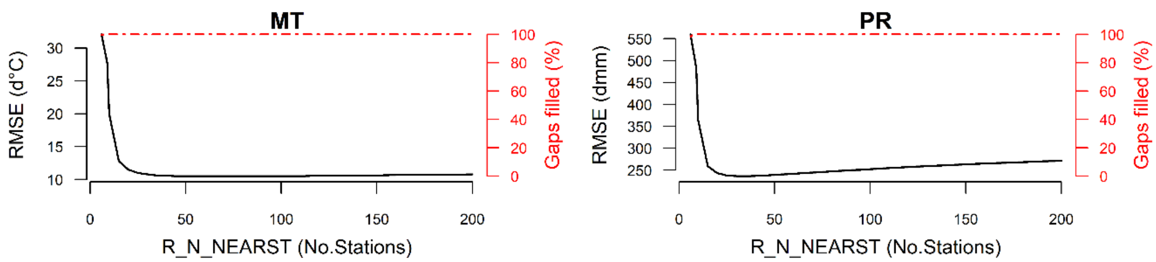

Figure 5. REGR 'test' mode RMSE and gap-filling results, estimated considering a set of covariates and 'm' nearest stations.

Finally, the IDW method was tested considering all the parameter combinations of a set of exponent values (*EXP=1,2,3*) and the *I_N_NEARST* parameter (same definition as in SIMILAR). Similarly to REGR, the filling capacity of the method was not compromised, as parametrizations filled 100 % of the gaps. Therefore, the results showed a minimum RMSE of 13.2 d°C for MT and 221.5 dmm for PR, considering parameters of *EXP=1* and 7 nearest stations (Figure 6).

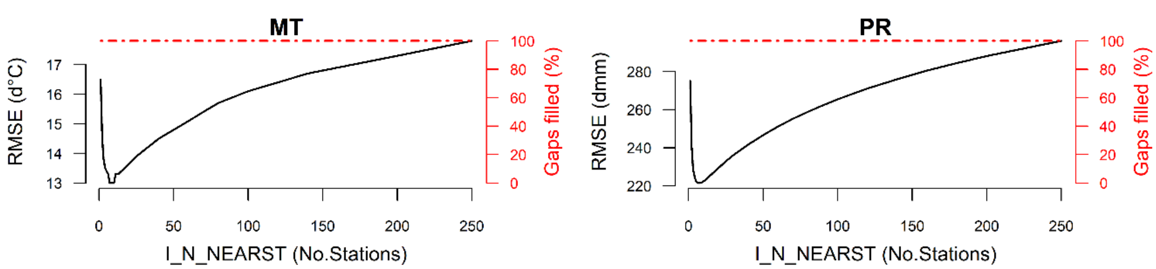

Figure 6. IDW 'test' mode RMSE and gap-filling results, estimated considering 'x' exponent values and 'm' nearest stations.

Figure 7 shows the RMSE spatial distribution. MONTH was the method with the highest overall RMSE, followed by IDW, REGR, and SIMILAR for temperature. REGR, and especially IDW, showed higher estimated errors in mountain areas, especially in the Iberian Peninsula's Atlantic, center and Mediterranean contexts. Likewise, MONTH had the largest overall RMSE for precipitation, and lower

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differences were observed between IDW, REGR, and SIMILAR. Unexpectedly, the north-west Atlantic context showed a higher overall RMSE compared with the Mediterranean. This pattern suggests that areas with high precipitation rates derived the larger errors, mainly associated with the high spatial variability of the precipitation.

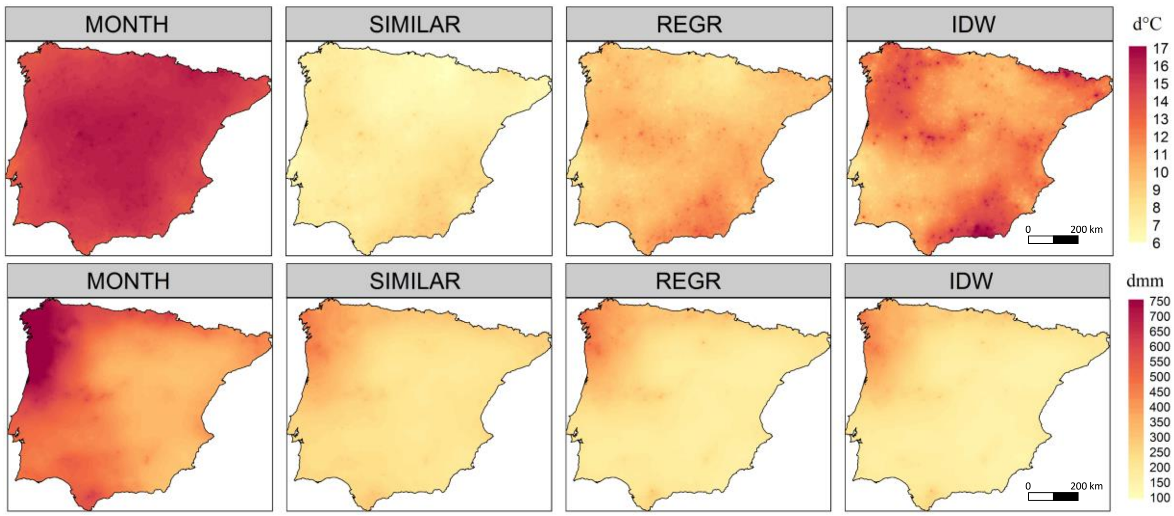

Figure 7. RMSE spatial distribution for temperature (upper) and precipitation (lower).

Table 2 shows the summary of the different parametrizations explained. In the ranking, SIMILAR clearly provides the best performance for MT even though it exhibits a trade-off between minimizing RMSE and the percentage of gaps filled, followed by REGR, IDW, and MONTH. Equally for PR, SIMILAR provides the best performance, followed by IDW, REGR, and MONTH.

Table 2. Parameterizations estimated in "test mode”. Three different cases are shown: minimizing the overall RMSE (white rows), maximizing the filling percentage (dark gray), and a trade-off between the two (light gray). Filled percentages correspond to simulated gaps (see section 2.4.)

	VAR	SUBMET	YESTIM	MIN_YESTIM	Filled (%)	RMSE (d°C)‖(dmm)
MONTH	MT	m	18	18	72.13	14.5
		m	7	7	92.93	14.7
		m	5	5	95.35	14.9
	PR	m	30	30	62.51	477.7
		m	9	9	93.95	496.0
		m	5	5	96.13	514.2

	VAR	SUBMET	YESTIM	MIN_YESTIM	N_NEARST	Filled (%)	RMSE (d°C)‖(dmm)
SIMILAR	MT	r	30	30	5	11.51	7.1
		r	6	6	70	94.27	8.5
		r	5	5	150	95.35	9.9

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	PR	r	23	23	5	34.72	207.2
		r	7	7	90	94.60	284.3
		r	5	5	150	95.47	361.8

	VAR	VARIABLES	N_NEARST	**Filled** (%)	**RMSE** (d°C)||(dmm)
REGR	MT	Latitude+Longitude+Altitude+ Dist.Coast+Solar radiation	45	100.00	10.5
	PR		35	100.00	236.3

	VAR	EXP	N_NEARST	**Filled** (%)	**RMSE** (d°C)||(dmm)
IDW	MT	1	7	100.00	13.2
	PR	1	7	100.00	221.5

3.2. Assessment of the completed datasets

The parametrizations described were applied to fill the gaps in the climatic datasets. MONTH and SIMILAR parametrizations were sorted and used iteratively to fill the climatic datasets. They achieved a high level of gap filling, comparable to that obtained through IDW and REGR; detailed lists are in Table A3, Appendix 1. The dataset completion almost achieved a complete filling: in the case of MT, the percentage was 99.98 % with MONTH and 99.95 % with SIMILAR, while in the case of PR, MONTH and SIMILAR completed 100 % of the gaps. Finally, the REGR and IDW methods completed 100 % of the MT and PR datasets.

The iterative gap-filling strategy showed different behaviors (Figure 8). MONTH increased the quantile 5 % (Q05) and decreased the quantile 95 % (Q95) for both MT and PR. For MT, the mean (MEAN) and the standard deviation (SD) decreased. Nevertheless, for PR, the mean showed an irregular pattern, but the standard deviation decreased. With SIMILAR, in the case of PR, the extreme quantiles (Q05, Q95) and the mean increased while the standard deviation decreased. However, for MT, the extreme quantiles and the mean decreased, but the standard deviation showed an irregular pattern. The number of gaps filled (NrOBS) increased progressively to a maximum around the 60th iteration, significantly contributing to the first iterations (ItOBS) in the filling process.

3.3. Repercussions of the filling method for climate trend analysis

The repercussions of the filling methods for long-term trends were evaluated considering stations with more than 20 years of original observations. The trend magnitude and significance were assessed using the Theil-Sen and Mann-Kendall estimators for the analysis periods.

According to Figure 9, all methods showed a similar behavior except MONTH, which showed a flattening pattern related to the method itself. The method uses the observations in the problem station to approximate the gap value by the local mean or median. Due to the lower number of observations in P1, the flattening effect was more intense than in P2. The propagation of values during iterations reduced the data variance, particularly in P1. This pattern was observed both for MT and PR. This can also be seen in the increase in the Q05 and the decrease in the Q95 in the MT and PR values (Figure 8).

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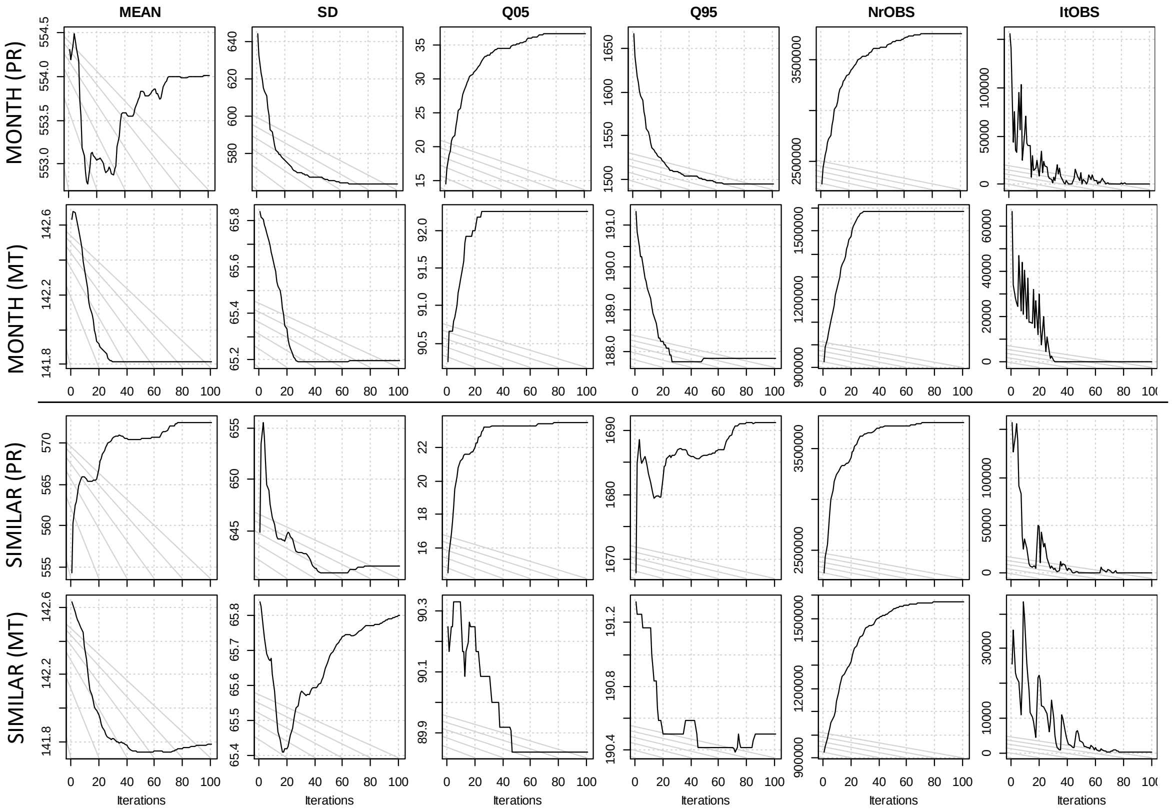

Figure 8. Monitoring the evolution of statistics during the iterative gap-filling. The whole dataset (1950–2019) is monitored. On the vertical axis, units are d°C for MT and dmm for PR.

Conversely, long-term trends denoted equal patterns in the other methods, but a higher dispersion between methods was observed in P1 (Table A2, Appendix 1). IDW in P1 showed a slightly higher dispersion than the other methods (the standard deviation of the trend was ± 0.45 for IDW, ± 0.25 for MONTH, ± 0.33 REGR, and ± 0.34 SIMILAR). For PR, larger differences were expected between filling methods due to the larger RMSE observed in the test mode. However, all the methods except MONTH predict equal climatic trends as in the case of MT. Detailed correlation matrices between the filled datasets are shown in Table A1 in Appendix 1. This similar pattern is consistent in all monthly trends.

Interestingly, when the spatial representation of the trends was analyzed (Figure 10), differences in the spatial patterns increased. In the case of MT and during P1, MONTH denoted the same flattening effect previously observed. However, IDW systematically showed larger trends in mountain range contexts, contrasting with REGR and SIMILAR. Moreover, similarities between IDW and REGR patterns were also observed. However, the methods differ from each other most significantly in the months August and September. Minor spatial differences between methods in all months were observed during P2. For instance, the IDW singular pattern in mountain contexts disappeared. Conversely, for PR, the spatial patterns observed in both periods were similar for the different methods, except for MONTH, which also occurred

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in the case of MT. The lack of a clear trend in the spatial patterns was associated with an alternation between wetter and dryer years in the series, which produced a more similar spatiotemporal pattern between methods.

We analyzed standardized series to compare MT and PR long-term trends. Figure 11 allowed us to identify a clear reduction in the dispersion (interquartile range) of the assessed trends between the original unfilled series and the SIMILAR selected filled dataset. We used the SIMILAR method for comparisons as it had the best performance during the 'test mode' stage. Trend patterns derived from the original and filled datasets were consistent between them. The most significant dispersion occurred in P1. When the MT and PR trends were compared, the MT denoted the largest dispersion. The trend variability was larger in the original series and smaller in the filled series. Moreover, a more significant reduction in the trend variability was observed in the entire period.

3.4. Climatic trend analysis.

We compared long-term trends considering all the stations without significance filter application for the whole period (1950–2019). In Table 3, a reduction in the number of stations was observed. For temperature, the reduction was less critical, as 71 % were significative trends. However, only 28 % were significative for precipitation. Therefore, even though the sign of the trend was equal (with and without the application of the significance filter), the magnitude of the trend of the significant series was logically larger. Considering the magnitude of the temperature trend, summer was the season with the largest trend (0.276 °C/decade), while autumn showed the lowest (0.211 °C/decade). Overall, an increase of 1.45 °C occurred in the whole period (0.21 °C/decade), considering the annual tendency. On the other hand, precipitation showed different seasonal patterns. A significant decrease was detected for winter (-18.746 mm/decade) and spring (-14.363 mm/decade), and an increase for autumn (6.894 mm/decade). Overall, figures showed a decrease of -233.748 mm (*i.e.*, -31.964 mm/decade × 7 decades = -233.748 mm) in the whole period considering the annual trend (Table 3).

Temperature patterns can be observed in Figure 11. Thus, winter followed a similar pattern during P1 and P2, with January and February tending to be warmer, but December did not have a clear tendency. In the case of spring and summer, a clear cooling tendency was observed in P1, but this pattern was inverted in P2. Regarding autumn, September showed no clear changes between periods, but October significantly inverted to a warmer trend in P2. Lastly, November showed a cooling pattern in P1 but was slightly warmer during P2. From an annual point of view, P1 showed a clear cooling trend, inverting the trend to a warmer one in P2. Finally, considering the whole period, all months showed an overall warming tendency.

In the case of precipitation, in winter, the patterns observed were similar in both periods, but February showed a slight decrease in P2. In spring, a wide variability was observed: March inverted from a negative tendency in P1 to a positive one in P2; May showed the opposite pattern, and April showed no clear tendency in any case. Summer showed no tendencies in either of the two periods. Autumn had an increasing tendency in all months in P2. From an annual point of view, no changes in the trends between periods were observed. Finally, no clear increasing or decreasing tendency was reported for any of the months considering the whole period.

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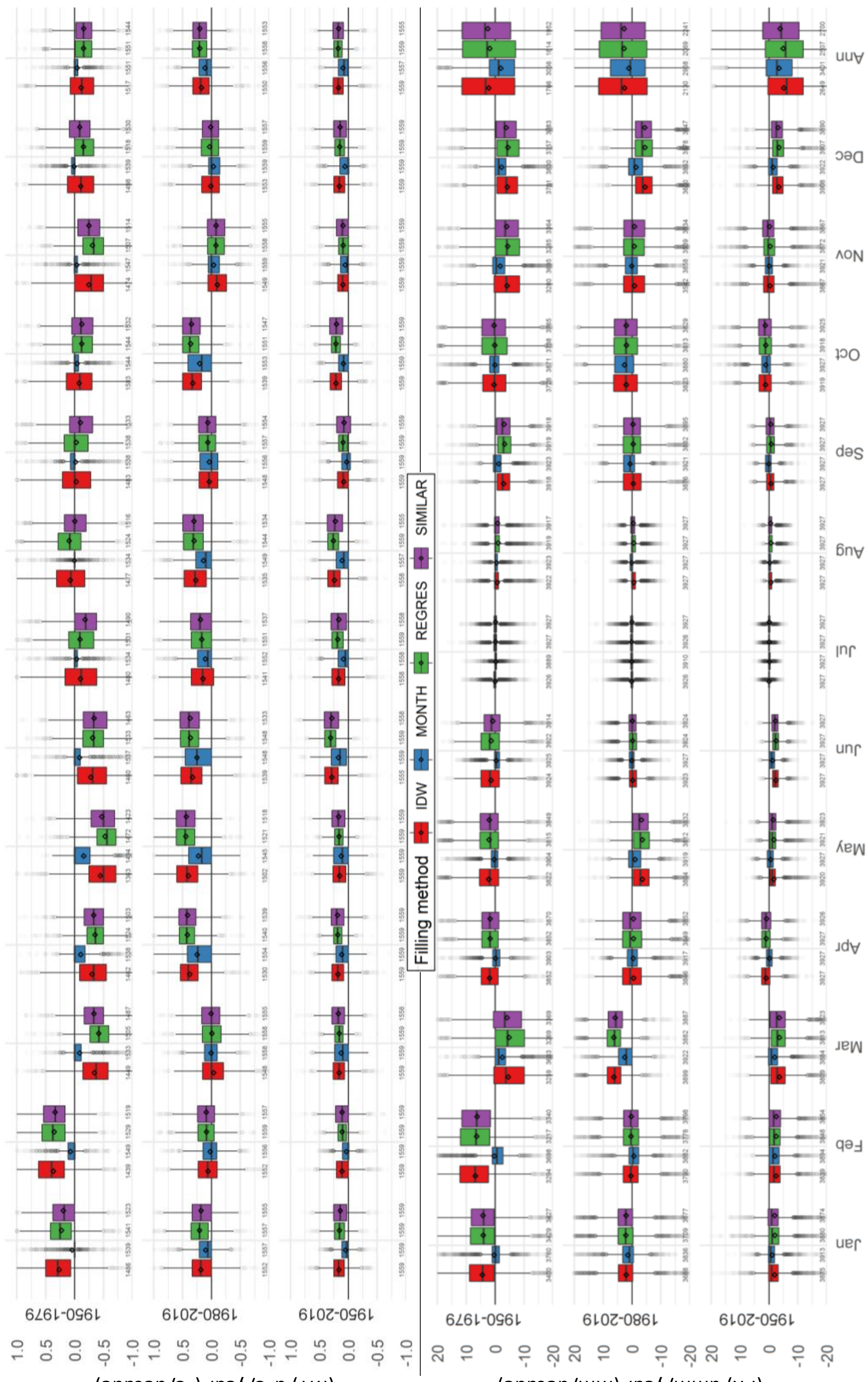

Figure 9. Mean temperature and precipitation long-term trend patterns evaluated for each filling method, temporal aggregation, and time period. Figures under the boxes refer to the number of gap-filled stations considered in each case. In the vertical axis, d°C/year and °C/decade (MT), and dmm/year and mm/decade (PR) are equivalents.

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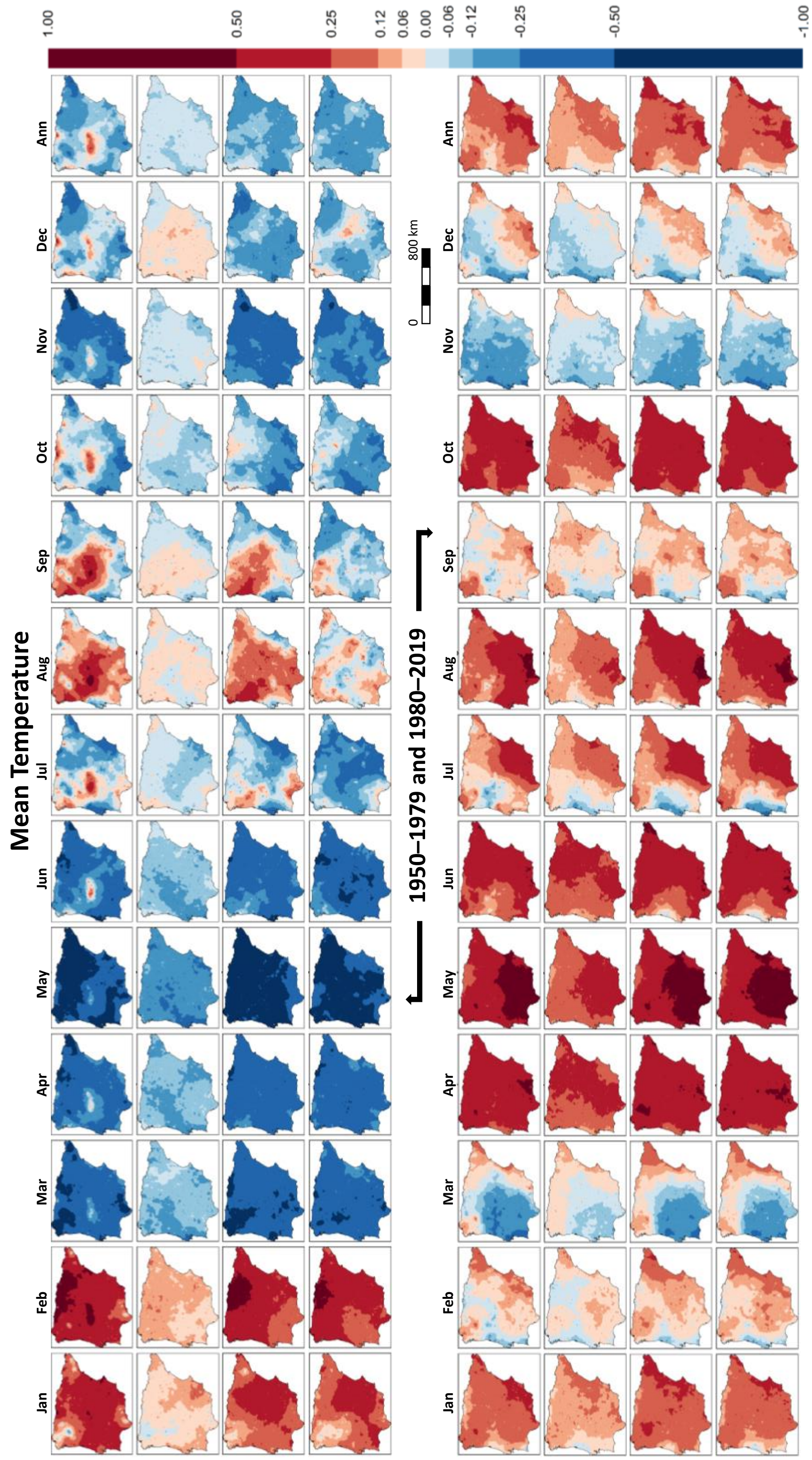

Figure 10. Mean temperature spatiotemporal trend patterns between 1950–1979 and 1980–2019, evaluated for each filling method. Trend values (not standardized, without MK filter) in d°C/year (°C/decade).

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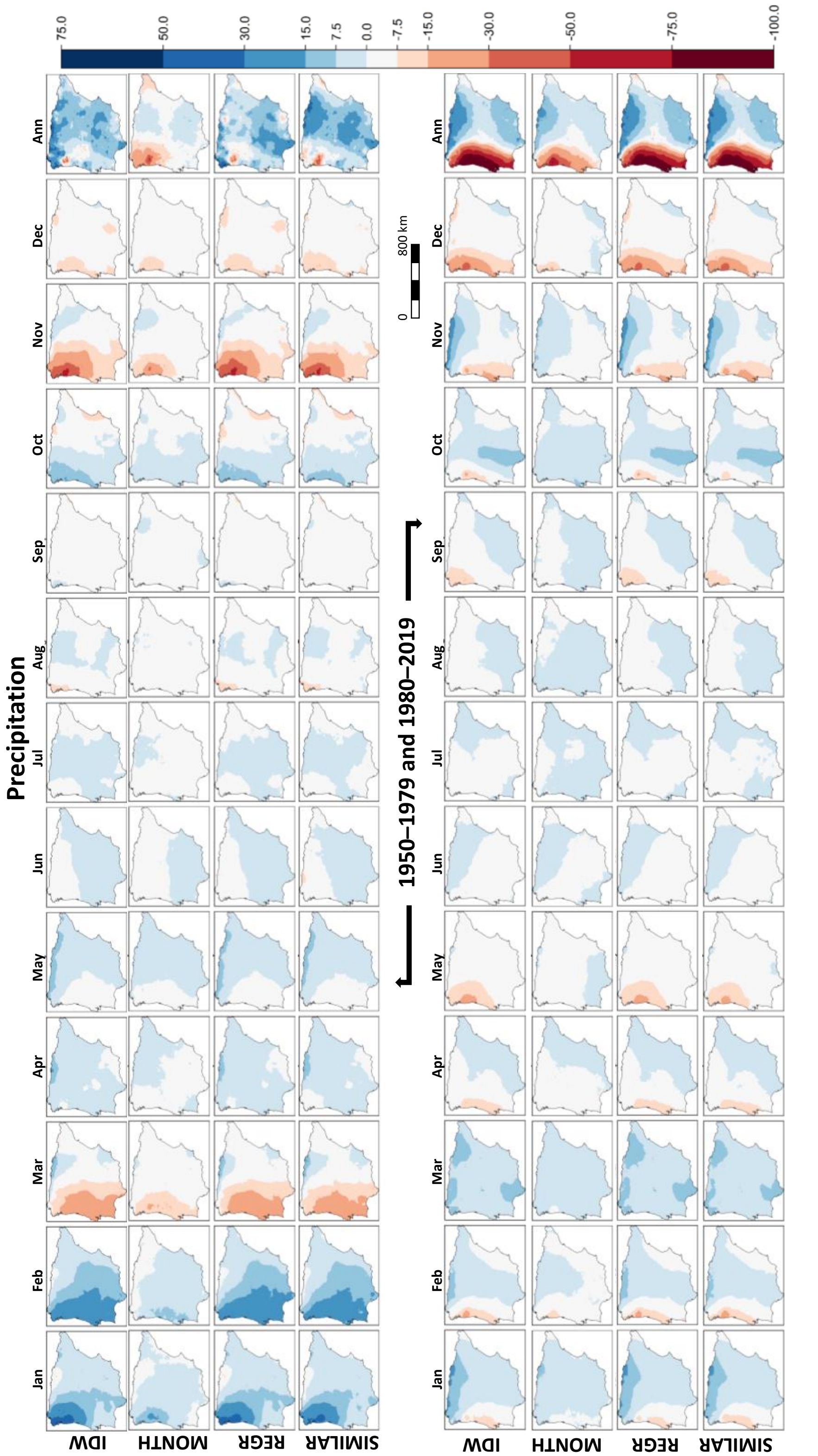

Figure 10 cont. Precipitation spatiotemporal trend patterns between 1950–1979 and 1980–2019, evaluated for each filling method. Trend values (not standardized, without MK filter) in dmm/year (mm/decade).

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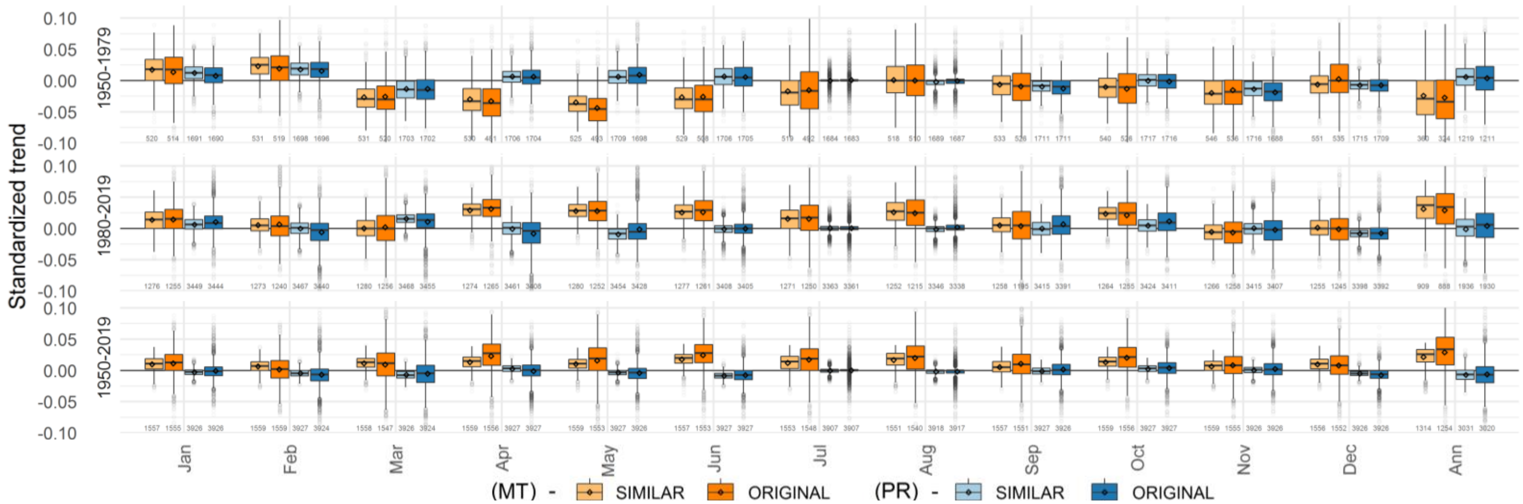

Figure 11. Mean temperature and precipitation standardized trend comparison between original series and SIMILAR gap filled series (without MK filter).

Table 3. Long-term trend comparisons between filled series using SIMILAR with and without a significance filter (MK filter at 0.05 significance). The period 1950–2019 is represented.

Var.	Filtering	Stations	Winter	Spring	Summer	Autumn	Annual	Trend °C||mm/period
MT	All stations	1557	0.133	0.191	0.233	0.135	0.176	1.232
	MK ≤ 0.05	1103	0.215	0.243	0.276	0.211	0.208	1.456
PR	All stations	3927	-7.519	-2.428	-2.556	1.094	-8.890	-62.230
	MK ≤ 0.05	1112	-18.746	-14.363	-4.424	6.894	-31.964	-223.748

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4. Discussion

Incomplete series and data gaps are common in climatic series and must be filled before the series can be analyzed. Gap-filling strategies can resolve this issue in different ways, inducing changes in the spatiotemporal structure of the filled dataset and hence in the related analysis (such as in long-term trends of climate change). For instance, a well-known effect is a reduction in the variance, so that the extreme values of the variable are compressed, which is of decisive importance for the analysis of extreme events phenomena (Acero *et al.*, 2014; Teegavarapu and Nayak, 2017). However, despite the importance of using gap-filling strategies, the consequences and implications of the methods for trends have been analyzed very little considering large climatic datasets, which are mainly affected by structural changes in space and time, such as an increasing number of stations over time (Table 1). In this framework, we analyzed the influence of four gap-filling methods on long-term (1950–2019) temperature and precipitation trends at monthly, seasonal, and annual temporal aggregations in three subperiods (1950–1979, 1980–2019, 1950–2019).

The gap-filling methods showed similar trend patterns at different temporal aggregation and periods. Only MONTH depicted a contrasting pattern related to the filling method itself. The iterative process propagated, by averaging, the observations in the stations and reduced the variability of the observed trends based on the completed dataset. The decrease in the variance in reconstructed datasets has been extensively reported in other research (Serrano-Notivoli *et al.*, 2017; Teegavarapu and Nayak, 2017; Beguería *et al.*, 2019). Thus, MONTH should be used to fill short-length gaps but not to fill a whole dataset, which seems logical. Singh and Xiaosheng (2019) reported filling small gaps using the averaging nearest neighbor, reconstructing long-term gridded daily rainfall time series. Nevertheless, for the rest of the gap-filling methods, similar patterns in the interquartile range were observed (Figure 9).

Although none of the gap-filling methods had large repercussions on the long-term trends, there were spatial differences, especially in P1 (1950–1979). During this period, the number of stations and observations was limited, and the IDW method differs from the others, especially in areas with contrasting elevations. Thus, in a temporal context with a limited number of stations in mountain areas, the nearest stations had a greater influence than those far apart, even more influenced when considering stations geographically more distanced (plain areas) and with more contrasting climatic patterns. The reason why the other methods did not show similar patterns in this context has not been identified.

It is important to note that the long-term trend was determined considering stations with more than 20 years of data in the whole period. However, the distribution of the observations could be uneven in the periods 1950–1979 and 1980–2019 at monthly, seasonal and annual data aggregations. Since five minimum observations was the limit considered to assess trends (which could be a considerably low threshold), this could have affected the larger trend variability observed in the unfilled series in the period 1950–1979. The existence of a larger proportion of short-length time series could lead to the large trend variability. However, gap-filled series showed more coherent trends in this period.

The influence of neighborhood stations was decisive for maximizing the goodness of fit of the models but resolved in a wide variability of cases: 35 and 45 predictor stations for REGR, 7 stations in the case of IDW and SIMILAR showing a better model performance at shorter distances (even though the gap-filling capacity was minimized). This suggests that there is no clear criterium, and testbeds are needed to explore each particular situation. Previous research has found specific solutions for approximating this value (Tardivo and Berti, 2014). Furthermore, the number of years (*i.e.*, temporal buffer) for similarity

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comparisons was decisive. Thus, the goodness of fit is maximized as the temporal buffer becomes more extensive, but this limits the gap-filling capacity of the MONTH and SIMILAR methods.

We expected a stronger influence of the number of available observations in the datasets when long-term trends were compared between periods; however, long-term trend patterns seemed to be hardly affected. One possible reason for this concern is how the N_NEARST parameter works. Each station is provided with a list in which the rest of the stations in the dataset are ranked by proximity. Thus, a problem station always has a candidate nearest station. Filling gaps in periods with a low number of stations and observations can be performed—i.e., only if there are observations at the gap date in the neighborhood—since no geographical restrictions are applied in the models.

Differences between long-term trends of temperature and precipitation were also expected due to the significant differences between the spatiotemporal dataset structures. We found a similar reduction in the trend variability associated with MONTH, with minor differences between the other methods. However, a larger dispersion in the trend was observed in P1, which is associated with a larger proportion of data gaps in the period.

The iterative gap-filling strategy was useful for applying parametrizations ordered according to the patterns observed in the test mode. This was a solution for the exiting trade-off between maximizing model performance and the gap-filling capacity. It also allowed us to explore the evolution of the spatiotemporal structure of the dataset throughout the process. Additional analyses are necessary for identifying differences in filled datasets when parametrizations that are ordered differently are used. Descriptive statistics measures, such as minimum, maximum, mean, and extreme quantiles, monitor the dataset structure during the gap-filling process.

A question not addressed in this article is the change observed in the spatial pattern of temperature and precipitation trends between Portugal and Spain, which are more intensive for precipitation (Figure 9). This effect could be attributable to the existence of differences between the meteorological networks and the possible differences in the data processing carried out by the different climate agencies. The observed effect requires an in-depth analysis to elucidate differences between climatic networks.

Standardized long-term trend comparisons between unfilled and filled series (SIMILAR) found very few differences. Nevertheless, the trend of reducing the variability in temperature and precipitation could be seen again. Focusing on precipitation, this variable has a high interannual variability, implying that regression methods are not the most suitable for detecting climatic trends. Previous research has reported that there is no clear tendency in precipitation and a high spatial and temporal variability (Gonzalez-Hidalgo *et al.*, 2009). This suggests that regression methods have limitations for evaluating the differences between gap-filling methods for precipitation and, therefore, for comparing gap-filling methods based on long-term trends. Thus, it could be of interest to explore other filling approaches. In our analysis, only 28 % of the precipitation trends were significant considering a gap-filled dataset with SIMILAR.

The climate trend in temperature showed a rate of change of 1.45 °C (0.21 °C/decade) in the whole period (1950–2019), slightly inferior to the reported in Luna et al. (2011). Summer was the season with the strongest warming trend and autumn and winter had the lowest. These results are in line with Bilbao *et al.* (2019), who evaluated trends from nine stations from 1950–2011. During the period 1950–1979, a decreasing trend was observed mainly in the spring months, and this pattern was inverted significantly in 1980–2019. In the case of precipitation, no clear trend was reported from an annual point of view. This has also been reported in other studies, which identified no significant trend in the 20th century in annual,

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seasonal, or monthly data (González-Hidalgo *et al.*, 2010). However, an increase in precipitation for autumn and early spring in the period 1980–2019, compared with the period 1950–1979 was observed, which is in line with previous studies by Rodriguez-Puebla *et al.* (1998). In accordance with the authors, a scarcity of rain in summer months rains was observed. However, the highest rainfalls were observed in winter in the period 1950–1979 (in the northwest part of the Iberian Peninsula), evolving towards lower rainfalls in the period 1980–2019 in the entire context.

Considering our first hypothesis, we found that temperature and precipitation exhibited analogous long-term trend behaviors with small singularities. Considering our second hypothesis, we found that only the MONTH method showed a different behavior from the others in terms of the magnitude and significance of trends. Spatial differences between the methods were observed, especially for IDW in the period 1950–1979. This period is characterized by lower availability of observations and stations. However, gap-filling methods were hardly sensitive to the spatiotemporal structure of the data, which can be related to the robustness of the applied filling methods. Regarding the third hypothesis, we found that the proportion of data gaps has not significantly conditioned the adjustment of the gap-filling methods, but a more significant variability of the trends was observed, especially in P1, when the patterns depicted greater spatial diversity.

Several aspects of our results require additional research to bring light to some considerations arising from this work. It is necessary to (i) perform gap-filling approaches in which the temporal structure of the gaps (distribution of the gaps regarding their temporal length) is considered, researching the repercussions of the gap-filling methods for them. In addition, (ii) the changes that occurred in 1975 at the administrative level in the datasets could have had an effect on the long-term trend analyzed; therefore, future studies could focus on thoroughly analyzing the repercussions of these changes.

5. Conclusions

The following conclusions can be highlighted about the different gap-filling methods used and their influence on long-term (1950–2019) temperature and precipitation trends. The methods behave in a similar way with regard to IDW, REGR, and SIMILAR, but contrast with MONTH due to its autocompletion scheme. The spatialization (maps) of the trends depicts the differences between methods, which cannot be seen in the boxplots, where the methods do not significantly differ from each other. Another aspect that should be highlighted is that the gap-filling process induced a clear reduction in the variability of the trends.

To conclude, the gap-filling series has a clear interest for generating continuous surfaces that reduce spatiotemporal discontinuities associated with data gaps. However, climate analyses can be affected by the aforementioned reduction in the data variability derived from the gap-filling processes, leading to a clear tendency towards flattening the derived trends, although they are perhaps more reliable.

6. Acknowledgements

This work was supported by the Spanish Ministry of Science and Innovation and Universities (MCIU) [grant number BES-2016-078262 to Mario Padial-Iglesias]. This work has been partially funded by the Catalan Government under Grant (SGR2017-1690) and by the Spanish MCIU Ministry through the NEWFORLAND research project (RTI2018-099397-B-C21/22 MCIU/AEI/ERDF, EU). Xavier Pons was a recipient of an ICREA Academia Excellence in Research Grant. Some of our colleagues at the Grumets Research Group gave useful insights into this research. We also want to acknowledge the data provided by the different meteorological agencies: AEMET, SNIRH and SMN.

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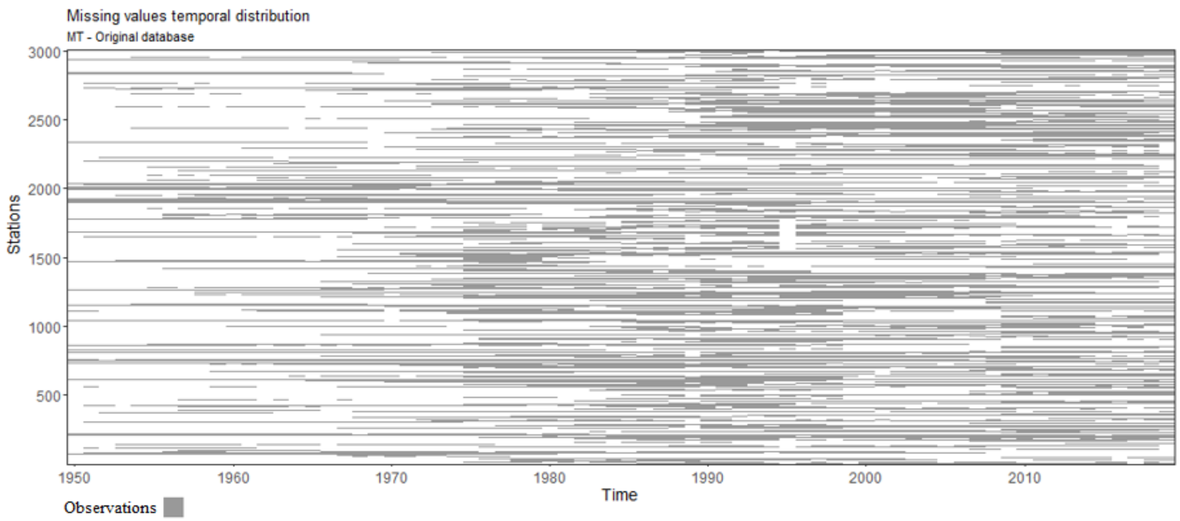
APPENDIX 1



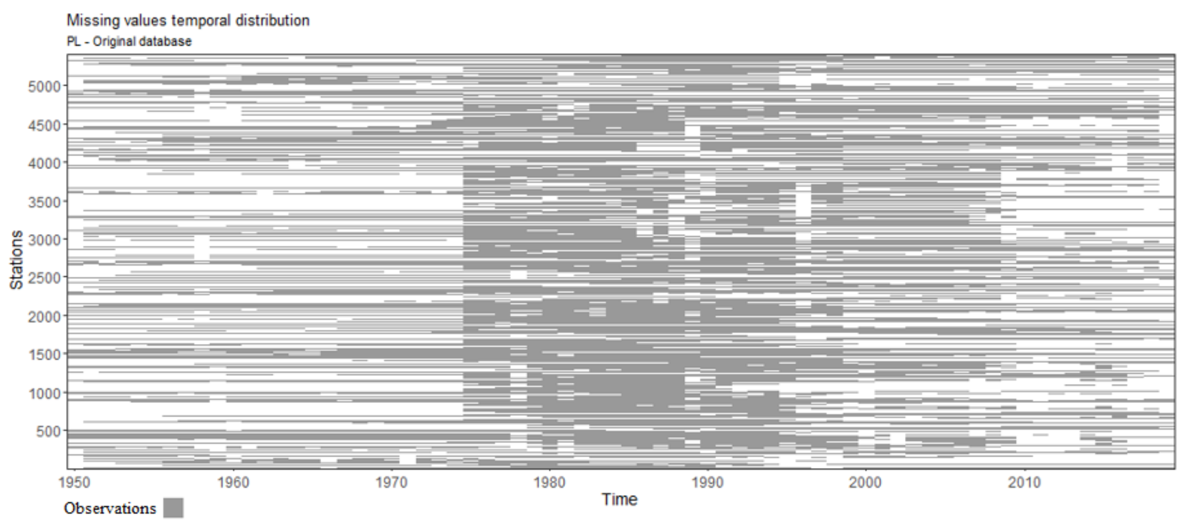


Figure A1. The temporal structure of the mean temperature (MT) and precipitation (PR) datasets. White spaces refer to data gaps.

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Table A1. Pearson correlation evaluated for the different methods and periods, beside the related plots. Lower values in bold.

Period\Method			IDW	MONTH	REGR	SIMILAR		IDW	MONTH	REGR	SIMILAR
1950–1979	IDW	MT	1.000	0.956	0.985	0.973	PR	1.000	**0.590**	0.963	0.915
	MONTH		-	1.000	0.965	0.973		-	1.000	**0.590**	**0.658**
	REGR		-	-	1.000	0.980		-	-	1.000	0.897
	SIMILAR		-	-	-	1.000		-	-	-	1.000
1980–2019	IDW	MT	1.000	0.959	0.989	0.979	PR	1.000	**0.542**	0.962	0.917
	MONTH		-	1.000	0.968	0.974		-	1.000	**0.545**	**0.600**
	REGR		-	-	1.000	0.986		-	-	1.000	0.898
	SIMILAR		-	-	-	1.000		-	-	-	1.000

(1950–1979) **(1980–2019)**

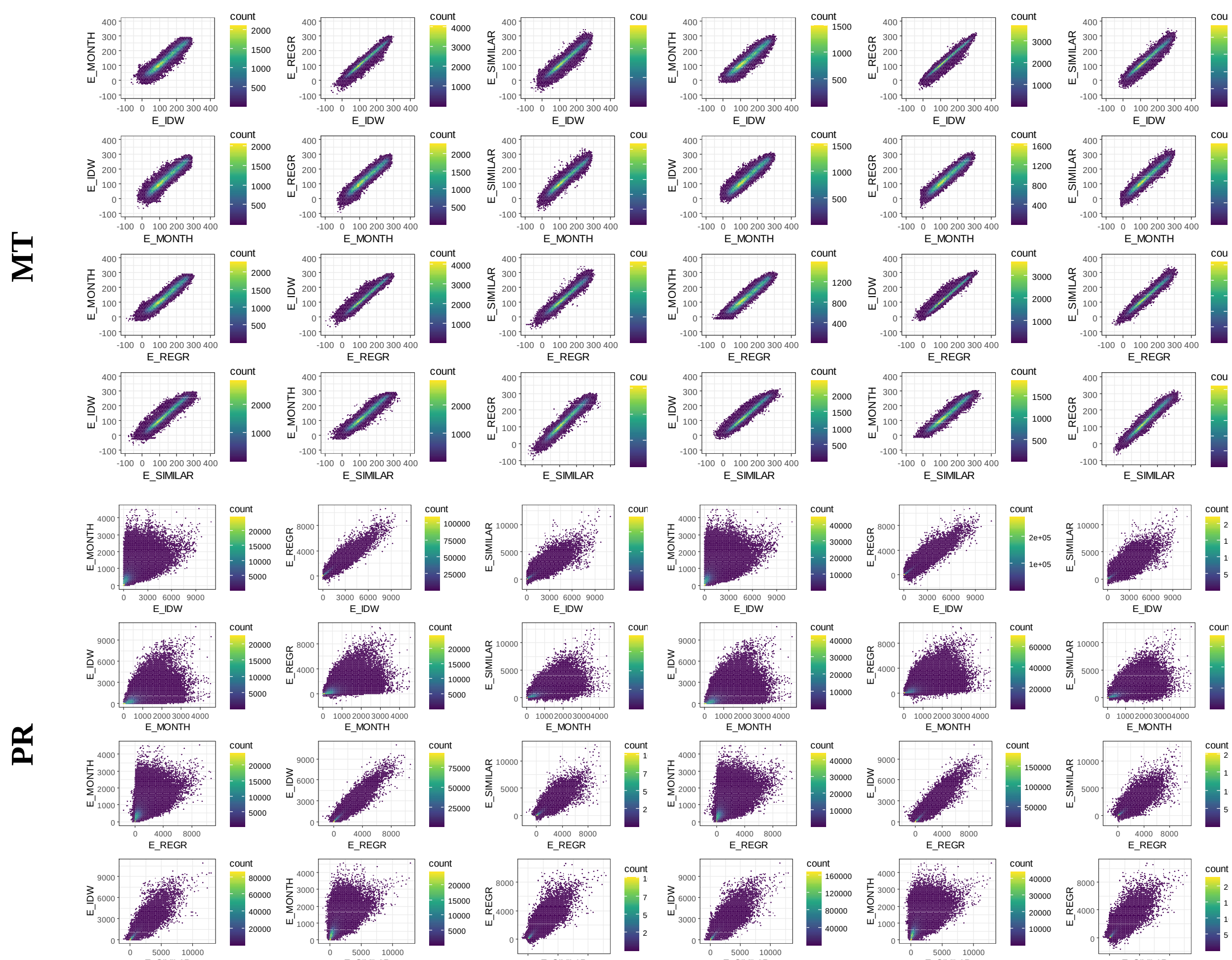

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Table A2. Mean trend and Std. Deviation disaggregated by variable, temporal aggregation, period, and filling method.

Climatic Variable	Temporal Aggreg.	IDW		MONTH		REGR		SIMILAR	
		P1*	P2**	P1	P2	P1	P2	P1	P2
MT (d°C/year (°C /decade))	Jan	0.30 ± 0.43	0.19 ± 0.26	0.05 ± 0.25	0.11 ± 0.20	0.24 ± 0.33	0.21 ± 0.24	0.22 ± 0.34	0.19 ± 0.24
	Feb	0.42 ± 0.45	0.06 ± 0.28	0.08 ± 0.23	0.02 ± 0.22	0.37 ± 0.31	0.09 ± 0.24	0.36 ± 0.33	0.09 ± 0.25
	Mar	-0.40 ± 0.45	-0.04 ± 0.31	-0.10 ± 0.28	0.01 ± 0.21	-0.44 ± 0.30	-0.01 ± 0.26	-0.37 ± 0.35	0.01 ± 0.26
	Apr	-0.35 ± 0.45	0.39 ± 0.29	-0.12 ± 0.26	0.25 ± 0.24	-0.37 ± 0.30	0.43 ± 0.23	-0.36 ± 0.34	0.42 ± 0.24
	May	-0.54 ± 0.47	0.43 ± 0.33	-0.20 ± 0.35	0.24 ± 0.26	-0.56 ± 0.32	0.46 ± 0.27	-0.53 ± 0.37	0.46 ± 0.27
	Jun	-0.32 ± 0.48	0.34 ± 0.32	-0.10 ± 0.28	0.26 ± 0.28	-0.32 ± 0.34	0.37 ± 0.27	-0.39 ± 0.39	0.38 ± 0.28
	Jul	-0.10 ± 0.50	0.15 ± 0.35	-0.05 ± 0.26	0.11 ± 0.24	-0.10 ± 0.39	0.17 ± 0.30	-0.21 ± 0.41	0.20 ± 0.30
	Aug	0.12 ± 0.48	0.28 ± 0.33	0.01 ± 0.25	0.14 ± 0.25	0.11 ± 0.38	0.31 ± 0.28	0.00 ± 0.38	0.31 ± 0.29
	Sep	-0.01 ± 0.47	0.04 ± 0.29	-0.02 ± 0.28	0.04 ± 0.26	-0.02 ± 0.36	0.06 ± 0.24	-0.10 ± 0.38	0.06 ± 0.25
	Oct	-0.08 ± 0.43	0.34 ± 0.28	-0.05 ± 0.25	0.21 ± 0.27	-0.13 ± 0.31	0.37 ± 0.23	-0.13 ± 0.34	0.35 ± 0.25
	Nov	-0.29 ± 0.43	-0.11 ± 0.27	-0.05 ± 0.24	-0.04 ± 0.20	-0.34 ± 0.34	-0.08 ± 0.23	-0.27 ± 0.34	-0.08 ± 0.24
	Dec	-0.12 ± 0.43	0.01 ± 0.28	0.01 ± 0.25	-0.03 ± 0.20	-0.17 ± 0.34	0.03 ± 0.25	-0.10 ± 0.34	0.02 ± 0.25
	Win	0.31 ± 0.42	0.10 ± 0.26	0.06 ± 0.22	0.04 ± 0.19	0.26 ± 0.31	0.12 ± 0.23	0.24 ± 0.29	0.11 ± 0.23
	Spr	-0.44 ± 0.44	0.29 ± 0.29	-0.15 ± 0.28	0.18 ± 0.20	-0.47 ± 0.29	0.33 ± 0.23	-0.43 ± 0.30	0.33 ± 0.22
	Sum	-0.06 ± 0.47	0.27 ± 0.32	-0.04 ± 0.23	0.18 ± 0.23	-0.07 ± 0.35	0.30 ± 0.27	-0.16 ± 0.33	0.32 ± 0.26
	Aut	-0.10 ± 0.42	0.09 ± 0.26	-0.04 ± 0.22	0.07 ± 0.20	-0.15 ± 0.30	0.11 ± 0.22	-0.15 ± 0.30	0.11 ± 0.21
	Ann	-0.12 ± 0.40	0.18 ± 0.26	-0.05 ± 0.20	0.11 ± 0.17	-0.15 ± 0.27	0.20 ± 0.21	-0.16 ± 0.26	0.20 ± 0.20
PR (dmm/year (mm/decade))	Jan	7.92 ± 13.48	2.70 ± 8.85	1.68 ± 9.08	1.97 ± 5.80	7.52 ± 13.54	2.76 ± 8.84	7.23 ± 12.69	2.52 ± 9.12
	Feb	10.34 ± 11.17	-0.17 ± 7.89	1.71 ± 9.07	-0.74 ± 4.93	10.24 ± 11.54	-0.13 ± 7.92	9.42 ± 10.93	-0.31 ± 7.78
	Mar	-7.20 ± 13.59	6.45 ± 4.43	-4.14 ± 9.34	2.57 ± 4.03	-7.24 ± 13.40	6.55 ± 4.60	-6.62 ± 12.85	6.07 ± 4.70
	Apr	2.41 ± 6.33	-0.99 ± 6.84	-0.04 ± 4.06	-0.41 ± 4.14	2.21 ± 6.22	-0.92 ± 6.74	2.04 ± 6.06	-0.86 ± 6.68
	May	2.69 ± 7.10	-4.33 ± 6.33	0.30 ± 4.20	-1.06 ± 3.95	2.61 ± 7.10	-4.26 ± 6.10	2.34 ± 6.72	-3.79 ± 5.82
	Jun	1.42 ± 5.15	-0.21 ± 3.29	-0.35 ± 3.15	0.11 ± 2.23	1.38 ± 5.20	-0.17 ± 3.30	0.77 ± 5.13	-0.07 ± 3.22
	Jul	0.01 ± 2.17	0.15 ± 2.02	-0.23 ± 1.39	0.14 ± 1.35	-0.13 ± 2.17	0.18 ± 2.05	-0.09 ± 2.30	0.10 ± 1.87
	Aug	-0.77 ± 3.57	-0.57 ± 2.00	-0.52 ± 2.12	0.10 ± 1.58	-1.06 ± 3.58	-0.53 ± 1.99	-0.88 ± 3.48	-0.37 ± 1.99
	Sep	-2.92 ± 4.20	-0.72 ± 5.77	-1.22 ± 3.54	0.67 ± 3.94	-3.30 ± 4.17	-0.65 ± 5.76	-3.10 ± 4.36	-0.47 ± 5.35
	Oct	0.65 ± 9.13	1.46 ± 8.32	0.13 ± 5.77	2.86 ± 6.00	0.16 ± 9.21	1.44 ± 8.33	0.18 ± 8.72	1.88 ± 7.69
	Nov	-9.27 ± 17.18	-0.21 ± 11.57	-3.98 ± 12.16	0.56 ± 6.12	-9.37 ± 17.28	-0.18 ± 11.49	-8.47 ± 16.47	-0.47 ± 11.59
	Dec	-4.82 ± 7.46	-7.08 ± 10.92	-2.90 ± 6.09	-1.85 ± 6.49	-5.13 ± 7.83	-7.08 ± 10.97	-4.58 ± 7.41	-6.62 ± 10.60
	Win	16.88 ± 30.69	-9.31 ± 25.60	2.02 ± 18.29	-3.03 ± 13.84	15.83 ± 31.67	-9.27 ± 26.02	15.24 ± 27.56	-9.08 ± 25.21
	Spr	-2.07 ± 24.78	1.55 ± 16.72	-3.49 ± 15.09	-0.09 ± 8.68	-2.25 ± 24.68	1.63 ± 16.42	-1.96 ± 22.71	1.43 ± 15.62
	Sum	0.97 ± 8.65	-1.87 ± 5.73	-0.71 ± 5.39	-0.17 ± 3.62	0.37 ± 8.98	-1.78 ± 5.68	0.44 ± 8.37	-1.46 ± 5.29
	Aut	-9.90 ± 18.59	-3.36 ± 20.81	-3.42 ± 13.84	2.12 ± 9.58	-10.57 ± 18.09	-3.32 ± 20.80	-9.48 ± 17.86	-2.90 ± 18.91
	Ann	10.20 ± 54.04	-9.35 ± 63.93	-3.76 ± 33.49	-2.02 ± 30.16	7.60 ± 54.35	-9.00 ± 63.18	9.08 ± 44.14	-8.98 ± 58.73

P1* refers to 1950–1979, and P2** refers to the 1980–2019 period.

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Table A3. SIMILAR and MONTH parametrizations used for filling temperature datasets. Only the first parametrizations are shown.

METHOD	M_SUBMET	M_YESTIM	M_MIN_YESTIM		% Filled	RMSE
MONTH	m	18	18		72.13	14.5
MONTH	m	17	17		73.67	14.5
MONTH	m	16	16		75.13	14.5
MONTH	m	15	15		76.58	14.5
MONTH	m	14	14		78.00	14.5
MONTH	m	13	13		84.04	14.5
MONTH	m	13	12		79.24	14.5
MONTH	m	12	12		86.45	14.5
MONTH	m	12	11		81.60	14.5
MONTH	m	11	11		89.36	14.5
MONTH	m	11	10		83.93	14.5
MONTH	m	10	10		91.84	14.5
MONTH	m	10	9		86.81	14.5
MONTH	m	28	28		52.66	14.6
MONTH	m	27	27		54.83	14.6
MONTH	m	26	26		60.94	14.6
MONTH	m	26	25		56.94	14.6
METHOD	**S_SUBMET**	**S_YESTIM**	**S_MIN_YESTIM**	**S_N_NEARST**	**% Filled**	**RMSE**
SIMILAR	r	30	30	5	11.51	7.1
SIMILAR	r	29	29	5	12.66	7.1
SIMILAR	r	28	28	5	14.03	7.1
SIMILAR	r	27	27	5	15.39	7.1
SIMILAR	r	26	26	5	16.78	7.1
SIMILAR	r	25	25	5	18.23	7.1
SIMILAR	r	24	24	5	19.66	7.2
SIMILAR	r	23	23	5	21.28	7.2
SIMILAR	r	22	22	5	23.07	7.2
SIMILAR	r	21	21	5	25.02	7.3
SIMILAR	r	20	20	5	26.99	7.3
SIMILAR	r	19	19	5	29.14	7.3
SIMILAR	r	18	18	5	31.18	7.3
SIMILAR	r	29	29	10	21.00	7.4
SIMILAR	r	28	28	10	23.00	7.4
SIMILAR	r	27	27	10	24.98	7.4
SIMILAR	r	26	26	10	53.77	7.4
SIMILAR	r	25	25	10	27.11	7.4

Padial-Iglesias, M., Pons, X., Serra, P., Ninyerola, M. (2022). Does the gap-filling method influence long-term (1950–2019) temperature and precipitation trend analyses? *GeoFocus (Artículos), Revista Internacional de Ciencia y Tecnología de la Información Geográfica*, 29, 5–33. https://dx.doi.org/10.21138/GF.773

Table A3 cont. SIMILAR and MONTH parametrizations used for filling the precipitation dataset. Only the first parametrizations are shown.

METHOD	M_SUBMET	M_YESTIM	M_MIN_YESTIM		% Filled	RMSE
MONTH	m	30	29		66.71	477.6
MONTH	m	30	28		69.99	477.7
MONTH	m	30	30		62.51	477.7
MONTH	m	29	28		68.53	477.7
MONTH	m	29	29		64.53	477.9
MONTH	m	28	28		66.29	478.0
MONTH	m	29	27		71.61	478.2
MONTH	m	28	27		70.13	478.2
MONTH	m	30	27		72.58	478.5
MONTH	m	27	27		67.83	478.5
MONTH	m	27	26		71.60	478.7
MONTH	m	28	26		73.09	478.8
MONTH	m	26	25		72.98	478.8
MONTH	m	27	25		74.48	478.9
MONTH	m	29	26		74.07	479.0
MONTH	m	26	26		69.26	479.0
MONTH	m	30	26		74.76	479.2
METHOD	**S_SUBMET**	**S_YESTIM**	**S_MIN_YESTIM**	**S_N_NEARST**	**% Filled**	**RMSE**
SIMILAR	r	23	23	5	34.72	207.2
SIMILAR	r	22	22	5	37.11	207.3
SIMILAR	r	24	24	5	32.43	207.4
SIMILAR	r	21	21	5	39.55	207.4
SIMILAR	r	25	25	5	30.68	207.6
SIMILAR	r	20	20	5	42.19	207.8
SIMILAR	r	26	26	5	28.96	208.0
SIMILAR	r	28	28	5	25.61	208.3
SIMILAR	r	19	19	5	44.77	208.3
SIMILAR	r	27	27	5	27.26	208.4
SIMILAR	r	29	29	5	24.00	208.9
SIMILAR	r	18	18	5	47.41	209.3
SIMILAR	r	17	17	5	50.05	209.9
SIMILAR	r	30	30	5	22.37	210.0
SIMILAR	r	16	16	5	52.84	211.2
SIMILAR	r	15	15	5	55.65	212.2
SIMILAR	r	28	28	10	38.07	212.4
SIMILAR	r	27	27	10	40.23	212.5