RESPONSE LETTER

Review of Manuscript No.: essd-2019-52
Title: STEAD: A high-resolution daily gridded temperature dataset for Spain
Author(s): Serrano-Notivoli R, Beguería S, de Luis M

GENERAL COMMENTS

The manuscript entitled "STEAD: A high-resolution daily gridded temperature dataset for Spain" shows a very serious analysis of daily precipitation spatial and temporal behaviour in an area where rainfall has been widely studied.
I really enjoyed reading this work about the methodological procedure for generating a high resolution gridded dataset for temperatures in Spain. The paper is, overall, very good and very well written. The objectives proposed are carried out rigorously following a proper structure. Moreover, the discussion is very well developed and carries out a very interesting deepening about the implications of considering different criteria to develop the dataset. The results shown are very consistent.
I do really appreciate the exhaustive quality control over daily temperature data base on paired comparisons between observations and standardized predictions shown in section 3.3, as well as the consideration of the distance to the coast as a source of variation of the local models.
I think that it fits the scope of the journal and can be published as it is, only with very with few corrections.

Thank you for your comments. We have been working in the development of the methodology for a long time, testing different approaches with different parameters. The present version is the most accurate given the great variety of temperature values in a large dataset as the Spanish network.

SPECIFIC COMMENTS

- p. 2 l. 24: "leads to high risks related to..." risks such as?

We added a short sentence in this part of the text to clarify the type of risks.

"[…] such as increments in the frequency and magnitude of extreme events."

- p. 5 l. 5-6: can you explain why you chose these thresholds or it is a subjective criteria?

The thresholds are based on the maximum and minimum absolute records of the Spanish Meteorological Agency (AEMET). This organism checks the reliability of the absolute temperature extremes, being the official ones -30.0 ºC (1963) for minimum temperature and +46.7 ºC (2017) for maximum temperature. We used -35 and +50, respectively, to discard wrong data.

- p. 10 l. 2: "and" instead of "&", the double condition is more understandable this way

Modified as suggested.

- p. 13: I suggest to move Table 1 to the previous page

Thank you. We agree that the table should be near to the beginning of section 4.1. We will report this back to the responsible of the publication production process.

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GENERAL COMMENTS

This manuscript describes a gridded temperature data set at daily and 5 km x 5 km spatial resolution for Spain. Compared to existing similar data sets it represents a valuable contribution considering the data set temporal and spatial resolution, the period covered (1901 to 2014 for continental Spain) and the powerful methodology employed, which favours the use of a high number of stations and the computation of uncertainty of the estimated variables. Overall I think it is a well written manuscript and the data set may indeed be useful for future studies, therefore it is a perfectly suited article and data set for this journal.

Thank you very much for your nice and constructive comments. Our aim was to create a useful dataset for a broad community of researchers, not only climatologists. We are happy to receive such a complete feedback of our research that we are sure that it will greatly improve the final manuscript.

However, I think it requires some clarifications and corrections before being acceptable for publication. For example, it is not clear to this reviewer why the spatial resolution used was chosen and what is the impact of the variable station number (and therefore density) upon the quality of the estimates during the different years considered in the dataset. These details may influence further studies (such as in the interpretation of temporal trends) so I think they should be commented here, in the description of the data set proposed. As explained in more detail below, I propose to modify or add some of the existing figures related to this aspect and also to the global uncertainty and mean error time series.

With the aim of make clear the choice of the 5 x 5 km spatial resolution of the gridded dataset, we added an explanation at the end of the “Input data” section. Furthermore, we also explain that, despite that the methodology includes a final stage when the estimates are standardized with the temporal structure of the original series, minimizing the impact of the number of stations. In addition, the final dataset provides an individual uncertainty value for each daily estimate, which informs about the reliability of the estimates through time. In regard of the use of data for temporal trends, both the standardization of the estimates based on the original series and the associated uncertainty values, provide the required information to assess the long-term trends of each series of estimates.

Another aspect that should be clarified are the data sources. The manuscript describes two institutions (AEMET and MAGRAMA) but in the data set description link provided by the authors in the manuscript, if I understood correctly, 12 providers are listed (which, according to descriptor "dc.relation.isbasedon" are: Spanish Meteorolog- ical Agency (AEMET); Ministry of Agriculture and Environment; Servei Meteorològic de Catalunya (METEOCAT); Navarra Government; SAIH Cantábrico; SAIH Duero; SAIH Ebro; SAIH Guadalquivir; SAIH Hidrosur; SAIH Júcar; SAIH Miño-Sil; SAIH Segura; SAIH Tajo), so that implies 10 sources more than those mentioned originally in the manuscript. Obviously one of the two descriptions is not correct so this should be clarified and corrected.

You are right, the description in the repository is wrong. A new version of the dataset has been uploaded and now the information is correct. Thank you for the notice.

Finally, there are a number of formal aspects that should be amended such as the use of correct symbol units, references quoted in the text but not listed in the references section, or minor problems with English language (I do not intend to be exhaustive in this aspect

but I list some issues below). For all the above, despite this is a very interesting contribution, I do not think the manuscript can be accepted in its current form and I recommend major revision.

We are grateful for your comprehensive review that gave us the opportunity to solve several formal aspects. We have addressed all your suggestions and the text is now much better understandable.

SPECIFIC COMMENTS

1. Page 2, line 20. Please add here the horizontal resolution of the E-OBS dataset, i.e. "with a horizontal resolution of .." or something similar.

Modified as suggested. We added the spatial resolution of the dataset to the text.

"The E-OBS dataset (Cornes et al., 2018), at a maximum spatial resolution of 0.1 degree, […]"

2. Page 2, lines 23. The first part and last parts of the sentence "The Spanish territory perfectly captures... this variability" is unclear and potentially misleading... what do you mean by "the great climatic variability"? The climatic variability of the world? I suggest to rewrite it, for example "The Spanish territory exhibits a great climatic variability with very different regimes in a relatively small area that leads to high risks such as.." (please complete with what you think are those risks) or something similar.

Thank you. We have modified the text based on your suggestion and, as mentioned by Reviewer #1, we have included the explanation of the risks part.

"The Spanish territory exhibits a great climatic variability with very different regimes in a relatively small area that leads to high risks such as increments in the frequency and magnitude of extreme events."

3. Page 3, line 13. Please complete the sentence with all data sources (as mentioned earlier) if there are more than two - or correct the 12 data sources given in the data set description repository.

Modified as suggested.

4. Page 3, figure 1. Map bottom panel of Canary Islands: please enlarge axis font sizes they can hardly be read

Modified as suggested.

5. Page 4, line 2. Please give a range of mean distances between stations, as it is done later for mean station elevations.

We added the figure of mean distance (65.9 km) in the corresponding line.

6. Page 4, Figure 2. This is a very important part of the data set description, as it gives an idea of temporal changes in mean altitude, minimum distance and number of stations. The methodology used by the authors allows the use of a variable number of stations, not constant in time, which is good because it maximizes the information introduced in the estimation. However, this introduces variability due to the changes in the station data set so this should be carefully described. Authors chose to show mean values only, which I think it is rather limited, and combined in the bottom panel two variables. I suggest to consider a three panel figure, one for each of the three variables considered, and to plot for each one the median and percentiles 25 and 75 - alternatively, if variables examined follow a Gaussian distribution mean values plus standard deviation could be also a possibility - however I would favour the first option. Then the new figure should be briefly

commented, and in particular, justify properly (here or in section 4.1) the selection of the 5 km x 5 km horizontal resolution, which in the current version seems arbitrary in this section (in the discussion the reader founds that it is consistent with an already existing precipitation data set for the same region, but this is not either mentioned in section 2 and could be also considered).

Thank you for your suggestion. We changed Figure 2 to show in three panels the annual median altitude, distance between stations and number of stations, respectively. We also added shadings representing the intervals between 25th and 75th percentiles. Moreover, we added a comment on this new figure and a justification of the selection of the spatial resolution of the gridded dataset:

"We used a 5 x 5 km regular grid covering the whole peninsular Spain, Balearic and Canary Islands to estimate maximum and minimum temperature values from the quality-controlled and serially-complete original series. Despite the differences in the data availability through time, the methodological process creates spatial references that are standardized with the temporal structure of the series to avoid biases or incoherencies. In this regard, the chosen spatial resolution accurately reflects the local characteristics of daily temperature in most of the temporal period, while the provided uncertainty values help to understand the reliability of the estimates when the original data have higher variability."

7. Page 5, section 3.1. Please introduce properly the meaning of TMAX and TMIN.

Modified as suggested, we added the definition of these two variables in the text.

8. Page 10, line 25. How many iterations of the procedure described are typically required?

The number of iterations depends on the quality of the data and the size of the dataset. We added a reference to Figure S6 where the number of iterations for the Spanish dataset is recorded.

9. Page 11, line 17. Pearson -> Pearson correlation coefficient ? [at least the first time you mention it]

Thank you. We added your suggestion in the text.

10. Page 14, section 4.1. Please justify or just comment briefly (if justified previously) the selection of the horizontal resolution.

We added, as suggested, a comment about the selection of the spatial resolution of the grid at the end of section 2.

11. Page 14, line 7. Suggest: case -> case using a leave-one out cross validation (LOO-CV) [this is mentioned later but not in the text]

Modified as suggested. Thank you.

12. Page 14, line 9. I think there is a rounding problem here and 0.95 should be 0.96 according to figure 7c - please check.

You're right, thank you. Corrected.

13. Page 14, figure 7. It is good the authors chose to show the four panels with the same x-axis and y-axis ranges to compare them properly. However, the panels are shown as rectangles and not as squares thus using a different scale for x and y axis. Could you please fix this?

Thank you for the suggestion. The Figure has been modified to show the same X and Y axis scales and all the panels are now squares.

14. Page 14, figure 7. Please indicate (in the figure caption is fine) the meaning of the dashed lines - confidence intervals perhaps? In that case specify the level.

We added the explanation in the caption:

"[…] Dashed lines represent ±1 standard deviation of the data."

15. Table 2 (and 3). Please use correct units where needed.

Modified as suggested. We added the units in the caption of the tables.

16. Table 2 title. When enumerated the variables displayed on the table, the last one is "Range: minimum and maximum..." but on the last row, first column, it appears "Pearson". Please correct. Note that including the units, as requested above, may help detect these problems.

Thank you. Corrected.

17. Table 2 (and 3). When you say decimal places you mean decimal digits? Please check.

Modified as suggested.

18. Table 3. Suggest adding in the first row, first column, the label "Altitude (m)" , referred to the values listed on the first row, next columns.

Modified as suggested.

19. Page 18, Figure 11. This is a very important part of the study and I think it deserves more attention. The uncertainty (upper panel) initially increases, ca. from 1900 to 1905, and then decreases from 1975. However, if I understood correctly, authors mention only a decreasing trend (page 17, line 10). Could you please clarify this? I suggest adding a background grid to the figure to allow an easier visual analysis.

Thank you for the suggestion. The text explains that the initial increase of uncertainty in the first years is due to the few available stations. We modified the paragraph to clearly explain this part.

"The uncertainty of the estimates showed a decreasing temporal evolution (Figure 11a) from the 1960s, while a positive trend was found in the first half of the period, especially in the first 15 years, coinciding with the moment of less observations and higher distance between them (see Figure 2b, c)."

The figure has been also modified to show a background grid and now the uncertainty values are represented by boxplots to better show the variability.

20. Page 18, Figure 11. I think that, given the variability of terrain heights in Spanish territory and different station densities at different altitudes, it is necessary to stratify Figure 11 into an additional 6 panel figure, considering to split the aggregated uncertainty and mean error values into different station altitudes. Looking at Table 3 altitude classes, probably 3 station groups, for example those with altitudes contained in the following intervals [0, 500), [500, 1500), [1500,) m above sea level, would be enough. Future studies examining aspects at different terrain heights may largely benefit from this additional figure to better interpret subsequent results.

That is a good suggestion. Based on your comments, we created a new figure that we added to the supplemental file (Figure S9). This figure represents, with boxplots, the annual evolution of uncertainty divided in three altitudinal ranges (< 500 m.a.s.l.; 500 to 1,500 m.a.s.l.; and > 1,500 m.a.s.l.).

21. Results given in sections 4.3 and 4.4 refer both to Figure 12. I suggest to split that figure into two figures (first and last four panels respectively) so that it is easier to read the comments referred to each part of the figure.

Modified as suggested.

22. Regarding Figure 12f and 12h I noted that the uncertainty values (expressed in days) over the islands (both Balearic and Canary Islands) are either very low (Figure 12f) -except for the highest terrains in Canary islands - or very high (Figure 12h). Could you please comment this result?

We added specific explanations to these points in the text to show that the high uncertainty values are due to the high variability of temperature between stations in the islands.

Technical Comments & Minor Details

23. Page 1, line 24. Typo?: team -> teams? Please check meaning and correct if necessary.

Modified as suggested.

24. Page 1, line 26. Jones et al 2010: reference quoted but not listed in references section. Is it perhaps Jones et al 2012?

You're right. Modified as suggested.

25. Page 1, line 26. Please check citation journal style: Willmott and Matsura (1900- 2014) (2001) -> Willmott and Matsura (2001) ?

Modified as suggested.

26. Page 1, line 29. Check citation journal style: 2015 and 2018 -> 2015; 2018?

Modified as suggested.

27. Page 2, line 13 and line 15. "e.g.:" -> "e.g." as in line 9, same page?

Modified as suggested.

28. Page 2, line 27. English: did not considered -> did not consider

Modified as suggested.

29. Page 3, line 12. check: down -> bottom map panel

Modified as suggested.

30. Page 3, line 12. Aemet -> AEMET

Modified as suggested.

31. Page 3, line 18. English, suggest: this moment -> then [or "that moment"]

Modified as suggested.

32. Page 5, Figure 3 caption. Suggest: RV -> Reference Values (RV) [I know it is already defined in the text, but this change improves the readability of the figure]

Modified as suggested.

33. Page 5, section 3.1. Please use correct Celsius degree symbols as you have done elsewhere in the manuscript.

Sorry that was a mistake produced by the font type. Corrected.

34. Page 5, line 7 (and elsewhere in the manuscript). English: please check the meaning of suspected, suspect and suspicious and use properly.

Corrected in the whole manuscript.

35. Page 8, line 8. English: supplemental -> supplemental material

Modified as suggested.

36. Page 9, line 1. English: finish -> finishes

Modified as suggested.

37. Page 10. For some reason, in this page, text before equations end with a "." and not ":" as it is done elsewhere in the manuscript - please check.

Modified as suggested.

38. Page 11, line 2. English, suggest check: obtain -> obtaining

Modified as suggested.

39. Page 12, line 11. English: "fulfil" is correctly spelled, but it is in the British form - being the American form "fulfill". As you use previously in the manuscript "neighbor" (American form) this is not consistent: you should chose either American or British forms, but not a mixture.

Modified as suggested.

40. Page 13, line 5. English: what -> which? Please check and correct if necessary.

Modified as suggested.

41. Page 13, Figure caption 6. upper (bottom) line -> upper (bottom) row

Modified as suggested.

42. Page 16, line 14 (and elsewhere in text): a X% -> X% (remove "a" if only values are given)

Modified as suggested.

43. Page 16, line 15. English: slightly -> slight [as in line 17 same page]

Modified as suggested.

44. Page 17, line 2. Please expand "approx."

Modified as suggested.

45. Page 18, line 13. Sentence "The northern half..", please check English - by "than" you mean "to"?, otherwise compared to what?

Modified as suggested.

46. Page 18, last line. higher -> highest?

Modified as suggested.

47. Page 21, line 14. Hofstra et al 2008: reference quoted but not listed in the references section. Idem in same page references Jarvis et al 2001, Jones et al 2010 (is it 2012?), Kurtzmann and Kadmon 1999 (is it 2009?) (next page) Hubbard et al You et al ... please check carefully and make necessary corrections.

Thank you for your comment, we have carefully checked the references and now all of them are listed in the references section.

48. Page 21, line 11. English: lies > lied?

Modified as suggested.

49. Page 21, line 14 English: comes -> come

Modified as suggested.

50. References: please check alphabetical order - the last one (Van Den ...) should not be there.

Modified as suggested.

RESPONSE LETTER

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Title: STEAD: A high-resolution daily gridded temperature dataset for Spain
Author(s): Serrano-Notivoli R, Beguería S, de Luis M

GENERAL COMMENTS

Overall this is a thorough piece of research, and the content is entirely suitable for this journal. The gridding method, including the quality control procedure, are well documented, but some clarifications are necessary prior to publication.

Thank you for your comments. We tried to be clear in the description of the methodological process and the resulting products. We hope that the changes made in the manuscript are fair enough for a straightforward understanding.

SPECIFIC COMMENTS

A common problem with datasets that grid tmax and tmin separately is that there is no guarantee that tmax will be greater than tmin in the final dataset. I have checked the dataset and there are several days where tmax<tmin values occur in certain grid cells. These mostly occur across the edges of the gridding domain. The highest frequency (11) of tmax<tmin is during the year 1996, although such occurrences are apparent for most years. I do not advocate changing the methodology to account for this, but this limitation needs to be highlighted in the paper.

Thank you for checking carefully the dataset, we appreciate the concern. We realized that the available dataset at the *digitalCSIC* repository is a previous version rather than the final one. We have uploaded the correct version, which was used to make the analysis in the manuscript. Sorry for the mistake. The methodological process creates new estimates for maximum and minimum separately. However, all the stages, from the quality control to the gridding, consider the differences between them to regularly check the internal consistency, so it is impossible to get situations in which tmax<tmin.

The methodology is broadly similar to the method used in the SPREAD precipitation dataset, produced by the same authors. I refer to the use of Reference Values and Generalized Linear Models, as for precipitation the skewed nature of the data and zero-cutoff were also taken into account. Nonetheless, given that there is a connection between STEAD and SPREAD I think that the precipitation dataset needs to be mentioned earlier in the introduction, and in the Methods Section the differences in the method used here for the temperature variables should be indicated.

Based on your suggestion, we added an extended explanation of SPREAD-STEAD relationship in the introduction:

"The experience acquired in the SPREAD dataset (Serrano-Notivoli et al., 2017a) development set the basis for a solid and reliable daily gridded precipitation datasets creation. Using the same framework with a complete renewal of the core calculations, we developed a new methodology for daily temperature datasets reconstruction and grids creation."

and also at the beginning of the methods section:

"The key stages of the methodological process (calculation of RV, quality control, gap filling and gridding) are the same to that used to create the SPREAD dataset (Serrano-Notivoli et al., 2017a). However, the method basics are completely different since the RV creation has been refined, the quality control has been adapted to temperature data, and

the gap filling and gridding processes include now an improved standardization procedure."

Section 2: Information needs to be provided about the time schedule over which the daily maximum and minimum values were recorded. This may not be available for all stations but where available it should be described briefly in this section, e.g. are tmax/tmin calculated over the full 24-hour period and does this change over time.

Since we used the daily products provided by AEMET and MAGRAMA, we don't have the information about the moment of the day in which maximum and minimum temperatures were recorded. Anyway, this issue doesn't affect to the temperature estimates because the method creates a prediction for each original observation, independently of when it was recorded. The final reconstructed series faithfully represents the temporal structure of the original ones, regardless of the moment of recording.

We added a sentence in section 2 explaining that we used the daily maximum and minimum values of temperature observations:

"Daily maximum and minimum values of temperatures series were used from all the observatories."

Section 2: As pointed out by reviewer #2, the changing number of input stations over time can have a profound influence on the gridded data, and is important for users who want to calculate long-term trends from the data to be aware of this. This limitation of the dataset needs to be highlighted.

We contributed to the minimization of the impact of the data availability over the time introducing a standardization procedure. The methodological approach creates spatial references that are standardized with the temporal structure of the series to avoid biases or incoherencies. Furthermore, the provided uncertainty values for each of the estimates inform about the reliability of the data. This was already mentioned in the discussion section (6th paragraph). However, we emphasized this interesting subject in section 2:

"[…] Despite the differences in the data availability through time, the methodological process creates spatial references that are standardized with the temporal structure of the series to avoid biases or incoherencies. In this regard, the chosen spatial resolution accurately reflects the local characteristics of daily temperature in most of the temporal period, while the provided uncertainty values help to understand the reliability of the estimates when the original data have higher variability."

Section 4.2: The verb "depurate" appears to me to be wrongly used for this procedure. Suggest changing to simply "Quality-controlled dataset".

Modified as suggested.

Section 5 (Discussion) lines 20-23: The key point about producing these gridded datasets is that the final values should reflect grid-box average values that are based on limited spatial sampling (unless the method produces values representative of point- values, which I understand that it does not). This relates to the comments by reviewer #2 about the choice of gridding resolution. This general aim of gridding is not articulated well in this discussions section and needs revision.

Whereas your comment is very interesting, maybe there is a misunderstanding at this point. The temperature estimates (as well as their corresponding uncertainty values) are created for specific individual locations represented by 4 parameters (i.e. latitude, longitude, altitude and distance to the coast). The representativeness of the grid-box in each case falls on that each of those parameters are the median value of all covering that area. For instance, in the STEAD dataset, each gridpoint is the centroid of a squared area of 5 x 5 km with the median of all the possible values of the parameters covering that area.

We added an explanation in the description of the grid (section 2) to avoid misunderstandings:

"[…] The predictor parameters (i.e. latitude, longitude, altitude and distance to the coast) for each grid point were computed as the median of all the possible values of those parameters, covering an area of 5 x 5 squared km in which the grid point is the centroid. […]"

Abstract and Conclusions: One of the key aspects of this paper is the use of many more stations than used in other datasets for the region. This needs to be stated more clearly in the abstract and conclusions, as the phrase "full total of available 5520 observatories" does not convey to the reader (especially those not familiar with the station density across the region) that this is an important feature of this dataset.

Despite the full total available number of stations is 5,520, this figure is for the whole period, so the station density has greatly varied though time. However, we included in the abstract and conclusion, as suggested, the theoretical density:

"[…] (about 1 station per 90 km2 considering the whole period) […]"

STEAD: A high-resolution daily gridded temperature dataset for Spain

*Roberto Serrano-Notivoli[1], Santiago Beguería[1] and Martín de Luis[2]

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Abstract. Using the full total of available 5,520 observatories covering the whole territory of Spain (about 1 station per 90 km2 considering the whole period), a daily gridded maximum and minimum temperature was built covering a period from 1901 to 2014 in peninsular Spain and 1971-2014 in Balearic and Canary Islands. A comprehensive quality control was applied to the original data and the gaps were filled on each day and location independently. Using the filled data series, a grid of 5 x 5 km spatial resolution was created by estimating daily temperatures and their corresponding uncertainties at each grid point. Four daily temperature indices were calculated to describe the spatial distribution of absolute maximum and minimum temperature, number of frost days and number of summer days in Spain. The southern plateau showed the maximum values of maximum absolute temperature and summer days, while the minimum absolute temperature and frost days reached their maximums at northern plateau. The use of all the available information, the complete quality control and the high spatial resolution of the grid allowed for an accurate estimate of temperature that represents a precise spatial and temporal distribution of daily temperatures in Spain. STEAD dataset is publicly available at http://dx.doi.org/10.20350/digitalCSIC/8622 and can be cited as Serrano-Notivoli et al. (2019).

1 Introduction

Despite a clear improvement over the last decades in meteorological measurement techniques, the inclusion of automated systems with near-real-time information submission, or the increasing number of stations with a growing number of recorded variables, the existing climatic information is still unrepresentative in many territories. The low density of stations in isolated areas and the great variability in the number and location of observations over time represent a substantial problem. Despite these problems, or perhaps due to them, different teams dedicated great effort to creating reliable gridded climatic datasets covering large time periods. Between all the climate variables, temperature datasets are among the most popular, such as the CRUTEM (1850-2017) (Jones et al., 2012), the dataset of Willmott and Matsura (2001) covering 1900-2014 period, WorldClim (1970-2000) (Fick and Hijmans, 2017), GISTEMP (1880-2017) (Hansen et al., 2010), or BEST (1850-2017) (Rohde et al., 2013). In this regard, temperature has been also widely studied in Spain, in terms of its spatio-temporal

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distribution (e.g. Peña-Angulo et al., 2016) and temporal trends (e.g. González-Hidalgo et al., 2015; 2018). Nevertheless, most of the existing works addressed coarse temporal scales or used individual stations for detailed regions (e.g. Villeta et al., 2018). Monthly gridded datasets have enabled a better understanding of the climatic dynamics of the planet, especially as an element of quantification and validation of climate change, due to their ability to reproduce the mid-frequency variability of temperature. However, most of the methodologies used in those works are not suitable for addressing the variability of temperature at the daily scale, due to the higher spatial and temporal variability and because of the larger number of input stations required to build a reliable dataset. Although climate change in respect to temperature is often quantified in terms of changes in its mean values, most of the risks attributed to climate change are, however, related to temperature extremes that occur at shorter time scales, such as the daily scale. The study of climate change signals in temperature extremes is therefore still largely pending due to the absence of reliable daily datasets representative of most of the territories. This absence of daily gridded datasets, with several remarkable exceptions (e.g. Cornes et al., 2018; Lussana et al., 2018), is linked to: i) an absence of contrasted reconstruction methodologies owing to the different temporal and spatial structure of daily data in contrast to monthly or annual values; and ii) an absence of contrasted quality control protocols for daily time series.

In addition, the reliability of a dataset not only depends on the resolution but on the consistency of the data. Quality control processes are crucial to create trustworthy datasets and, although the many existing approaches (e.g. Haylock et al., 2008; Klein-Tank et al., 2002, Klok and Klein-Tank, 2009) apply basic procedures, some others go beyond and check for spatial consistency (e.g. Lussana et al., 2018; Feng et al., 2004), which is recommended when using high-density networks.

The same problems intervene, though more severely, in global datasets. At the sub-regional and local scales, the understanding of high-resolution climatic variability is of key importance in a context of global change, and these datasets often are not adequate to address specific research questions such as extremes or small variations affecting other components of the natural system, due to a low spatial or temporal resolution.

Daily scale in temperature information is of key importance in many areas. The E-OBS dataset (Cornes et al., 2018), at a maximum spatial resolution of 0.1 degree, is the best example of daily gridded dataset for large international areas thanks to the integration of thousands of transboundary climate data. However, it does not pretend to be comprehensive for specific regions (Van Den Besselaar et al., 2015) and a deeper analysis with more information is required for higher spatial scales. The Spanish territory exhibits a great climatic variability with very different regimes in a relatively small area that leads to high risks such as increments in the frequency and magnitude of extreme events. Currently, there are only two daily gridded datasets available for Spain: E-OBS (the Spanish part of the European dataset) and Spain02 (Herrera et al., 2016). Although both of them have been checked for their reliability, and are useful for specific purposes, they have limitations that prevent several climatic analyses. For instance, in their construction they did not consider all the available information but only a few stations as basis for creating the grid (229 and 250, respectively), prioritizing the longest data series over a higher spatial density. This approach is suitable for wide-ranging temperature studies, yet insufficient when addressing small areas with great variability. The experience acquired in the SPREAD dataset (Serrano-Notivoli et al., 2017a) development set the basis for a solid and

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reliable daily gridded precipitation datasets creation. Using the same framework with a complete renewal of the core calculations, we developed a new methodology for daily temperature datasets reconstruction and grids creation.

This article introduces the STEAD (Spanish TEmperature At Daily scale) dataset, a new high-resolution daily gridded (maximum and minimum) temperature dataset for Spain covering the period 1901-2014 for peninsular Spain and 1971-2014 for Balearic and Canary Islands. Based on the available quality-controlled temperature information in Spain (more than 5,000 stations), we used the same spatial resolution as SPREAD, its corresponding precipitation dataset. We propose: 1) a methodology for an exhaustive quality control; and 2) a reconstruction methodology using all the available information and based on local regression models.

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Section 2 describes the input data and section 3 explains the methodology used to apply the quality control, fill the gaps in the original series and the gridding process. Section 4 shows the results of the method applied to the Spanish temperature network as well as the validation of the reconstruction and gridding procedures. Also, a brief description of four climatic indices based on daily temperature is shown. Results are discussed in section 5 and summarized in the conclusions at section 7 after the specification of the availability of the dataset in section 6.

2 Input data

We used the full total of available 5,520 observatories covering the whole territory of Spain, which was divided in three areas to compute the grid: 1) Peninsular Spain (492,175 km2) with 5,056 stations covering the period 1901-2014; 2) Balearic Islands (4,992 km2), with 124 stations covering 1971-2014 and 3) Canary Islands (7,493 km2) covered 1971-2014, using 340 stations (Figure 1 bottom panel). The data sourced from the Spanish Meteorological Agency (AEMET) and from the Spanish Ministry of Environment and Agriculture (MAGRAMA). Daily maximum and minimum values of temperatures series were used from all the observatories.

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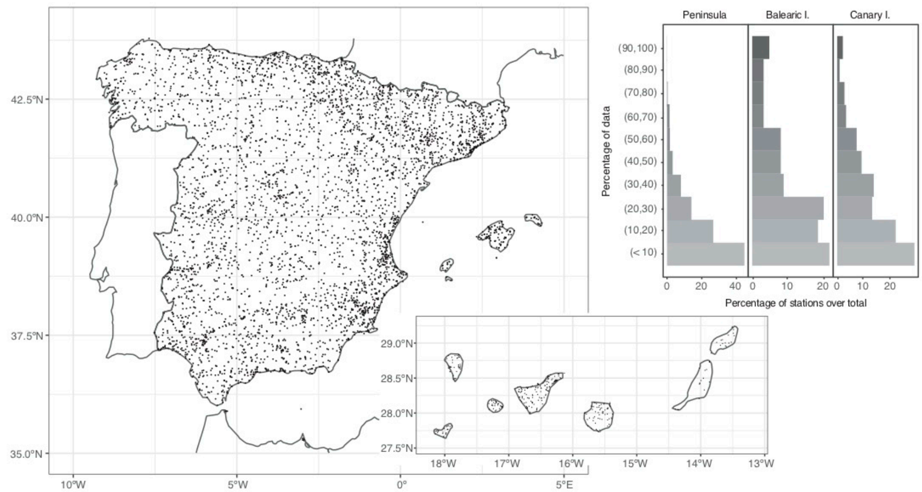
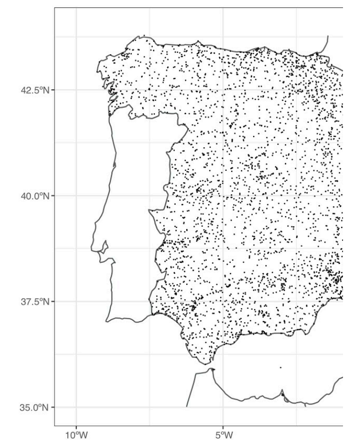


Figure 1: Location of the temperature stations and categorisation by percentage of recorded data.

The mean number of stations per year increased all over the studied period (Figure 2b). The first years of the 20th century had only a few stations available (Brunet et al., 2006; González-Hidalgo et al., 2015) with a great distance between them. Then, the number increases with the break of the Civil War (1936 – 1939) until the decade of the 1990s. Until then, all the information sourced from AEMET and from that, MAGRAMA stations began to register data until the end of the period (2014). As noted in González-Hidalgo et al. (2015), the mean distance between stations (65.9 km for the whole period) barely changed from middle century as well as their mean elevation (between 500 and 550 m a.s.l.). Before that, the mean altitude experimented hard changes due to the removing or relocation of existing stations and new incorporations.



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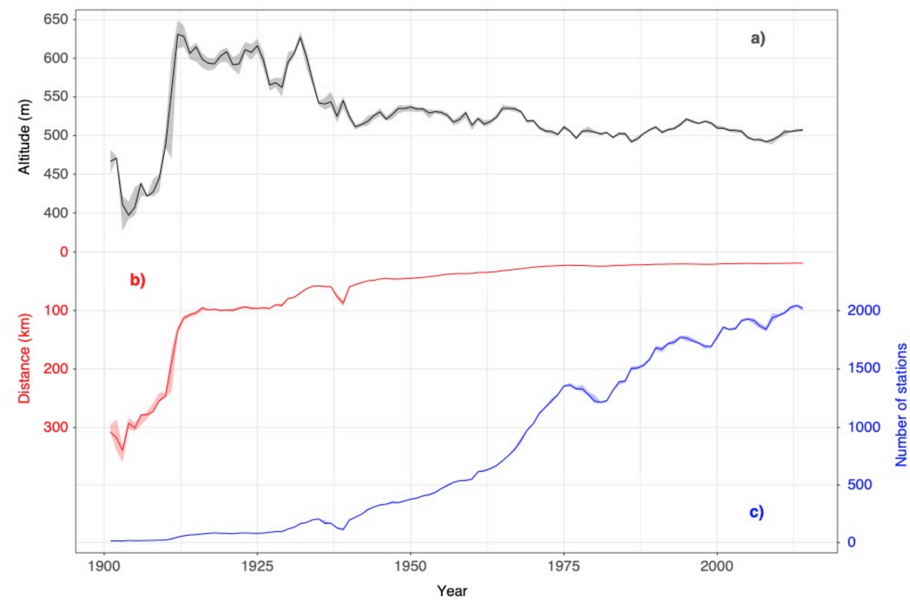
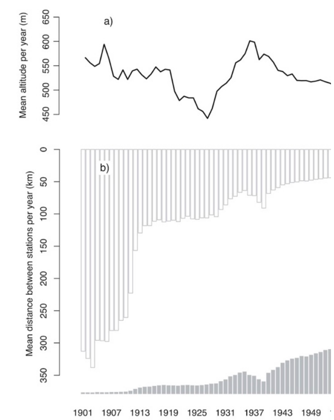


Figure 2: Median altitude of the stations by year (a, black), median distance between stations (b, red) and median number of stations per year (b, blue). Coloured shadings indicate intervals between 25th and 75th percentiles.

Furthermore, the first 40 years of the 20th century showed a high intra-annual variability in altitudes (Figure 2, grey shaded areas) and, to a lesser extent, in distance between stations (Figure 2, red shaded areas), being almost negligible in the number of stations (Figure 2, blue shaded areas). This higher inter- and intra-annual variability in the first years than the rest of the period showed that the few available stations were very different between each other. The variability is reduced from 1950 onwards while the number of stations is increased.

We used a 5 x 5 km regular grid covering the whole peninsular Spain, Balearic and Canary Islands to estimate maximum and minimum temperature values from the quality-controlled and serially-complete original series. The predictor parameters (i.e. latitude, longitude, altitude and distance to the coast) for each grid point were computed as the median of all the possible values of those parameters, covering an area of 5 x 5 squared km in which the grid point is the centroid. Despite the differences in the data availability through time, the methodological process creates spatial references that are standardized with the temporal structure of the series to avoid biases or incoherencies. In this regard, the chosen spatial resolution accurately reflects the local



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characteristics of daily temperature in most of the temporal period, while the provided uncertainty values help to understand the reliability of the estimates when the original data have higher variability.

3 Methods

The first stage is a quality control of the original dataset to remove the most obvious wrong data. From this starting point the process (Figure 3) is based on the computation of reference values (RV), which are computed for each location and day and then compared with the original values to assess the quality of the data. After a process of standardization, new values are estimated for those days without observations (or removed in the quality control process) to obtain serially-complete data series. In a final stage, the complete series are the basis to create new data series for specific pairs of coordinates that may or not form a regular grid, including a measure of uncertainty for each location and day. The key stages of the methodological process (calculation of RV, quality control, gap filling and gridding) are the same to that used to create the SPREAD dataset (Serrano-Notivoli et al., 2017a). However, the method basics are completely different since the RV creation has been refined, the quality control has been adapted to temperature data, and the gap filling and gridding processes include now an improved standardization procedure.

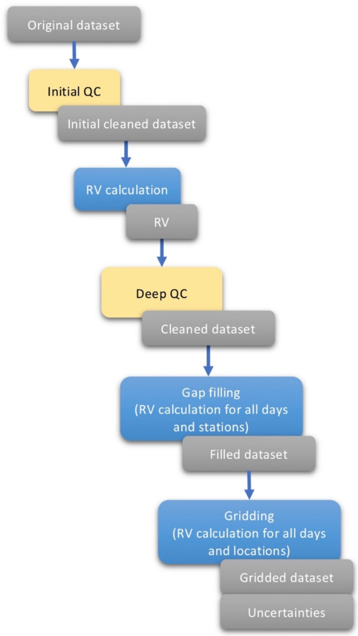

Figure 3. Methodological protocol in a nutshell. Grey boxes represent products; yellow boxes are correction processes; and blue boxes involve Reference Values (RV) calculations.

3.1 Initial quality control

The *initial quality control* (*iQC*) includes five basic criteria over maximum (Tmax) and minimum (Tmin) temperature: i) Internal coherence, ii) removal of months containing less than 3 days of data, iii) the removal of those days out of range considering: Tmax >= 50 ºC or Tmax<= –30 ºC and Tmin >= 40 ºC or Tmin <= –35ºC; iv) removal of all days in a month with a standard deviation equal to zero (suspect repeated values in the series); and v) removal of all days in a month if the sum of the differences between maximum and minimum temperatures is equal to zero (suspect duplicated values in TMAX and TMIN).

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3.2 Reference values (RV) as key process for quality control and reconstruction

Further steps in the quality control and the reconstruction process are based on the computation of reference values (RV). RV are obtained by using a *k-nearest* neighbors regression approach, which is applied to maximum and minimum temperature and to each day and location independently. The RV are estimated through the combined use of Generalized Linear Mixed Models (GLMM) and Generalized Linear Models (GLM). The predictors (independent variables) were latitude, longitude, altitude and distance to the coast. The inclusion of these four independent variables and the building of independent models for each site and day considering only the neighborhood of the site of interest allows for large flexibility and enables capturing local features that may not be captured using other methods which result in larger spatial and temporal regularization.

The methodological procedure is as follows: i) *Rough Monthly RV*, which are average monthly estimates (i.e. a climatology), obtained using GLMM and all the available data; ii) then, *Fine Monthly RV*, which are monthly time series of temperature, computed using GLM and data from only the 15 nearest neighbours, and including the Rough Monthly RV obtained in the previous stage as a covariate; iii) finally, *Daily RV* are computed using GLM and data from the 15 nearest daily observations, plus the *Fine Monthly RV* of the corresponding month as added covariate. The whole process is explained in detail in the following sections.

3.2.1. Rough Monthly RV (rmRV)

Monthly time series of daily temperature means and standard deviations were computed. Only the months with complete daily observations were used to fit the model. We used latitude, longitude, altitude and distance to the coast as fixed factors, and the year as random factor. The introduction of the year as random factor allows for isolating the fact that one particular year might be colder or warmer than the average on the whole dataset, and thus eliminates the random variability arising from the fact that the time period with observed data changes from station to station. The model, fitted independently for each month of the year and for each one of the four dependent variables defined above, can be represented as:

$$\begin{gathered} \boldsymbol{y} \sim \mathcal{N}(\boldsymbol{X\beta} + \boldsymbol{Zb},\ \ \sigma^2) \\ \boldsymbol{b} \sim \mathcal{N}(\boldsymbol{0},\ \ \boldsymbol{G}) \end{gathered} \tag{1}$$

where $\boldsymbol{y}$ is a known vector of observations with mean $E(\boldsymbol{y}) = \boldsymbol{X\beta}$ and variance $var(\boldsymbol{y}) = \sigma^2$; $\boldsymbol{\beta}$ is an unknown vector of fixed effects; b is an unknown vector of random effects, with mean $E(\boldsymbol{b}) = \boldsymbol{0}$ and variance-covariance matrix $var(\boldsymbol{b}) = \boldsymbol{G}$; and $\boldsymbol{X}$ and $\boldsymbol{Z}$ are known model matrices containing the values of the fixed and random variables for the observations $\boldsymbol{y}$. The models were fit by the maximum likelihood method using the R package *lme4* (Bates et al., 2015).

Once the model parameters $\boldsymbol{\beta}, \boldsymbol{b}$ and σ are obtained, best linear unbiased predictions (BLUPs) of the mean and standard deviation of daily temperature are calculated for each station (i), year (y) and month (m). At this stage a global model is fit, since all the data are used to fit the model and therefore the coefficients are assumed to be constant in space, an assumption that it is a rough simplification of reality. On the other hand, this configuration allowed us to include all the data for estimating the random year effect. The obtained estimates of mean and standard deviation for maximum and minimum temperature represent highly spatially regularized patterns of monthly temperature, and do not consider local spatial variability in the influence of the covariates.

3.2.2. Fine Monthly RV (fmRV)

In a second stage, monthly time series of the mean and standard deviation of daily temperature were computed again, but using a local (*k-nearest* neighbors) regression approach. For each station, the model was fit to data from the 15 nearest observations of each month plus the *rmRV* values calculated in the previous step. Inclusion of the latter as if they were legitimate observations incorporates a certain amount of spatial regularization that helps alleviating a problem that may arise when using a purely local regression approach, i.e. an excess of spatial variability, especially in areas where the model extrapolates (in latitude, longitude, altitude or distance to the coast) with respect to the neighboring locations. A Generalized Linear Model was thus built for each station and month:

$$\boldsymbol{y'} \sim \mathcal{N}(\boldsymbol{X'\beta'},\ \ \epsilon) \tag{2}$$

were $\boldsymbol{y'}$ is the local neighbourhood dataset, including the *Rough Monthly RV* with mean $E(\boldsymbol{y'}) = \boldsymbol{X'}\boldsymbol{\beta'}$; $\boldsymbol{\beta'}$ is an unknown vector of local fixed effects; $\boldsymbol{X'}$ is a known model matrix containing the values of the covariates at the 15 neighbouring sites; and ϵ is an unknown random error, which in the case of the mean temperature was assumed to be normally distributed with zero mean, $\epsilon \sim \mathcal{N}(0,\ \sigma'^2)$, and in the case of the temperature standard deviation was modelled as following a Poisson distribution, thus taking only positive values. The obtained estimates of mean and standard deviation for maximum and minimum temperature incorporate the local variability that was lacking in the estimations of the previous step.

An example of *rmRV* and *fmRV* for a specific month is shown in the supplemental material (Figure S2).

3.2.3. Daily RV (dRV)

In a third stage, daily maximum and minimum temperatures were predicted based on the 15 nearest observations and the *fmRV* for the corresponding month, using once again a GLM with Gaussian link:

$$\boldsymbol{y''} \sim \mathcal{N}(\boldsymbol{X'}\boldsymbol{\beta''},\ \sigma''^2) \tag{3}$$

where $\boldsymbol{y''}$ is the local daily neighbourhood dataset, including the *fmRV* with mean $E(\boldsymbol{y''}) = \boldsymbol{X''}\boldsymbol{\beta''}$ and variance $var(\boldsymbol{y'}) = \sigma''^2$; $\boldsymbol{\beta''}$ is an unknown vector of daily local fixed effects; and $\boldsymbol{X'}$ is a known model matrix containing the values of the covariates at the 15 neighbouring sites. The daily estimates of each station ($dRV_{i,d,m,y}$) are then standardized (4) with the *fmRV* ($fmRV\_mean_{i,m,y}$ and $fmRV\_sd_{i,m,y}$) data to keep an equivalent standard deviation as the monthly prediction:

$$dRV\_std_{i,d,m,y} = \frac{(dRV_{i,d,m,y} - fmRV\_mean_{i,m,y})}{fmRV\_sd_{i,m,y}} \tag{4}$$

3.3. Quality control

After the initial quality control and the RV calculation, we have the original dataset without the most obvious anomalies and an estimate for each observation. Clearly, the *iQC* is not enough to remove inconsistencies in temporal and spatial fields. Here is presented a novel approach of an exhaustive quality control over daily temperature data based on paired comparisons between observations ($Tobs_{i,d,m,y}$) and standardized predictions ($dRV\_std_{i,d,m,y}$). All stages of this process are carried out independently for maximum and minimum temperature. What we call *deep quality control* (*dQC*) considers similarities between observations and estimates through: i) a correlation analysis between daily observations and predictions at each analyzed location, year and month and ii) a quantification on how the differences between daily observed and predicted values (anomalies) are spatially and temporarily distributed.

The process is iterative, which means that when *dQC* finishes in the first run, and the suspect detected data are removed from the original dataset, the RV are computed again over this dataset and the *dQC* runs again. This is iterated until *dQC* does not detect any suspect data.

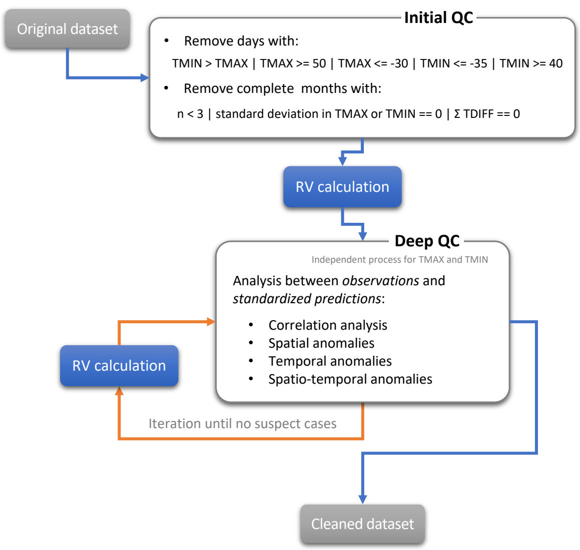

Figure 4. Methodological protocol for quality control.

3.3.1. Correlation analysis

This analysis is based on the correlation between observations and standardized predictions, and it is independent for each series of daily observations in each month. Considering a single site (i), month (m) and year (y) the correlation ($COR_{i,m,y}$) between observed and predicted daily data is computed and then compared with the correlation of its 15 nearest stations in the same month and year ($CORv_{i,m,y}$). The index *ZCOR* ($ZCOR_{i,m,y}$) is then computed as the number of standard deviations that the observed correlation deviates from the observed at their neighbours (5):

$$ZCOR_{i,m,y} = \frac{\left(COR_{i,m,y} - mean(CORv_{i,m,y})\right)}{sd(CORv_{i,m,y})} \quad (5)$$

At this point, the correlations and their deviations are used to remove all daily data from the site i and month m if:

a) $COR_{i,m,y} \leq 0$ or,

b) $COR_{i,m,y} > 0$ AND $ZCOR_{i,m,y} < 0$ AND $p(ZCOR_{i,m,y}) < 0.001$

being p the *p-value* of $ZCOR_{i,m,y}$. A negative $ZCOR_{i,m,y}$ indicates a lower observed correlation than the neighbours and $p(ZCOR_{i,m,y}) < 0.001$ indicates that it is highly unlikely that the correlation is plausible in the referred spatial and temporal context.

This part of the quality control procedure aims to detect, amongst others, (partially) repeated sequences of data, duplicated months or sequences in consecutive years, shifted dates in series or, for instance, sequences of data extremely abnormal in their spatial context. All of these anomalies, which are hard to detect with classical approaches, can be potentially identified in this stage.

3.3.2. Daily differences

Using the differences between the observations and the standardized predictions ($Tdif_{i,d,m,y} = Tobs_{i,d,m,y} - dRV\_std_{i,d,m,y}$), two types of anomalies are computed:

- Spatial anomaly: Each difference is compared with the differences of their 15 nearest stations ($Tdif\_v_{i,d,m,y}$). The index $Zdif\_spatial_{i,d,m,y}$ is then computed as the number of standard deviations that the observed difference deviates from their neighbours (6):

$$Zdif\_spatial_{i,d,m,y} = \frac{\left(Tdif_{i,d,m,y} - mean(Tdif\_v_{i,d,m,y})\right)}{sd(Tdif\_v_{i,d,m,y})} \quad (6)$$

- Temporal anomaly: Each difference is compared with the differences in same station in the rest of the days of the same month and year ($Tdif\_t_{i,d,m,y}$). The index $Zdif\_temporal_{i,d,m,y}$ is then computed as the number of standard deviations that the observed difference deviates from the rest of the days of the month in same station (7):

$$Zdif\_temporal_{i,d,m,y} = \frac{\left(Tdif_{i,d,m,y} - mean(Tdif\_t_{i,d,m,y})\right)}{sd(Tdif\_t_{i,d,m,y})} \quad (7)$$

The daily data from the site i and month m is removed if the absolute value of the mean of both spatial and temporal anomalies is higher than the value representing the probability of $\alpha < 0.0001$ (8):

$$\alpha_{abs\left(Zdif_{mean_{i,d,m,y}}\right)} < 0.0001 \quad (8)$$

When the suspect data has been removed using the daily similarities and differences criteria, the RV are computed again and the quality control process starts over. This procedure is repeated until no suspect data is detected and removed (see Figure S6 in supplemental material).

3.4. Gap filling

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Once quality control process is finished, a final set of RV are computed from the cleaned dataset for those locations and days with missing data. These RV corresponding with days without observations will fill the gaps, completing the series of original debugged observations ($T\_fill_{i,d,m,y}$).

3.5. Gridding and uncertainty

With the aim of obtaining a gridded product (a regularly distributed set of data series over space), new RV are created for each location (id), month (m) and year (y) of the grid in three steps:

1) Grid $fmRV$ ($GfmRV\_mean_{id,m,y}$ and $GfmRV\_sd_{id,m,y}$) are created using the filled dataset ($T\_fill_{i,d,m,y}$);

2) Grid dRV ($GdRV_{id,d,m,y}$) are created using the original filled dataset ($T\_fill_{i,d,m,y}$) and the computed mean monthly references;

3) Finally, the estimates are standardized using the standard deviation monthly references (9):

$$GdRV\_std_{id,d,m,y} = \frac{GdRV_{id,d,m,y} - GfmRV\_mean_{id,m,y}}{GfmRV\_sd_{id,m,y}} \quad (9)$$

In addition to the estimates of temperature for each grid point (in the second step of gridding process), we computed their corresponding uncertainty, which was calculated as the standard error of the difference between the predicted and the observed values of the 15 neighbours in each day and location.

3.6 Validation

The validation process consisted in the comparison between the observations and the estimates computed for each one of those observations. The assessment was carried out through seven statistical and graphical analyses:

i) A graphical comparison and Pearson correlation coefficient calculation of the means of all the 5,520 stations considered in the study. Also, the 95th percentile of maximum temperature and 5th percentile of minimum temperature were considered to ascertain the accuracy of the extremes' prediction;

ii) a graphical representation of the Pearson correlation frequencies, by months, to show the agreement between observations and estimates;

iii) a graphical representation of counts of temperature values, by categories based on absolute values. This is useful to show potential biases in specific ranges of temperature;

iv) a collection of statistical tests to compare observations and estimates by altitudinal ranges using daily values. The tests include the mean of observations (OBSm), the mean of estimates (PREDm), the mean absolute error (MAE), the mean error (ME), the ratio of means (RM) and the ratio of standard deviations (RSD);

v) same as (iv) but by months instead of elevations;

vi) a graphical representation of the count of temperature differences between observations and estimates; and

vii) a graphical representation of the temporal evolution of mean annual uncertainty.

3.7 Example of applications: daily spatial distribution and uncertainties of temperatures

Based on the gridded dataset created from the original data and with the described method, we computed four indices to show the potential applications of the grid: 1) the mean annual maximum value of daily maximum temperature; 2) the mean annual minimum value of daily minimum temperature; 3) the average annual count of days when daily minimum temperature is below 0 ºC (frost days); and 4) the average annual count of days when daily maximum temperature is over 25 ºC (summer days). All the indices were presented with their corresponding uncertainty estimate.

4 Results

4.1 Quality control

Although the quality control was carried out separately, it removed approximately a 7.4% of the original daily values both in maximum and minimum temperatures (Table 1). The initial quality control process (*iQC*) removed a sum of 59 days out of range (less than 0.01% of the total) and 1,349 months (0.53%) containing 4,308 days (0.04%) that did not fulfill with the minimum standards set at the beginning (see section 3.1). Furthermore, the deep quality control (*dQC*) removed between 4.5 and 5.6% of the months and days considering the similarities between the observations and the estimates, being the number of removed data slightly higher in minimum temperatures. Most of the correlations in removed data were negative or very low (Figure 5), which indicates that the observations were very different from the estimates built with their surrounding original values. The average correlations in removed data were negative both in maximum and minimum temperature, showing that the similarities were very low.

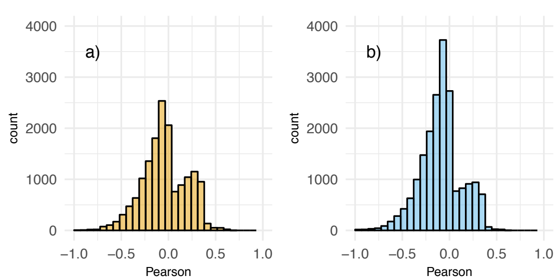

Figure 5. Correlation frequencies between observations and estimates of removed data in quality control process. Maximum (a) and minimum (b) temperatures are shown.

The number of removed days in maximum temperatures was higher when considering the daily spatio-temporal anomalies (Figure 6a), without a significant bias in positive nor negative differences (Figure 6b) in contrast to minimum temperatures (Figure 6e) where negative differences prevailed.

The removed values do not necessarily correspond with climatic extremes but with values that are out of the spatio-temporal context of its neighboring observations. The fact that the maximum frequency of removed data matches with the average of maximum and minimum temperatures (Figure 6a and d) suggests that there is no bias in the suspect data detection and, indeed, the deletions are due to errors in original data (which we intend to detect) and not to climatic extremes. Furthermore, when looking at the removed data by differences between observations and estimates (Figure 6b and e), it is noted that the maximum frequency of deletions corresponds to differences near to ±10 ºC, which is not unusual if we think that, probably, those removals are due to recording or transcription errors, related with missing decimals.

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Despite the fact that the magnitudes of some of the removed data do not represent anomalous values (Figure 6c and f), they correspond to significant anomalies in their spatial and temporal context. Beyond the magnitude in absolute terms, the differences between observations and estimates suggest, with an $\alpha < 0.0001$, that those values are very unlikely to be representative in their spatio-temporal context.

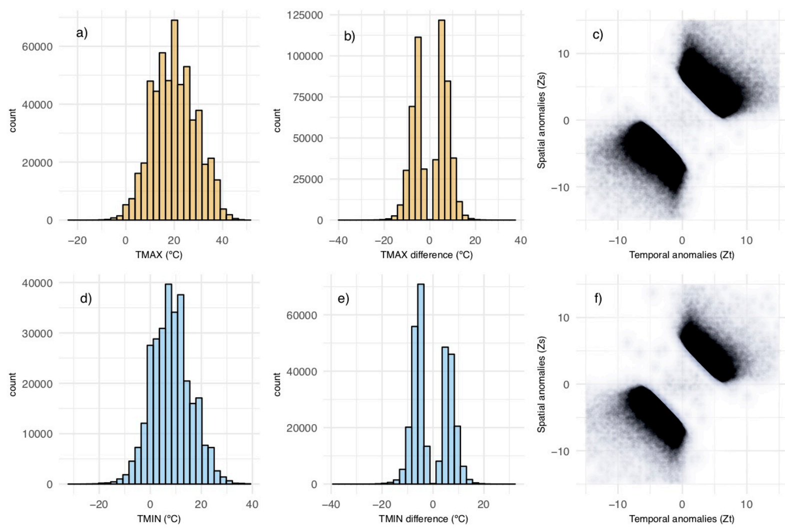

Figure 6. Daily maximum (orange, upper line) and minimum (blue, bottom row) temperature data removed by quality control process. Left column: removed data by magnitude; central column: removed data by differences between observations and estimates; and right column: temporal anomalies (Zs) vs spatial anomalies (Zs).

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Table 1. Number of removed days and complete months based on the quality control criteria.

		Count
Daily similarities (number of removed months and days)		
TMAX	Number of removed months	15,641 (4.48%)
	Number of removed days	450,502 (4.12%)
TMIN	Number of removed months	19,492 (5.58%)
	Number of removed days	566,435 (5.27%)
Daily differences (number of removed days)		
TMAX	Number of removed days	551,275 (3.27%)
TMIN	Number of removed days	299,804 (2.09%)

Using the reconstructed series, we built a 5x5 km spatial resolution gridded dataset of maximum and minimum temperature. The values were estimated for 1901-2014 period in peninsular Spain and for 1971-2014 period in Balearic and Canary Islands. A measure of uncertainty was added to each day and grid point of the dataset.

4.2 Quality-controlled dataset: Observations – estimates comparison

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Daily temperatures were estimated at the same location and days as the original data series but without considering the original values in each case using a leave-one out cross validation (LOO-CV). The comparison between the estimated temperatures and the observations showed very high correlation considering the average by stations for maximum (Figure 7a) and minimum temperatures (Figure 7c) (Pearson correlation coefficients of 0.97 and 0.96 respectively) as well as the extremes, considering the 95th percentile of maximum temperature (Figure 7b) with a Pearson correlation of 0.95 and the 5th percentile of minimum temperature (Figure 7d) with 0.96.

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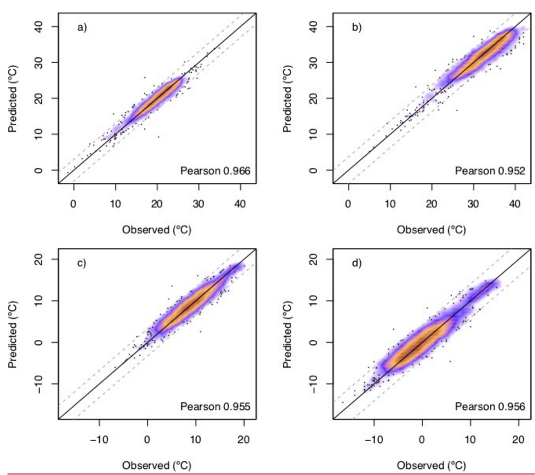

Figure 7. Comparison between observations and estimates, by stations (n = 5520), of the mean maximum temperatures (a) and their 95th percentiles (b) and of the mean minimum temperatures (c) and their 5th percentiles comparison (d). Dashed lines represent ±1 standard deviation of the data.

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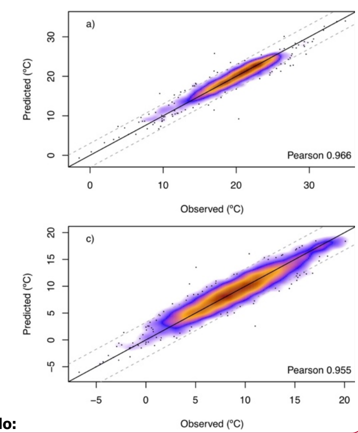

The mean Pearson correlations between the daily observations and the estimates, by months, were 0.87 and 0.82 in maximum and minimum temperature, respectively (Figure 8). However, more than 80% of the months in maximum temperature and more than 68% in minimum got a correlation higher than 0.8. Low correlations (Pearson < 0.5) represented 3% and 5% of the months in maximum and minimum temperature, respectively.

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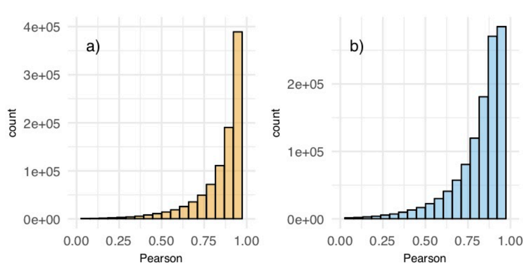

Figure 8. Correlation frequencies between daily observations and estimates, by months, in the final dataset. Maximum (orange) and minimum (blue) temperatures are shown.

The frequency of observed temperature and their estimates (Figure 9) showed a good general agreement. Although maximum temperature was slightly overestimated in lower values (from 0 to 10 ºC), it was slightly underestimated in higher ones (from 20 to 35 ºC). The higher differences in minimum temperature were found in low values (an overestimation from -5 to 0 ºC) and in mid values (an underestimation from 10 to 20 ºC).

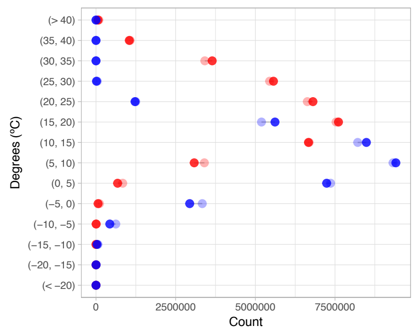

Figure 9. Comparison of frequencies by categories between observed (solid) and predicted (transparent) maximum (red) and minimum (blue) temperatures.

In regard of monthly aggregates (Table 2), the ratio of means (RM) was 1 in all cases in TMAX, showing a similarity in the means between observed and estimated temperature, while the coldest months (November to February) showed a slight underestimation in TMIN. A bias in variance estimation was observed with ratios of standard deviation (RSD) under 0.95 in all months in TMAX and under 0.93 in TMIN. However, ME values were very low in both cases and ME values near to zero in all cases. Pearson correlations between observations and estimates were over 0.90 in all months in TMAX and ranging from 0.85 in July and August to 0.93 from November to February in TMIN.

Table 2. The leave-one-out, cross-validation (LOO-CV) statistics showing the goodness of fit between maximum and minimum temperature observations and estimates of monthly aggregates. MAE: mean absolute error (ºC); ME: mean error (ºC); RM: ratio of means; RSD: ratio of standard deviations; Pearson: Pearson correlation coefficient. Results were constrained to 2 decimal digits.

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
TMAX	MAE	0.62	0.61	0.63	0.66	0.70	0.78	0.84	0.80	0.71	0.64	0.60	0.62
	ME	-0.01	-0.01	-0.01	-0.01	-0.03	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	0.00
	RM	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	RSD	0.88	0.92	0.92	0.92	0.93	0.92	0.89	0.88	0.91	0.94	0.91	0.87
	Pearson	0.93	0.96	0.96	0.95	0.96	0.95	0.91	0.91	0.94	0.96	0.94	0.91
TMIN	MAE	0.81	0.81	0.82	0.77	0.79	0.83	0.90	0.90	0.87	0.84	0.81	0.81
	ME	0.01	0.02	0.01	0.03	0.03	0.05	0.02	0.02	0.03	0.01	0.01	0.02
	RM	0.94	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.96
	RSD	0.90	0.92	0.86	0.87	0.89	0.87	0.84	0.84	0.87	0.89	0.92	0.91
	Pearson	0.93	0.93	0.88	0.89	0.89	0.88	0.85	0.85	0.88	0.91	0.93	0.93

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The number of stations decreases as the elevation increases (Table 3). In Spain, only 1.8% of temperature stations are over 2,000 m a.s.l. while a 37.40% are below 300 m a.s.l. This great difference, also shown in precipitation (Serrano-Notivoli et al., 2017a), necessarily affects the estimation of the variable. A slight underestimation was observed in TMIN from 1,300 to 2,000 m a.s.l. and an overestimation in TMAX from 1,500 m a.s.l. The figures showed also a good agreement at all elevation ranges with the largest differences at high elevations (slight overestimation in TMAX and underestimation in TMIN). The MAE values were increased along with the elevation in TMAX from 0.65 to 1.21, while in TMIN were more constant. The ME also experimented an increase with the elevation in TMAX, but in TMIN all the values were near to zero.

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Table 3. The leave-one-out cross-validation (LOO-CV) statistics showing the goodness of fit between observations and estimates of daily maximum and minimum temperature separated by altitudes (m a.s.l.). N: number of stations; OBSm: mean observed temperature (ºC); PREDm: mean predicted temperature (ºC); MAE: mean absolute error (ºC); ME: mean error (ºC); RM: ratio of means; RSD: ratio of standard deviations. Results were constrained to 2 decimal digits.

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	Altitude (m)	0-100	100-300	300-500	500-700	700-900	900-1,100	1,100-1,300	1,300-1,500	1,500-2,000	>2,000
TMAX	N	1,028	1,036	943	874	807	422	227	81	73	27
	OBSm	22.40	21.80	20.90	20.30	18.50	17.20	16.00	15.10	11.60	9.30
	PREDm	22.70	21.90	20.90	20.40	18.50	17.20	16.00	15.20	11.90	10.10
	MAE	0.66	0.65	0.68	0.71	0.76	0.80	0.86	1.06	0.99	1.21
	ME	0.07	-0.03	-0.06	-0.04	0.01	-0.07	-0.09	0.21	0.36	0.54
	RM	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.01	1.03	1.05
	RSD	1.01	0.99	0.99	0.99	0.99	0.99	0.99	0.99	1.01	1.07
TMIN	N	1,028	1,036	943	874	807	422	227	81	73	27
	OBSm	11.90	10.00	8.90	8.00	6.30	5.40	4.60	4.20	3.20	1.70
	PREDm	12.10	10.10	8.90	8.00	6.30	5.30	4.70	4.10	2.30	1.40
	MAE	0.82	0.80	0.82	0.86	0.85	0.95	0.97	0.97	0.91	0.88
	ME	0.00	0.08	0.02	-0.04	0.03	0.11	-0.12	-0.05	-0.55	-0.13
	RM	1.00	1.01	1.00	1.00	1.01	1.02	0.97	0.99	0.88	0.92
	RSD	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.95	0.96

Approximately, a 70% of the differences between observations and estimates both in TMAX and TMIN were lower than 1 ºC (Figure 10a), which assures the feasibility of the predicted series. Also, most of the spatial and temporal anomalies (approximately 80%) were lower than 1 (Figure 10b and c).

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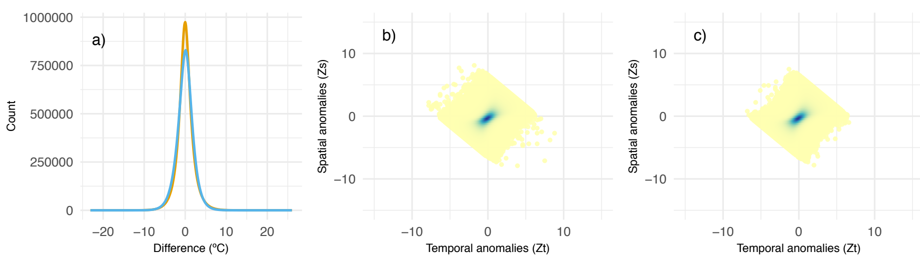

Figure 10. Comparison of observations and estimates in the final dataset. Left column: maximum (orange line) and minimum (blue line) temperature differences between observations and estimates; central and right columns: temporal anomalies (*Zs*) vs spatial anomalies (*Zs*) of final dataset.

The uncertainty of the estimates showed a decreasing temporal evolution (Figure 11a) from the 1960s, while a positive trend was found in the first half of the period, especially in the first 15 years, coinciding with the moment of less observations and higher distance between them (see Figure 2b, c). The values in maximum temperature were lower than minimum until the 1950s an then they were similar during a couple decades until they converge at the end of 1980s, when they diverged and the uncertainty in maximum temperature decreased at a higher rate than minimum. Likewise, the annual mean error (Figure 11b) showed a great variability until the end of 1940s with similar values in TMAX and TMIN, when they separate being TMAX over TMIN in the rest of the series. Since the 1970s, an approach between the two series is shown, being nearer to zero TMAX than TMIN, which is always in negative values.

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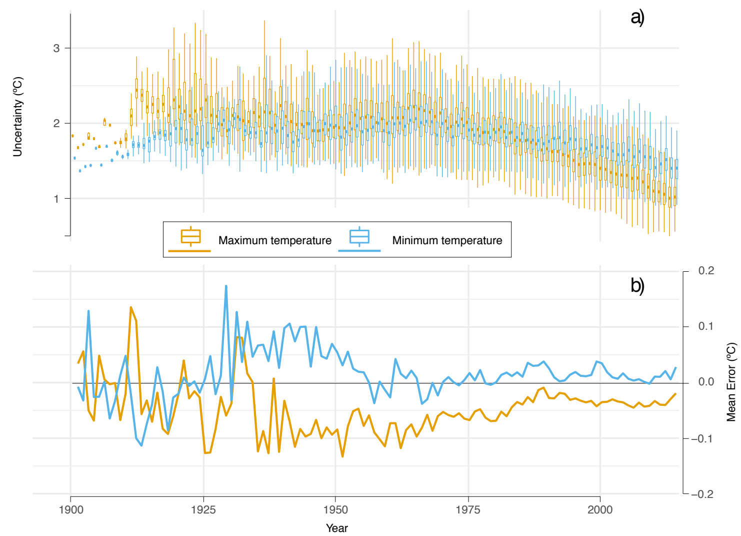

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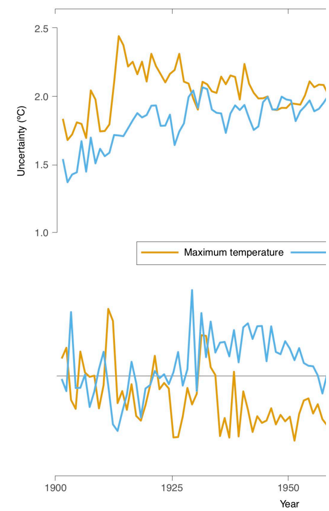

Figure 11. Annual evolution of median daily uncertainty (a) and mean error (b) of maximum and minimum temperature in peninsular Spain.

4.3 Spatial distribution and uncertainty of daily maximum and minimum temperature

The mean annual absolute daily maximum temperature (Figure 12a) showed a great variability, with highest values (> 44 ºC) in the central part of the Guadalquivir Valley and widespread areas with values over 40 ºC in southern half of Iberian Peninsula (IP), the lowest areas of the Ebro Valley and inner areas of larger islands, reflecting a continentality effect. The lowest values were found in highest elevations as the Pyrenees and the Iberian Range and also at northern IP. In this case, the uncertainty was inverse to the spatial distribution of the variable (Figure 12b), with higher values at north and at highest elevations in the Canary Islands, and lower in areas where maximum temperature is higher. On the other hand, the mean annual absolute daily minimum temperature presented a completely different spatial distribution (Figure 12c) especially in southern part of the IP, where there was a southwest-northeast gradient interrupted by high elevations of Sierra Nevada and Cazorla. The northern half of the IP showed a similar pattern to the previous index with coldest temperatures (< -10 ºC) coinciding with lower values of

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maximum temperature. The uncertainty of this variable (Figure 12d) was lower than the previous one with almost all the Spanish territory below 1 ºC. The lowest values were found at northwest IP and the highest ones in coastal areas of Mallorca.

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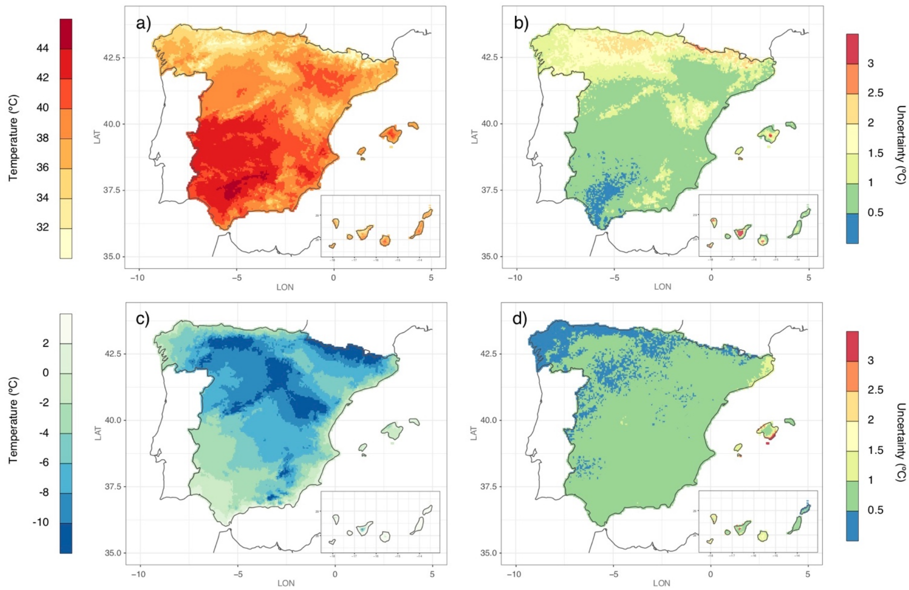

Figure 12. Mean annual (1981-2010) values for a) absolute daily maximum temperature; c) absolute daily minimum temperature and their corresponding uncertainty (b, and d, respectively).

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4.4 Spatial distribution and uncertainty of frost days and tropical nights

The mean annual number of frost days (Figure 13a) varied from less than 10 in coastal areas of IP and in all Balearic and Canary Islands, to more than 200 in highest elevations of the Pyrenees. Between these extremes, a similar increasing gradient as the minimum temperature was found in the southern part of the IP and in the Ebro Valley, while the northern plateau was dominated by a range of 50-100 days. The spatial distribution of the uncertainty (Figure 13b) coincided with the variable, with highest values where the number of frost days was higher. However, some exceptions were found: one at northeast IP, with a high uncertainty of relatively low number of frost days; and other at high elevations of the Pyrenees, where the uncertainty was low in regard of the high number of days. Low values of uncertainty in the Balearic and Canary Islands are due to the few frost days per year.

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The mean annual number of summer days (Figure 13c) showed a similar spatial pattern than the maximum temperature but with a stronger effect of the orography. The highest values were found in the Guadalquivir Valley with more than 150 days, as well as in southern part of the Mediterranean coast and eastern Canary Islands. The lowest number of summer days (< 25) coincided with highest elevations of Central and Iberian Range, Pyrenees and Sierra Nevada. Also, all along the Cantabric coast showed values lower than 75 summer days. The uncertainty related to this index (Figure 13d) was higher than the frost days, with a clear gradient from less than 2 days in central southern IP to more than 3 days in all northern IP, the Iberian Range, the Canary Islands and most of the inner areas of the Balearic Islands. Although the occurrence of summer days in both groups of islands is relatively high, they obtained considerable values of uncertainty due to the high variability of temperatures between stations in these small areas.

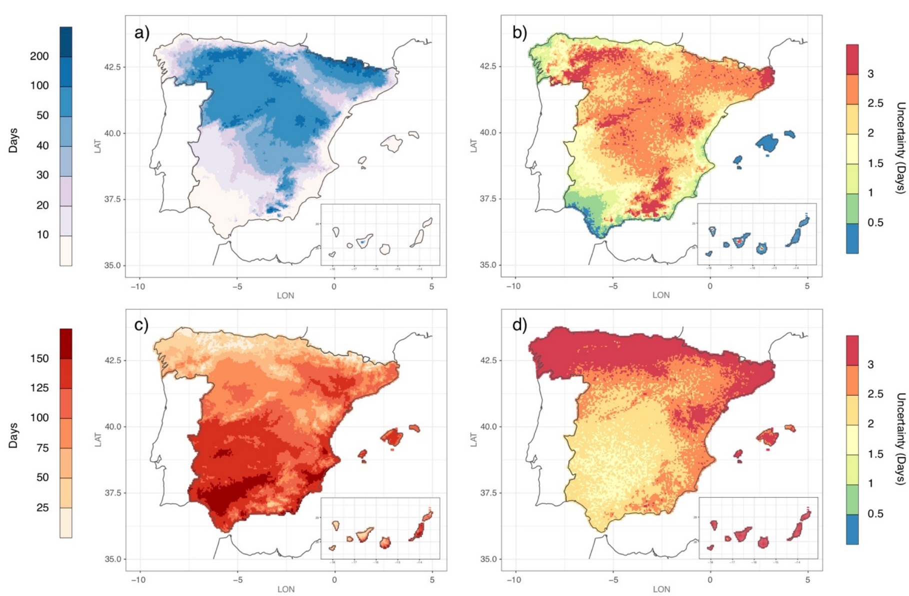
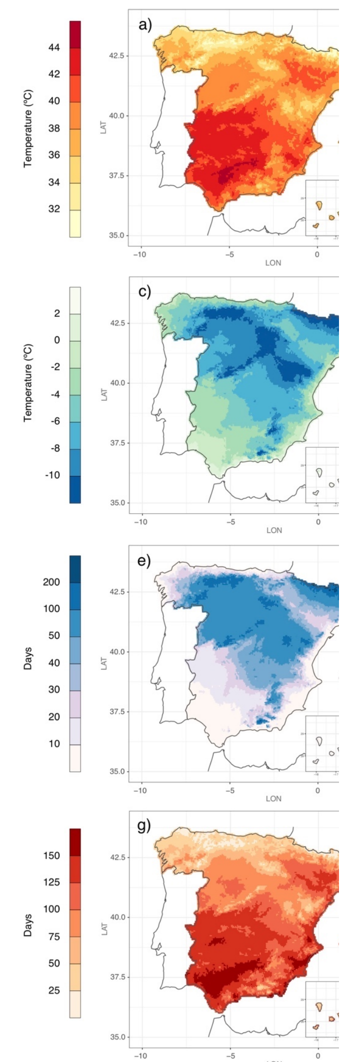


Figure 13. Mean annual (1981-2010) values for a) number of frost days ; c) number of summer days and their corresponding uncertainty (b, and d, respectively).

5 Discussion

This work introduces two important novelties in regard of high-resolution climatic analysis: i) a new methodology to reconstruct *in situ* temperature data series over time and space, and ii) a new daily gridded temperature dataset for Spain.

Eliminado: 12g…3c) showed a similar spatial pattern than the maximum temperature but with a stronger effect of the orography. The highest values were found in the Guadalquivir Valley with more than 150 days, as well as in southern part of the Mediterranean coast and eastern Canary Islands. The lowest number of summer days (< 25) coincided with highest elevations of Central and Iberian Range, Pyrenees and Sierra Nevada. Also, all along the Cantabric coast showed values lower than 75 summer days. The uncertainty related to this index (Figure 12h ... [1]



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The method, which is based on reference values (RV) computed from nearest observations instead of reference series (RS), follows the protocol developed for precipitation reconstruction in Serrano-Notivoli et al. (2017b). However, we included the distance to the coast as a source of variation of the local models in addition to the three used in the previous work (altitude, latitude and longitude). This parameter has been proved to be important for temperature estimation (Fick and Hijmans, 2017) and lets the models be more flexible.

One of the most valuable keys of the approach presented here is the use of all the available climatic information, which is crucial for a high-resolution output due to the observations network density has a major influence in gridded datasets results, controlling the skill of the final estimate of the variable (Hofstra et al., 2008). This is especially true in high percentiles, with a disproportionate effect in extreme values and, therefore, in extreme indices (Hofstra et al., 2010). Hence, a method using all the information instead of longest data series seems appropriate. Indeed, there are several temperature estimation methods in literature, and the choice of one or another is not a trivial matter since the gridded dataset will be built from estimates. The inference or interpolation of any climatic variable in different locations from the recording sites always implies some kind of variation in final estimates regarding the observations. The aim is, therefore, using an approach minimizing these errors. Previous comparatives of interpolation methods do not conclude on any definitive one. For instance, Shen et al. (2001) make a review of daily interpolation methods resolving that almost all of them smooth the data, and Jarvis et al. (2001) did not found large differences between them either. However, Hofstra et al. (2008) accept as more appropriate a global kriging for they work at European scale and others as Jeffrey et al. (2001) use simpler methods as thin splines.

In this work, we use GLMMs and GLMs as a general approach to the daily temperature estimation, using as support monthly estimates based on daily data of months with complete observations. This part gives consistency to all the temporal structure of the data series, as similar approaches used in previous works (e.g. Jones et al., 2012). On the other hand, the use of regressions in temperature estimation is not new. For example, several works establish that regression models are more reliable than other interpolation methods for monthly temperatures (Kurtzman and Kadmon, 1999; Güler and Kara, 2014). Li et al. (2018) built a high-resolution grid for urban areas in USA using geographically weighted regressions (GWR) and reported Pearson correlations between 0.95 and 0.97, similarly to the present work. However, Hofstra et al. (2008) found that, for European scale, daily temperature regressions worked worse than other interpolation methods.

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The present work constitutes a novelty regarding previous methodological approaches mainly due to: i) all the available information is used, being the longer series supported by shorter ones, and ii) it includes a comprehensive iterative quality control checking the spatial and temporal consistency of the data until no suspect values are detected. In addition to the developed validation process, the results in the form of spatial coherence show that the method is able to reproduce realistic climatic situations. The new approach of the quality control detects a number of suspect data in line with previous research, assuring the deletion of anomalies in a spatial and a temporal dimension. Although many works dedicate little efforts to this part of the reconstruction, it is one of the most important since it will have a decisive weight in the final result. For instance, Jeffrey et al. (2001) simply remove those data exceeding a fixed threshold in regard of the residuals of the splines; and in ECA&D (Klok and Klein-Tank, 2009) the quality tests are absolute, without a comparison with neighbouring data series.

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Nevertheless, a similar approach to our spatial check of quality was developed in Estévez et al. (2018) but comparing nearest stations in all their data series instead of daily individual data. They used the spatial regression test (SRT) following You et al (2008) and Hubbard and You (2005). Others such Durre et al. (2010) also applied spatial consistency checks to test if temperature data lied significantly outside their neighbours. They flagged as suspect a 0.24% of all the (worldwide) data considering temperature, precipitation, snowfall, and snow depth, a quite low figure.

One of the key elements in any gridded dataset creation is to provide an uncertainty value, which informs about the reliability of the data and should be a standard to all the climatic information. The uncertainty values presented in this work come from each of the individual models for each timestep and location, therefore it apprises about the changes in the reliability of the day-to-day data. Now, several datasets provide this kind of information, though it can be obtained from different methods. For example, Cornes et al. (2018) applied a smart calculation of the uncertainty using 100-member ensemble realizations for each day; Stoklosa et al. (2015) and Di Luzio et al. (2008) used PRISM (Parameter–Elevation Regressions on Independent Slopes Model) to compute uncertainty in two ways: i) a leave-one-out cross-validation (LOO-CV) as we do in the present work, and ii) modeling the uncertainty –which could lead to a propagation of the errors– using the prediction intervals of their weighted linear regression. In all cases the method is valid because the goal is to extract the potential bias for each considered timestep.

Concerning to the new dataset, although some previous works created daily temperature datasets for Spain, only a few are gridded (only Herrera et al., 2016 built one for whole peninsular Spain and Balearic Islands) and none of them are dedicated to analyse the spatial distribution of daily temperature indices but the trends (e.g.: El-Kenawy et al., 2011; Fonseca et al., 2016). We show here only four examples of the capabilities of STEAD dataset in the research of temperatures in Spain. The northern half of the IP showed a stronger influence of orography and Atlantic influences, just like in annual precipitation and maximum precipitation in 1 and 5 days (SPREAD, Serrano-Notivoli et al., 2017a), showing a potential covariability with other precipitation indices or temporal scales (Sánchez-Rodrigo, 2018 and 2014; Fernández-Montes et al., 2016). Besides, the availability of maximum and minimum temperature (STEAD) and precipitation (SPREAD) at same temporal (daily) and spatial (5x5 km) scale, opens up possibilities of new prospective research in many fields as agricultural climatology, natural hazards, paleoclimatic reconstructions or hydrological modelling, amongst others.

In our attempt to create a useful reconstruction and gridding methodology, some of the stages of the method imply arbitrary decisions that could be changed based on user-defined options. For instance, we use 15 neighbouring observations to build the model but there is not an objective number. We are building these models with 4 cofactors, which need certain degrees of freedom. An increase in the neighbours could lead to a loss of local representativeness, but also a gain of statistical robustness and lower influence of anomalous data.

In respect of the quality control process, the initial thresholds were set at the beginning only to remove outliers that are sometimes included in the original datasets (e.g. -999 or nonsenses as 54354 that is one of the removed values in this work) but that sometimes have a meaning to identify specific situations or local codes. There are a lot of sources and types of errors as repeated series, duplicities or coding errors, that we try to identify through a simple collection of criteria. For example, we

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use the correlation between series and the differences between observations and estimates to remove data based on probability thresholds that we defined based on our experience, but maybe others could be useful depending on the dataset.

The effort of this research has been mainly dedicated to create an accurate estimate of temperature using all the available information and providing a validation as complete and transparent as possible, as well as afford an uncertainty measure tailored for each value allowing the assessment of data in each day and location.

6 Data availability

The STEAD dataset is freely available in the web repository of the Spanish National Research Council (CSIC). It can be accessed through http://dx.doi.org/10.20350/digitalCSIC/8622, and cited as Serrano-Notivoli et al. (2019). The data is arranged in 12 files (daily maximum and minimum temperature estimations and their uncertainties for peninsular Spain, Balearic Islands and Canary Islands) in NetCDF format that allows an easy processing in scientific analysis software (e.g. R, Python…) and GIS (list of compatible software at http://www.unidata.ucar.edu/software).

7 Conclusions

We present a new high-resolution daily maximum and minimum temperature dataset for Spain (STEAD). Using all the available daily temperature data (5,520 stations, representing about 1 station per 90 km2 considering the whole period), a 5 x 5 km spatial resolution grid was created. The original data were quality-controlled and the missing values were filled based on the monthly estimates and using the 15 nearest observations. A serially complete dataset was obtained for all stations from 1901 to 2014 for peninsular Spain and from 1971 to 2014 for Balearic and Canary Islands. Based on this dataset, daily temperatures were calculated for each grid node, resulting in a high-resolution gridded dataset that we used to compute four daily temperature indices: mean annual absolute maximum and minimum temperatures, mean annual number of frost days and mean annual number of summer days.

The spatial distribution of mean annual maximum and minimum temperatures showed a strong relationship with the altitude, (decreasing along with the elevation) and with the distance to the coast, revealing a high effect of continentality with increased values of the indices in both inner mainland Spain and islands. The mean annual number of frost days was higher in northern half of peninsular Spain and in high-elevation areas of the south, while the mean number of summer days obtained the highest values at south, in the Guadalquivir Valley and southern Mediterranean coast, progressively decreasing to the north.

The use of all the available information in combination with a methodology based on local variations of temperature over a high-resolution grid, provided a daily dataset that is able to reproduce the high spatial and temporal variability.

Author contribution

M. de Luis designed the methodological approach in collaboration with R. Serrano-Notivoli, who applied it to the reconstruction of the climate data and the development of the gridded dataset. S. Beguería contributed to the validation process and the climatic analysis of the results. R. Serrano-Notivoli prepared the manuscript with contributions from all co-authors.

Acknowledgements

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Movido (inserción)[1]

Movido hacia arriba[1]: Van Den Besselaar, E. J. M., Klein Tank, A. M. G., Van Der Schrier, G., Abass, M. S., Baddour, O., Van Engelen, A. F. V., Freire, A., Hechler, P., Laksono, B. I., Iqbal, Jilderda, R., Kamga Foamouhoue, A., Kattenberg, A., Leander, R., Martínez Güingla, R., Mhanda, A.S., Nieto, J. J., Sunaryo, Suwondo, A., Swarinoto, Y. S., Verver, G.: International climate assessment & dataset: Climate services across borders, BAMS, 96(1), 16-21, doi: 10.1175/BAMS-D-13-00249.1, 2015.

1 Input data

The study area comprises the whole Spanish territory (Figure S1) including the Iberian Peninsula (IP), the Balearic Islands (BAL) and the Canary Islands (CAN), covering a total area of 504,660 km^2 (IP: 492,175 km^2; BAL: 4,992 km^2; CAN: 7,493 km^2). The altitudes range from 0 m a.s.l. at the coast to maximums of 3,404 m a.s.l. (Aneto summit) in the IP, 358 m a.s.l. (Toro Mountain summit) in BAL and 3,718 m a.s.l. (Teide summit) in CAN.

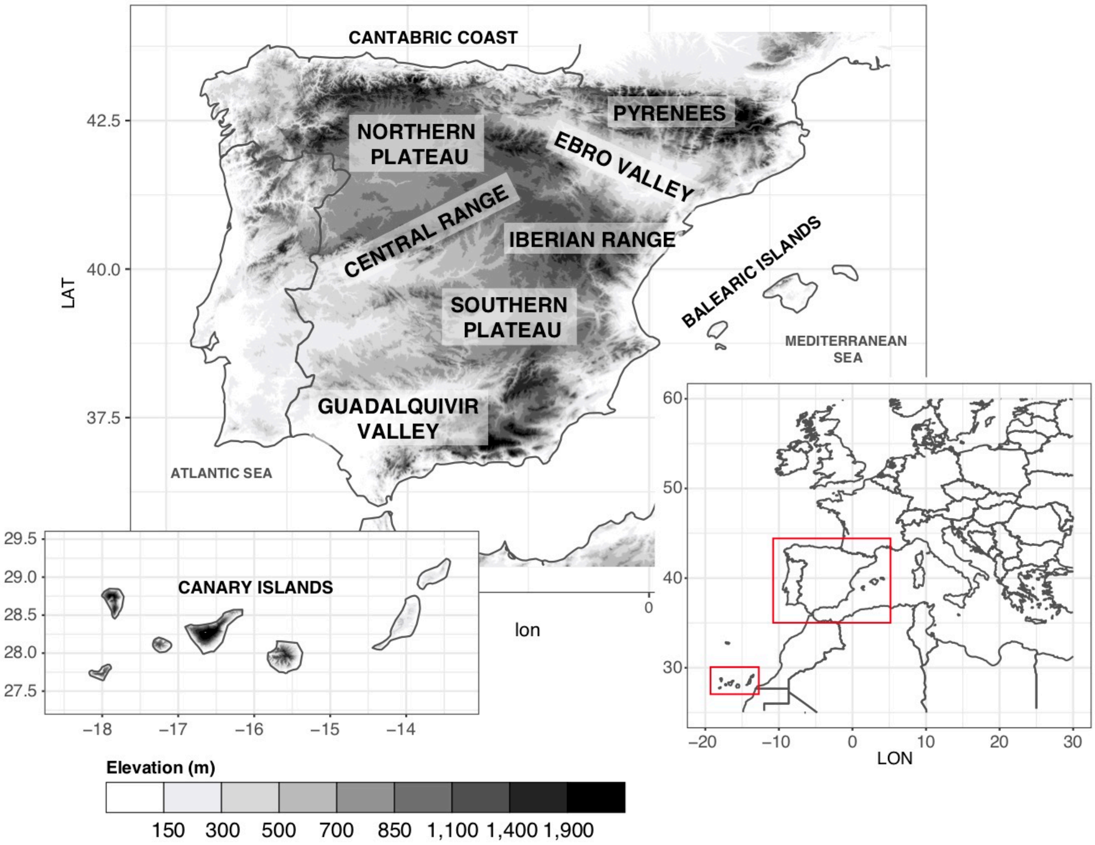

Figure S1: Geographical context of the study area and names of places mentioned in the text.

Most of the input data sourced from the Spanish Meteorological Agency (Aemet) (IP: 90.8%; BAL: 90.1%; CAN: 90.7%) and from the Spanish Ministry of Agriculture and Environment (MAGRAMA) (IP: 8.2%; BAL: 8.9%; CAN: 8.3%) using the 1901-2014 period for IP and 1971-2014 period for BAL and CAN. More than 5,000 stations were used as original observations with more than 33 millions of raw data (Table S1).

Table S1. Summary of all the used information of maximum and minimum temperature in the Spanish Iberian Peninsula (PEN), the Balearic (BAL) and Canary Islands (CAN). Number of months: months with at least 1 daily record in TMAX or TMIN; Number of complete months: months with records in all days; Number of daily pairs: days with record of TMAX and TMIN. The figures are referred to 1901-2014 period in PEN and 1971-2014 in BAL and CAN.

	PEN	BAL	CAN
Number of stations	5,056	124	340
Number of months	1,133,100	21,875	51,210
Number of complete months	1,057,941	18,530	39,831
Number of daily pairs	33,972,660	639,134	1,485,160

2 Results of quality control

The *iQC* results disaggregated by territorial unit (PEN: Peninsular Spain; BAL: Balearic Islands; CAN: Canary Islands) are presented in absolute figures and in percentage of the total number of available days and months in the original dataset (Table S2). The number of removed days corresponding to those out of range ($TMAX >= 50 \mid TMAX <= -30 \mid TMIN <= -35 \mid TMIN >= 40$) and to complete months ($n < 3 \mid sdTMAX == 0 \mid sdTMIN == 0 \mid meanTDIF == 0 \mid sdTDIF == 0$) were very similar.

Table S2. Number of data and percentage of total removed by the initial quality control (*iQC*) in the Spanish Iberian Peninsula (PEN), the Balearic (BAL) and Canary Islands (CAN).

	PEN	BAL	CAN
Number of removed days *(out of range)*	52 (<0.01%)	7 (<0.01%)	0 (0.00%)
Number of removed months	1,179 (0.10%)	34 (0.16%)	136 (0.27%)
Number of removed days *(complete months)*	3,965 (0.01%)	57 (0.01%)	286 (0.02%)

Once the data series passed the *iQC*, daily reference values (*dRV*) were computed for each station based on a general monthly reference (rmRV) and a local monthly reference (fmRV). Figure S2 shows the differences between them on an example month (July 2005). Results show that they only differ in some decimal points, being these differences always lower than 1 ºC.

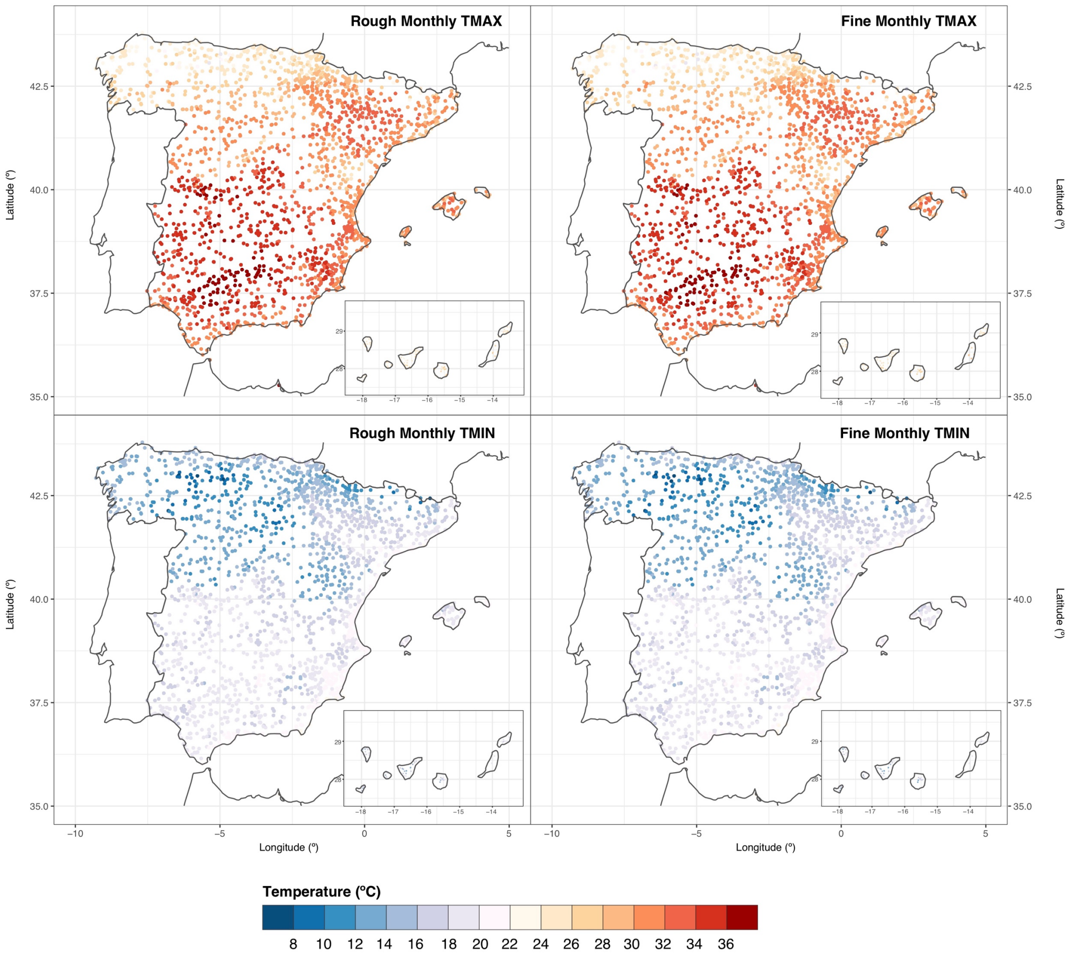

Figure S2. Rough Monthly RV (left) and Fine Monthly RV (right) for maximum (top) and minimum (bottom) temperature of an example month (July 2005).

Higher differences than the *iQC* were shown between territories in the results of the deep quality control (*dQC*) (Table S3). In regard of daily similarities, more data were removed in the Canary Islands than the rest of the areas (about three times more than PEN and almost five times more than Balearic Islands in TMAX). The number of removed data regarding the daily differences was more similar between zones, only in PEN was higher than 1% (in TMAX).

Table S3. Number of data and percentage of total removed by the deep quality control (*dQC*) in the Spanish Iberian Peninsula (PEN), the Balearic (BAL) and Canary Islands (CAN).

		PEN	BAL	CAN
Daily similarities (number of removed months and days)				
TMAX	Number of removed months	14,181 (1.25%)	144 (0.66%)	1,316 (2.57%)
	Number of removed days	411,880 (1.21%)	3,521 (0.55%)	35,101 (2.36%)
TMIN	Number of removed months	17,706 (1.56%)	204 (0.93%)	1,582 (3.09%)
	Number of removed days	517,790 (1.52%)	5,383 (0.84%)	43,262 (2.91%)
Daily differences (number of removed days)				
TMAX	Number of removed days	534,363 (1.57%)	6,262 (0.98%)	10,650 (0.72%)
TMIN	Number of removed days	286,696 (0.84%)	4,066 (0.64%)	9,042 (0.61%)

When we look at the correlations between observations and estimates of removed data (daily similarities stage of *dQC*), we note that the patterns of correlation frequencies are similar in TMAX and TMIN in peninsular Spain (Figure S3a and b) and in Canary Islands (Figure S3e and f) (always higher in TMIN in both cases), but different in Balearic Islands (Figure S3c and d). Nevertheless, the average correlation in almost all cases is negative near to zero (except in BAL TMAX, Figure S3c).

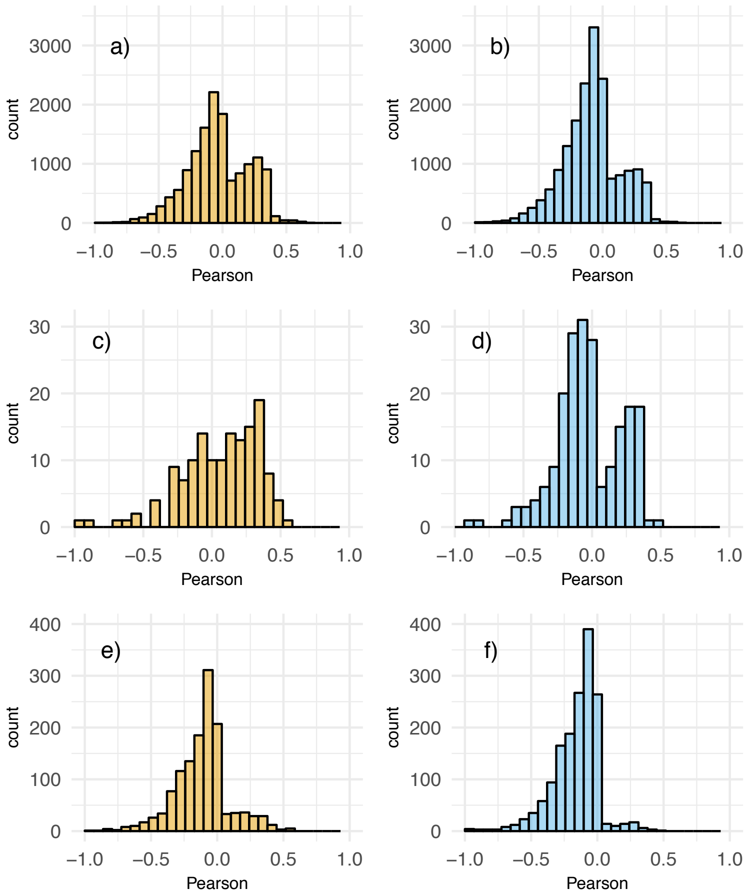

Figure S3. Correlation frequencies between observations and estimates of removed data in quality control process. Maximum (orange) and minimum (blue) temperatures are shown for peninsular Spain (a and b), Balearic Islands (c and d) and Canary Islands (e and f). Dashed orange and blue lines represent mean correlation of maximum and minimum temperature, respectively.

The differences between observations and estimates were very similar in the three areas both in TMAX (Figure S4b, e and h) and TMIN (Figure S5b, e and h). It is noteworthy that the mean difference was always zero or near to zero, which means that the removed data are very different from their corresponding observations. The display of the anomalies (Figures S4 and S5c, f and i) showed a clustering of the data in two groups: negative and positive anomalies in both spatial (Zs) and temporal (Zt) dimensions. However, most of the data were concentrated near to zero. The interpretation of this clustering is that the majority of the data in the plot was removed due to a combination of (negative or positive) anomalies between -10 and 10. Thus, these anomalies were not very extreme but enough to be as different as be rejected. Some of the removed data in the plot of anomalies with low Zs or Zt should not be present. Though, they derive from situations in which other daily values of one month are removed because different criteria and then, that month has less than three daily values. Subsequently, these values are removed fulfilling the *iQC* criteria.

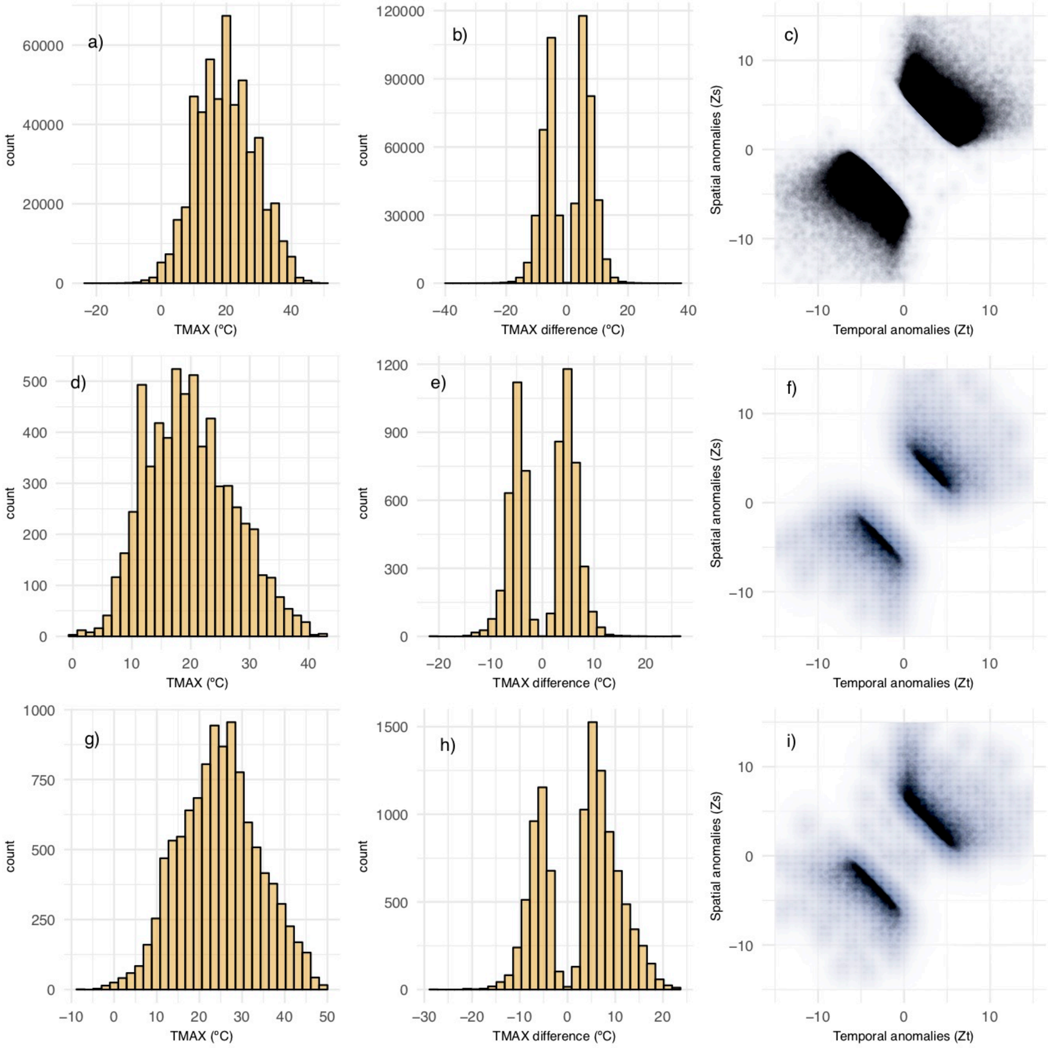

Figure S4. Daily maximum temperature data removed by quality control process in peninsular Spain (a, b and c), Balearic Islands (d, e and f) and Canary Islands (g, h and i). Left column: removed data by magnitude; central column: removed data by differences between observations and estimates; and right column: temporal anomalies (Zs) vs spatial anomalies (Zs). Dashed vertical lines in histograms represent mean values.

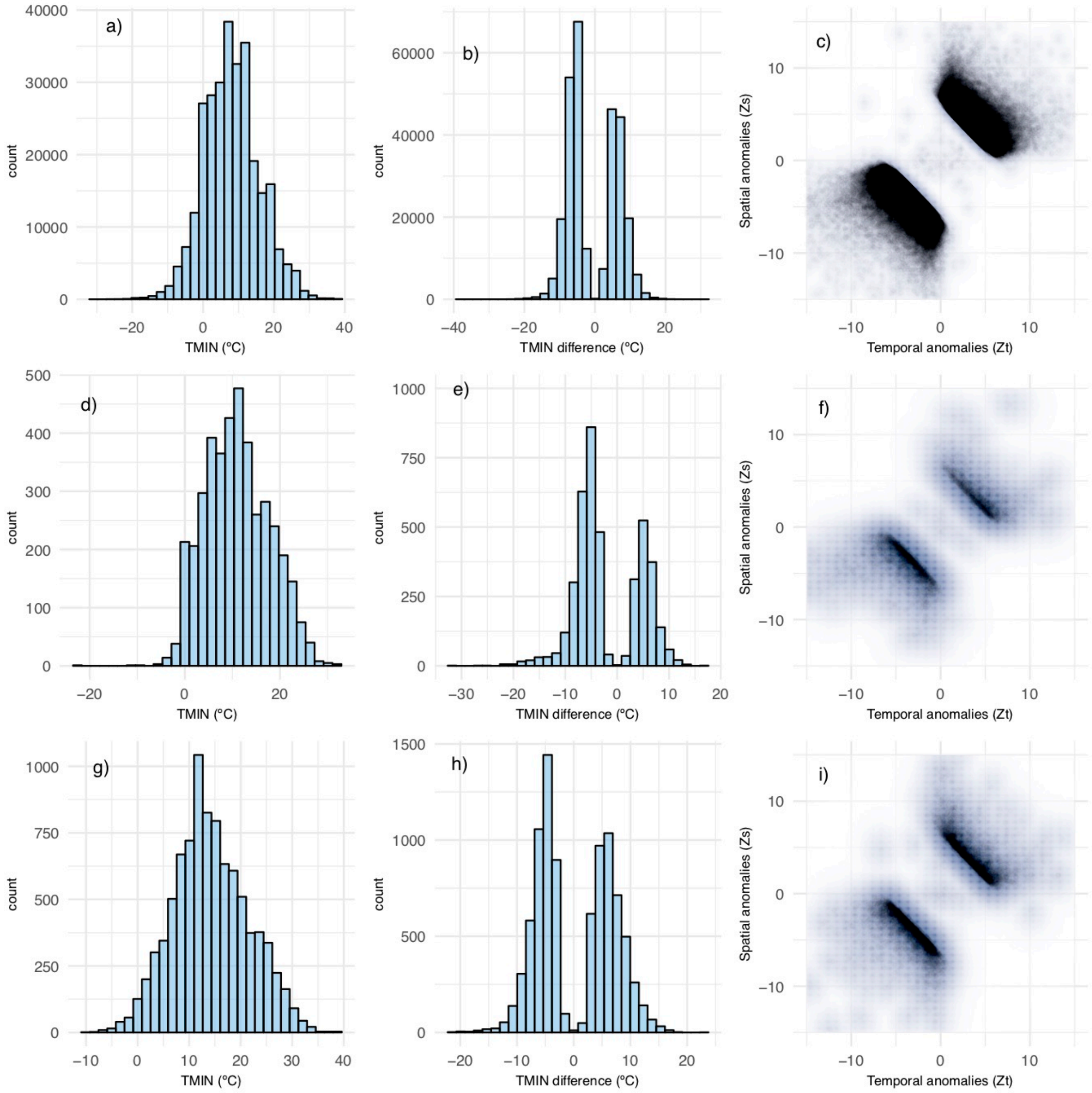

Figure S5. Daily minimum temperature data removed by quality control process in peninsular Spain (a, b and c), Balearic Islands (d, e and f) and Canary Islands (g, h and i). Left column: removed data by magnitude; central column: removed data by differences between observations and estimates; and right column: temporal anomalies (Zs) vs spatial anomalies (Zs) of removed data. Dashed vertical lines in histograms represent mean values.

As the *dQC* process is iterative, the detection, flagging and removing of suspect data is repeated until no suspect data is detected. The number of iterations depends on the original number and quality of the data, being more likely the need of more iterations when the dataset is higher. In case of Spain (Figure S6), PEN required between 12 and 14 iterations to complete the quality control process, while BAL and CAN used less than 10 (7 and 8, respectively).

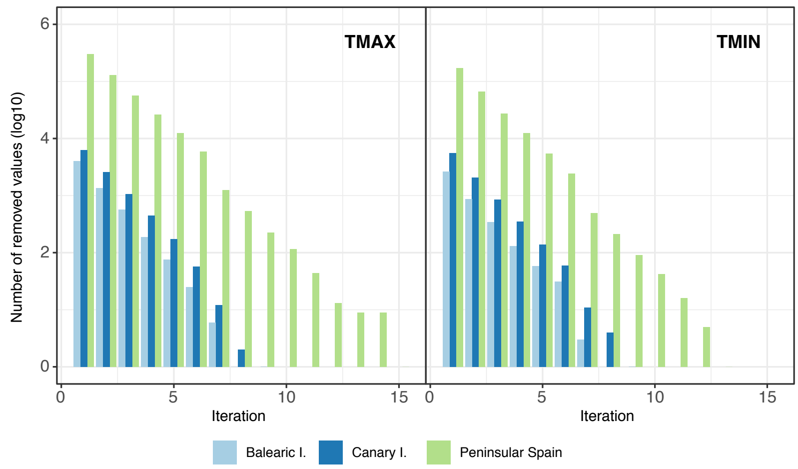

Figure S6. Number of removed values (in logarithmic scale) by iteration in *dQC* process in maximum (left) and minimum (right) temperature.

3 Observations-estimates comparison

Most of the correlations between daily observations and estimates in the final (reconstructed) dataset were near to 0.8 (Figure S7). However, the Canary Islands showed slightly lower correlations (near to 0.75), probably due to the great differences between observatories in raw data. This was also noted in daily precipitation (Serrano-Notivoli et al., 2017a) showing that the great variations in orography and the high differences in the climate between sides of same islands, have a key influence on the differences between data series of observatories, having an impact on climatic reconstructions.

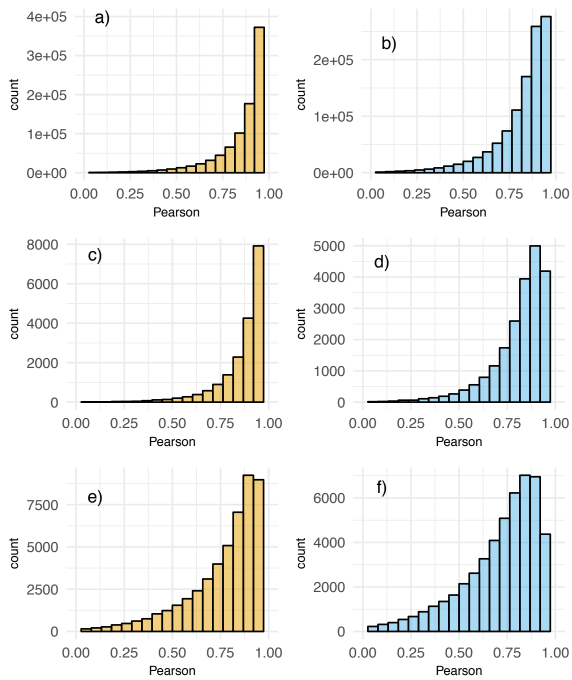

Figure S7. Correlation frequencies between observations and estimates of data in the final dataset. Maximum (orange) and minimum (blue) temperatures are shown for peninsular Spain (a and b), Balearic Islands (c and d) and Canary Islands (e and f). Dashed orange and blue lines represent mean correlation of maximum and minimum temperature, respectively.

The structure of the final dataset, after the iterative quality control and the estimate of TMAX and TMIN for gap filling, showed very low differences between observations and estimates (Figure S8a, d and g). Most of these differences were near to zero, being the TMAX in Balearic Islands slightly broader than the rest of the areas. This means that the maximum temperature in this region is more difficult to estimate due to higher differences in original values. The spatial (Zs) and temporal (Zt) anomalies in this case (Figure S8b, c, e, f, h and i) are the inverse of those in the removed data. The great majority of the Zs and Zt in peninsular Spain were concentrated between -1 and 1, while this figure is higher in the islands from -2 to 2. Nevertheless, the extreme anomalies are extended to absolute values not higher than 4 in the IP and 6 in BAL and CAN.

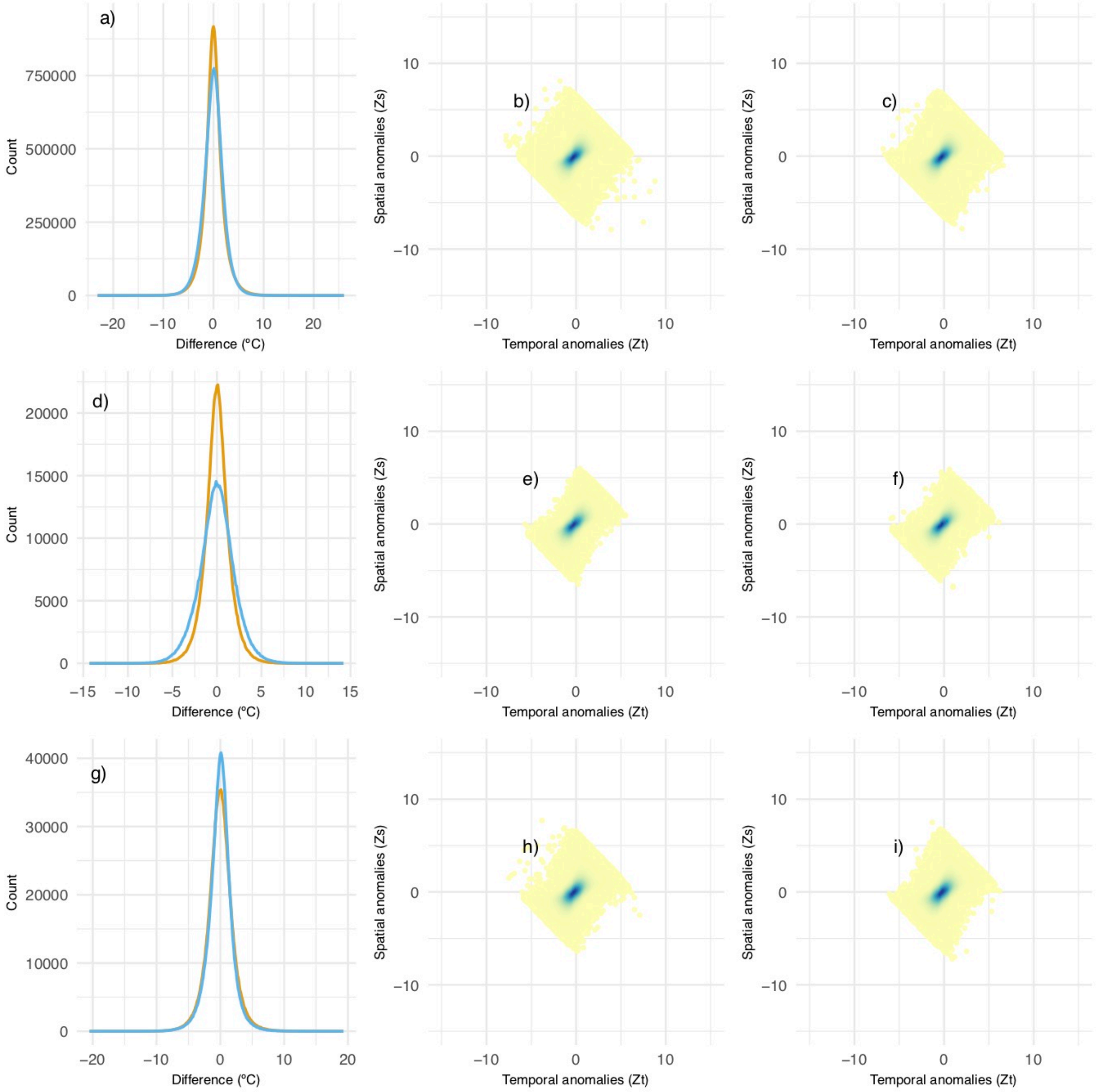

Figure S8. Structure of the final dataset in peninsular Spain (a, b and c), Balearic Islands (d, e and f) and Canary Islands (g, h and i). Left column: temperature differences between observations and estimates; central and right columns: temporal anomalies (Zs) vs spatial anomalies (Zs) of final dataset.

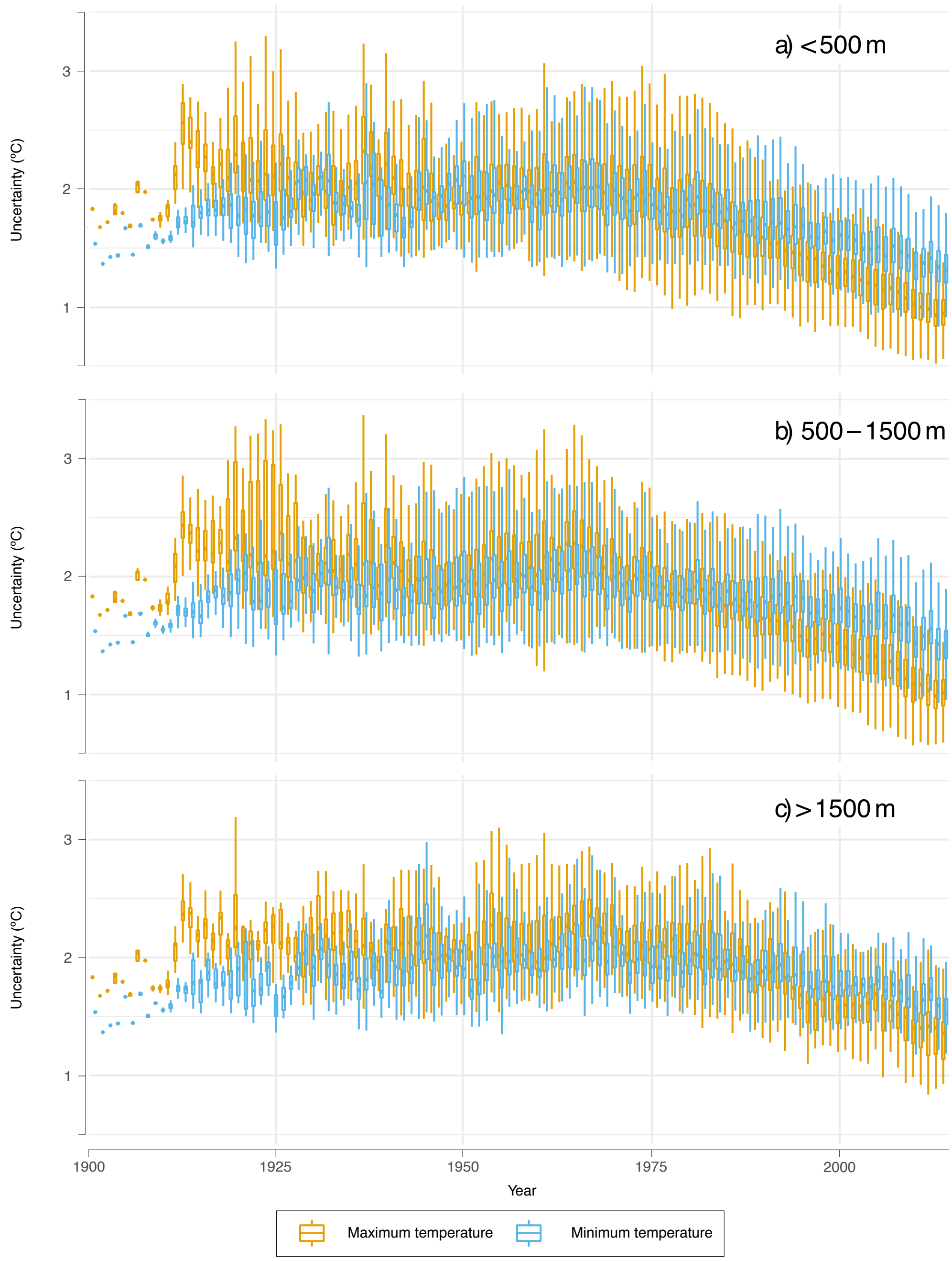

Figure S9. Annual evolution of median daily uncertainty of maximum and minimum temperature in peninsular Spain by altitudinal ranges: (a) gridpoints lower than 500 m.a.s.l.; (b) gridpoints between 500 and 1,500 m.a.s.l.; (c) gridpoints higher than 1,500 m.a.s.l.