A Southeastern South American Daily Gridded Data Set of Observed Surface Minimum and Maximum Temperature for 1961-2000

*Bárbara Tencer [1,2] *, Matilde Rusticucci [1,2], Phil Jones [3] and David Lister [3]*

[1] Laboratorio de Extremos Climáticos en Sudamérica, Departamento de Ciencias de la Atmósfera y los Océanos, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires, Argentina

[2] CONICET, Argentina

[3] Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich, UK

* *Corresponding author address:*

Departamento de Ciencias de la Atmósfera y los Océanos, FCEN, UBA

Ciudad Universitaria - Pabellón II - 2º piso

(1428) Buenos Aires, Argentina

Tel: (54 11) 4576-3356/3364 ext. 32

Fax: (54 11) 4576-3356/3364 ext. 12

E-mail: btencer@at.fcen.uba.ar

Abstract

This study presents a southeastern South American gridded data set of daily minimum and maximum surface temperatures for 1961-2000. The data used for the gridding are observed daily data from meteorological stations in Argentina, Brazil, Paraguay and Uruguay from the EU FP6 CLARIS database, with some additional data series. This gridded data set is new for the region not just for its spatial and temporal extension, but also for its temporal resolution. The region for which the gridded dataset has been developed is 20º-40º S, 45º-70º W, with a resolution of 0.5º of latitude by 0.5º of longitude. Since the methodology used produces an estimation of grid box averages, the developed data set is very useful for the validation of Regional Climate Models. The comparison of gridded and observed data provides an evaluation of the usefulness of the interpolated data. According to monthly mean values and daily variability, the methodology of interpolation developed during the EU FP6 ENSEMBLES project for its application in Europe, is also suitable for southeastern South America. Root mean squared errors for the whole region are 1.77 degrees Celsius for minimum temperature and 1.13 for maximum temperature. These errors are comparable to values obtained for Europe with the same methodology.

1. Introduction

A gridded data set is of great value for many applications, one of which is the validation of climate models. Since observations at meteorological stations represent variables at specific locations while climate model simulations give information as area averages, the comparison between observed and simulated data is not simple. Therefore, it is important to develop interpolation methodologies that convert data sets of observed unevenly-distributed meteorological variables in a region into data sets of observed values for grid boxes, evenly distributed in space and representing areal means. Furthermore, a gridded data set can provide a reliable interpolation of certain climatic variables for small regions where no observations are available, allowing local climatological studies in regions with scarce meteorological stations.

The climate observing system over South America exhibits serious deficiencies in spatial resolution and in data quality control. The European Union Framework Programme 6 (FP6) CLARIS project aimed at building an integrated high-quality daily meteorological station database and at improving/automating quality control procedures (Boulanger et al., 2010). The CLARIS database gathered stations from Argentina, Brazil, Uruguay and Chile, although with a relatively low spatial density, considering that most of these stations were only provided by governmental institutions. However, in the La Plata Basin, many non-government institutions have their own networks and can also provide good-quality data. During the EU FP6 ENSEMBLES project, the University of East Anglia (UEA) developed interpolation procedures for Europe to grid daily precipitation totals and maximum and minimum temperatures, principally for its comparison with a range of Regional Climate Model (RCM) simulations (Haylock et al., 2008).

In this paper, a southeastern South American daily high-resolution gridded data set of observed surface minimum and maximum temperature for 1961-2000 is presented, together with different experiments that determine the influence of several factors in the gridding procedure. This new data set was developed as part of the EU FP7 CLARIS LPB - A Europe-South America Network for Climate Change Assessment and Impact Studies in La Plata Basin project, with the aim of using it for the validation of Regional Climate Models (RCMs). The interpolation methodology was adapted from the one developed for Europe as part of the EU FP6 ENSEMBLES-based Predictions of Climate Changes and their Impacts project (Haylock et al., 2008).

For the EU FP7 CLARIS La Plata Basin (LPB), we propose to undertake the same gridding procedures and comparisons of the raw and gridded products. The density of daily observations across the LPB is markedly less than that available for Europe, so the proposed resolution will be 0.5º by 0.5º (latitude/longitude).

Other data sets of observed gridded temperature already exist for the region, however none can compare to the one presented here in terms of length of record, and spatial and temporal resolution. The data set developed at the Climatic Research Unit (CRU, University of East Anglia, UK) by Mitchell and Jones (2005) includes observed temperature data from all over the globe, but only at the monthly scale. Caesar et al. (2006) developed a global gridded daily temperature data set for minimum and maximum temperature which covers the period from 1946 to 2000, but it has a very poor coverage in South America due to lack of available data at that time. Liebmann and Allured (2005) developed a dense daily gridded data set for South America, but it only includes precipitation data.

The daily gridded series will be used to validate the RCM integrations undertaken over southern South America, among other possible uses. Within the timeframe of CLARIS LPB, it will not be possible to feed model deficiencies back to the modelling centres, so instead, the differences between the RCM integrations and the real-world gridded data (in terms of means and variances) will be applied to future integrations of the RCMs when these will be used for impact assessment.

2. Data and methodology

The gridded data set presented in this study was developed from daily surface minimum and maximum temperature data observed at meteorological stations from Argentina, Brazil, Paraguay and Uruguay, compiled during the EU F6 CLARIS project, with additional Brazilian data gathered after the end of that project. Figure 1 shows the region (20º-40ºS, 45º-70ºW) and the stations used to develop the gridded data set.

For each month, only stations with less than 20% missing data are considered to produce values at each grid box. Therefore, the number of stations per month considered for the interpolation process with this criterion changes from to month. Figure 2, which presents the evolution of the number of stations used for each month, shows an increase in the number of available stations until 1976, followed by a continual drop until the end of the period, with a sharp dip in the number of stations in November 1994. The number of stations with at least one observation per month (shown in Figure 2 as the number of stations with less than 99% of missing data) also shows a decline after 1976, suggesting that the decrease in the amount of useful stations is caused by a reduction in the number of stations rather than an increase in the amount of missing data. This is consistent with Boulanger et al. (2010), who found that 40% of the Argentinean network was lost during the 1970s. As a result of the criterion used regarding missing data, only a maximum of 194 stations are used each month (see Figure 1b) from the original 265 stations with at least one day of data shown in Figure 1a.

It is also noticeable that the spatial distribution of stations is not homogeneous throughout the region. In particular, only three stations are available in Paraguay and just a few in southern Brazil. However, Argentina and Uruguay are much better sampled.

The interpolation methodology used to convert irregularly-spaced observations at station points to regular grid boxes was developed during the EU FP6 ENSEMBLES project, and consists of a three-step procedure. Firstly, monthly means are interpolated using the method of *thin-plate splines*. Secondly, the *kriging* method is applied to the interpolation of daily anomalies with reflect to the monthly mean. Finally, the combination of both fields gives the final product. For a more detailed explanation on the methodology, see Haylock et al. (2008).

This three-step process allows the use of two different methods for the interpolation of monthly and daily values. Hofstra et al. (2008) performed a study comparing six different interpolation methods and determined *kriging* to be the best interpolation method for daily data. A similar cross validation was carried out for monthly data which showed *thin-plate splines* to be the best method (Haylock et al, 2008).

The interpolation methods selected were adjusted to represent as accurately as possible a point observation. However, since the aim of the gridding exercise was to produce grid square averages, it is more convenient to produce grid box values that represent area averages instead of point values. This can best be achieved by interpolating to a finer grid with each point having a temperature occurrence distribution similar to that of an observing station, then averaging these to create a coarser grid. Therefore, both daily and monthly values were first interpolated with a finer resolution and then area averages were calculated to produce a final coarser resolution. Details on the resolution are explained in Section 3.c.

3. Results

a. Monthly data

A first data set was produced for the period 1961-2000 in the region 20º-40ºS, 45º-70ºW with a fine resolution of 0.5ºx0.5º and then area averaged to a coarser resolution of 1ºx1º (Section 3.c shows results with an increased resolution). In order to evaluate the performance of the interpolation method in the region, monthly mean values and standard deviations calculated for each grid box were compared to those calculated for each station point. Figures 3 and 4 show monthly mean values for January, April, July and October for minimum and maximum temperature respectively, for station points and grid boxes. For those regions with an acceptable –though not optimal- number of stations, monthly mean values represent point values with a high level of similarity, both for minimum and maximum temperature. For regions with an inadequate number of stations covering the surroundings of a grid point, the method does not estimate a value for that grid box. These regions are always near the limits of the domain and vary from month to month due to the missing data criterion used to discard stations. Figures 5 and 6 show maps of standard deviation for grid points and station values for January, April, July and October for minimum and maximum temperature, respectively. Each map represents the daily deviation from the monthly mean averaged over the whole period. Both figures show that gridded data underestimate daily variability with respect to station data. This underestimation is expected since spatial interpolation implies areal averaging which results in smoothing of day-to-day variability. The analysis of standard deviation also shows that even in regions with few station points the method is still able to generate values on grid points from the interpolation of nearby values, with no significant differences between regions with a lot or just a few station series.

b. Skill scores

It is of special interest to study how well the gridded data set represents daily values. Therefore, different skill scores were computed based on the difference between daily values from each station and the nearest grid point. Figures 7 and 8 show results from three different skill scores: root mean squared error (RMSE), compound relative error (CRE) and mean absolute error (MAE). A description of the skill scores used in this study can be found in Table 1 (for more details refer to Hofstra et al, 2008). A global RMSE of 2.06ºC (1.48ºC) is obtained for minimum (maximum) temperature. In general terms, maximum temperature seems to be better represented by gridded data. Poorer skill scores (higher values), meaning less accurate interpolated series, are found near the *Cordillera de los Andes*, where the topography introduces more uncertainty into the interpolated data. The Pearson correlation coefficient between daily temperature at each station and the nearest grid point series was also calculated, resulting in values greater than 0.9 for almost every station and global values greater than 0.97, both for minimum and maximum temperature. These results are consistent with those found by Hofstra et al. (2008) for the European region.

c. Resolution increase

Since 1ºx1º is still a relatively poor resolution for a gridded database, especially if it is to be used for validation of RCMs which usually have greater resolution, an attempt to double this resolution was made with the same amount of station data. Monthly means, standard deviations and skill scores were recalculated for a higher resolution version of the gridded data set, where the interpolation was made to a fine resolution of 0.25ºx0.25º and then area averages were calculated to produce the final resolution of 0.5ºx0.5º. A global RMSE of 1.77ºC (1.13ºC) was found for minimum (maximum) temperature, showing a marked improvement in the estimation of both variables. The spatial pattern of uncertainties is very similar to the previous version of the gridded data set, with higher uncertainties in the western part of the region, near the *Cordillera de los Andes* (see Figures 9 to 14 compared to Figures 3 to 8). The skill scores obtained for southeastern South America are of the same magnitude as the ones obtained for the European region (see Hofstra et al., 2008), indicating a similar performance of the interpolation methodology in our region.

d. Extremes

Since this data set is likely to be used in extreme events studies, it is of particular interest to analyse how the interpolation methodology affects the extremes. It is expected that extremes will be smoothed by the kriging and spline interpolation as well as by area averaging to a coarser resolution than that expected from a high-resolution grid. A comparison of extremes at station locations and grid boxes will allow a quantification of the smoothing of the estimated extremes. This comparison is undertaken using the high resolution version of the gridded data set described in section 3.c based on the difference between percentiles calculated on a monthly basis at each station and the nearest grid box (see Figures 15 and 16). Differences are calculated as station percentile minus grid-box percentile, so negative values indicate overestimation of percentiles in the gridded dataset compared to station points.

As expected, the 5th percentile shows an overestimation of the estimated values while the 95th percentile shows an underestimation, both in minimum and maximum temperature, except in the western part of the domain. These differences imply an underestimation of cold and warm extremes. Averaged over the whole region, these differences are positive and show an underestimation of 1.3ºC for minimum temperature and 0.8ºC for maximum temperature. Differences are generally higher for minimum than for maximum temperature, as expected since daily data was better represented by the interpolation method for the latter. However, in the western part of the region, near the *Cordillera de los Andes*, differences are always negative, for all percentiles and months and for both variables. And this region is also the one that presents the biggest differences of the whole domain, with differences greater than 3.0ºC in most cases. Since the nearest grid box center can be up to 50 km away from the station due to the spatial resolution of the gridded dataset station elevation may differ from the nearest grid-box elevation (see Figure 17), especially in the western part of the domain which is characterised by high and irregular topography. These elevation differences can explain the bigger differences found in daily data and extremes when comparing station data to the nearest grid box in mountainous regions. Figure 17 shows that station elevations tend to be lower than grid-box elevations, due to stations being located in valleys.

Due to the urban heat island effect, minimum temperature in Buenos Aires city (34.58ºS-58.48ºW) is higher compared to stations nearby (Camilloni and Barros, 1997). Since all available data in a radius of 500km around the grid box center are used for the estimation, interpolated minimum temperatures will be smoothed compared to Buenos Aires, and therefore the comparison between this station and its nearest grid box will show bigger differences than the stations nearby. This is especially noticed in minimum temperature cold extremes (5^{th} percentile, Figure 15, upper right panel).

Temporal variability of extremes was also analysed by comparing the time-series of seasonal percentiles at each station and its nearest grid box. Figure 18 shows 95^{th} percentile of summer (DJF) maximum temperature and 5^{th} percentile of winter (JJA) minimum temperature at three different locations (indicated by stars in Fig. 1). All variables and extremes show a close agreement, except for the case shown in Fig. 18c in which station percentile values are always several degrees above grid box values. This difference is explained by the elevation difference of more than 1000 m between the grid box and the station.

e. Comparison with CRU data set

Monthly means obtained from daily interpolated data were compared to CRU TS3.0 (Mitchell and Jones, 2005) for the common period and region. Figures 18 and 19 show differences in monthly climatological minimum and maximum temperatures, respectively, for each month. Differences are calculated as CRU data minus the interpolated data presented in this paper. Since resolution and grid boxes are the same in both data sets, the comparison is made directly by computing differences for each grid box. Overall, differences between both data sets are less than 2ºC, except near the Cordillera de los Andes where high negative (positive) values are found for maximum (minimum) temperature. These greater differences are due to the different interpolation methodologies used for each data set and the influence of the spatial and temporal variability of input station density, compounded by the effect that a mountainous terrain has on the gridding process. Since correlation decay lengths are shorter for daily data, a smallest radius of influence is used when interpolating daily. In fact, the search radius used to select neighboring stations in CRU data set is more than twice the one used in the data set presented in this paper and therefore smoother patterns are obtained. In regions of high relief, this effect is increased, especially when high elevation stations are scarce and the available stations used for the interpolation are either in valleys or located close to the border of the radius of influence where lower relief prevails. Even more, most of the high elevation stations were closed during the 1970s, introducing a bias in the interpolated values afterwards in this region.

4. Discussion and Conclusions

A daily high-resolution gridded data set of observed surface minimum and maximum temperature has been developed for southeastern South American covering the period from 1961 to 2000. The interpolation methodology was adapted from the gridding procedure developed by Haylock et al. (2008) for the European region to be used in La Plata Basin (LPB). Evaluation results show that the methodology is suitable for this region since skill scores of similar magnitudes were obtained. As in Europe, results for maximum temperature are slightly better than for minimum temperature. LPB is a region which gathers parts of five countries (Argentina, Bolivia, Brazil, Paraguay and Uruguay), and for which economic wealth strongly depends on agriculture and hydropower production. So, the development of a high-quality hydroclimatic observational database for extreme event and decadal-to-interdecadal variability analysis is a main objective of EU FP7 CLARIS LPB project. In particular, the development of a daily gridded data set of observed surface temperature in the LPB region is of great importance since it allows a direct comparison with model simulation outputs, or even with reanalyses, in a region that has always been characterised by the lack of available data.

Previous gridded products have focused on precipitation data, or on monthly timescales. Several efforts have been made before to produce a daily gridded data set for observed surface temperature, with no results in South America due to the lack of available data (Caesar et al., 2006). Instead, since indices of extremes are available for the region, temperature extreme event studies were based on gridded data sets of these indices (Alexander et al., 2006). However, the indices are on a monthly or annual basis and, therefore, nothing could be said on the daily variability of temperature extremes.

When compared on a monthly basis to previously developed gridded data sets, such as the CRU data set, values showed a close agreement between data sets, except near the Cordillera de los Andes, where the complex topography and the lack of good quality daily data adversely affects the skill of the interpolation method. The strong decline in the number of available daily series in the 1970s compounded by the mountainous terrain can adversely affect the interpolation process, so special attention should be given to the analysis of data in high relief regions starting before 1976.

Gridded historical data is also a useful tool in decadal and interdecadal studies and observed climate change assessments. It will also allow a better interpretation of changes in frequency of occurrence and intensity of extreme events given by model simulations for future climate change scenarios, for its use in adaptation strategies. This gridded data set has an optimal resolution for RCM validation studies, which are the baseline for climate change studies based on simulations of future climate scenarios. However, due to scarce good quality high elevation stations, special attention should still be taken when analysing high relief regions.

Although this study presents a gridded data set for the southern part of LPB region, the gathering of more observed station data will allow us to extend the region, applying the same methodology. The fulfillment of the observed database that is being developed as part of the CLARIS LPB project will not only lead to a spatial extension of the region but also to a temporal extension of the period covered by the gridded data set.

Acknowledgments. The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) under Grant Agreement N°212492 (CLARIS LPB. A Europe-South America Network for Climate Change Assessment and Impact Studies in La Plata Basin), the University of

Buenos Aires (UBACyT X170) and the Agencia Nacional de Promoción Científica y Tecnológica (PICT05 38273-ANPCYT). Special thanks to Malcolm Haylock, who helped in the adaptation of the interpolation method to our region.

References

Alexander L. V., X. Zhang, T. C. Peterson, J. Caesar, B. Gleason, A. M. G. Klein Tank, M. Haylock, D. Collins, B. Trewin, F. Rahimzadeh, A. Tagipour, K. Rupa Kumar, J. Revadekar, G. Griffiths, L. Vincent, D. B. Stephenson, J. Burn, E. Aguilar, M. Brunet, M. Taylor, M. New, P. Zhai, M. Rusticucci, and J. L. Vazquez-Aguirre, 2006: Global observed changes in daily climate extremes of temperature and precipitation. *J. Geoph. Res.*, **111**, D05109, doi:10.1029/2005JD006290.

Camilloni, I., and V. Barros, 1997: On the Urban Heat Island effect dependence on temperature trends. *Climatic Change*, **37,** 665–681.

Boulanger J. P., J. Aizpuru, L. Leggieri, and M. Marino, 2010: A procedure for automated quality control and homogenization of historical daily temperature and precipitation data (APACH): part 1: quality control and application to the Argentine weather service stations. *Climatic Change*, **98**, 471–491.

Caesar, J., L. Alexander, and R. Vose, 2006: Large-scale changes in observed daily maximum and minimum temperatures: Creation and analysis of a new gridded data set. *J. Geoph. Res.*, **111**, D05101, doi:10.1029/2005JD006280.

Haylock M. R., N. Hofstra, A. M. G. Klein Tank, E. J. Klok, P. D. Jones, and M. New, 2008: A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *J. Geoph. Res.*, **113**, D20119, doi:10.1029/2008JD010201.

Hofstra N., M. Haylock, M. New, P. Jones, and C. Frei, 2008: Comparison of six methods for the interpolation of daily, European climate data. *J. Geoph. Res.*, **113**, D21110, doi:10.1029/2008JD010100.

Liebmann B. and D. Allured, 2005: Daily Precipitation Grids for South America. *Bull. Am. Met. Soc.*, **86**, 1567-1570.

Mitchell T. D. and P. D. Jones, 2005: An improved method of constructing a database of monthly climate observations and associated high-resolution grids. Int. J. Climatology, 25, 693-712, Doi: 10.1002/joc.1181.

CAPTIONS

Figure 1. Stations used for the interpolation. Colors show stations from different countries: blue for Argentina, red for Uruguay, orange, for Paraguay and green for Brazil. (a) All stations. (b) Stations with less than 20% of missing data on a single month. Stars indicate stations used in Section 3.d.

Figure 2. Number of stations used for the interpolation with (*black*) less than 20% of missing data per month and (*blue*) less than 99% of missing data per month for (*solid line*) maximum and (*dotted line*) minimum temperature.

Figure 3. Mean minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

Figure 4. Mean maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

Figure 5. Standard deviation of minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

Figure 6. Standard deviation of maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

Figure 7. Skill scores for minimum temperature. Global values calculated as average over the whole region are indicated in the figure. Gridded data resolution is 1ºx1º.

Figure 8. As in figure 7, for maximum temperature.

Figure 9. Mean minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

Figure 10. Mean maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

Figure 11. Standard deviation of minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

Figure 12. Standard deviation of maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

Figure 13. Skill scores for minimum temperature for the higher resolution version. Global values calculated as average over the whole region are indicated in the figure. Gridded data resolution is 0.5ºx0.5º.

Figure 14. As in figure 13, for maximum temperature.

Figure 15. Difference between (*upper panels*) 5th percentile calculated on station data and nearest grid box for (*left*) January and (*right*) July for minimum temperature. (*lower panels*) Same as before, for 95th percentile. Negative values indicate overestimation of the interpolated values.

Figure 16. As in Figure 16, for maximum temperature.

Figure 17. Station elevation (in meters) versus nearest grid box elevation (in meters) for all stations used in this study.

Figure 18. 95th percentile of summer (DJF) maximum temperature (*red*) and 5th percentile of winter (JJA) minimum temperature (*blue*) at three different locations (*solid line*): (*a*) 22.02S, 60.6W, 181m, (*b*) 36.57S, 64.27W, 191m and (*c*) 29.38S, 66.82W, 429m and their nearest grid box (*dotted line*).

Figure 19. Monthly differences (in ºC) between CRU dataset and the gridded dataset presented in this study for minimum temperature. Negative values indicate that CRU has minor values.

Figure 20. As in Fig. 18, for maximum temperature.

Table 1. Description of skill scores used to quantify the skill of the interpolation method.

TABLES AND FIGURES

Skill Score	Equation*
Root mean squared error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2}$
Mean absolute error (MAE)	$MAE = \frac{1}{n}\sum_{k=1}^{n}\lvert y_k - o_k \rvert$
Compound relative error (CRE)	$CRE = \frac{\sum_{k=1}^{n}(y_k - o_k)^2}{\sum_{k=1}^{n}(o_k - \bar{o})^2}$

* Explanation of the variables: y is the grid point data, o is the station data, k is the number of the day, n is the total number of days.

Table 1. Description of skill scores used to quantify the skill of the interpolation method.

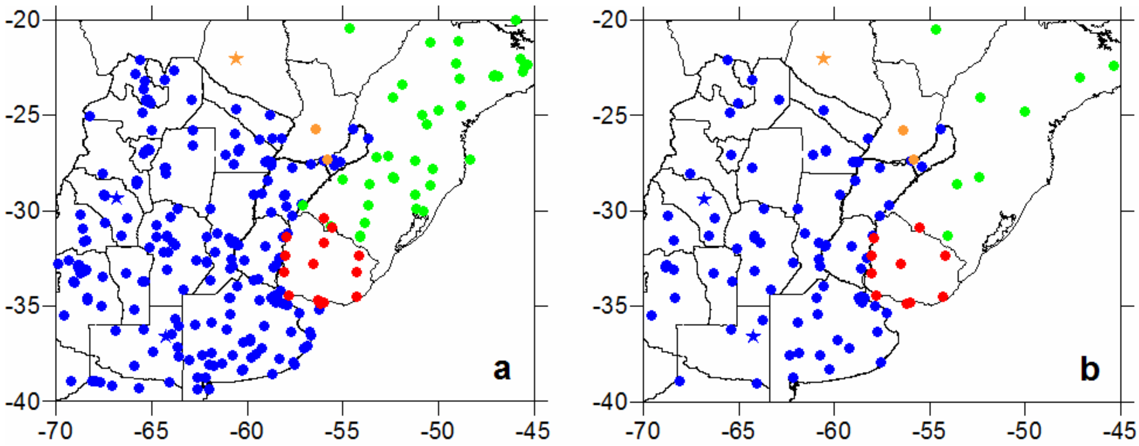

Figure 1. Stations used for the interpolation. Colors show stations from different countries: blue for Argentina, red for Uruguay, orange, for Paraguay and green for Brazil. (a) All stations. (b) Stations with less than 20% of missing data on a single month. Stars indicate stations used in Section 3.d.

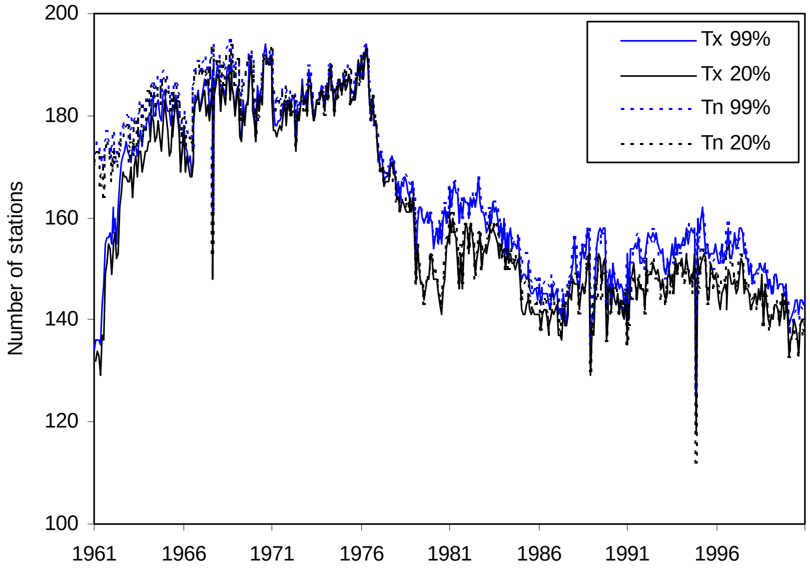

Figure 2. Number of stations used for the interpolation with (*black*) less than 20% of missing data per month and (*blue*) less than 99% of missing data per month for (*solid line*) maximum and (*dotted line*) minimum temperature.

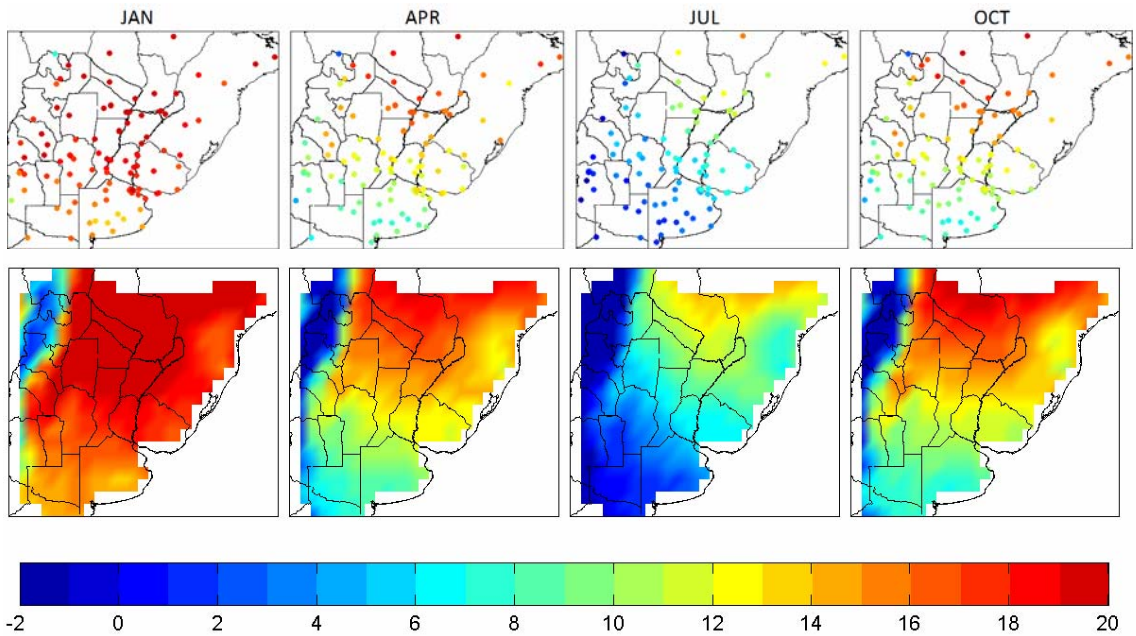

Figure 3. Mean minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

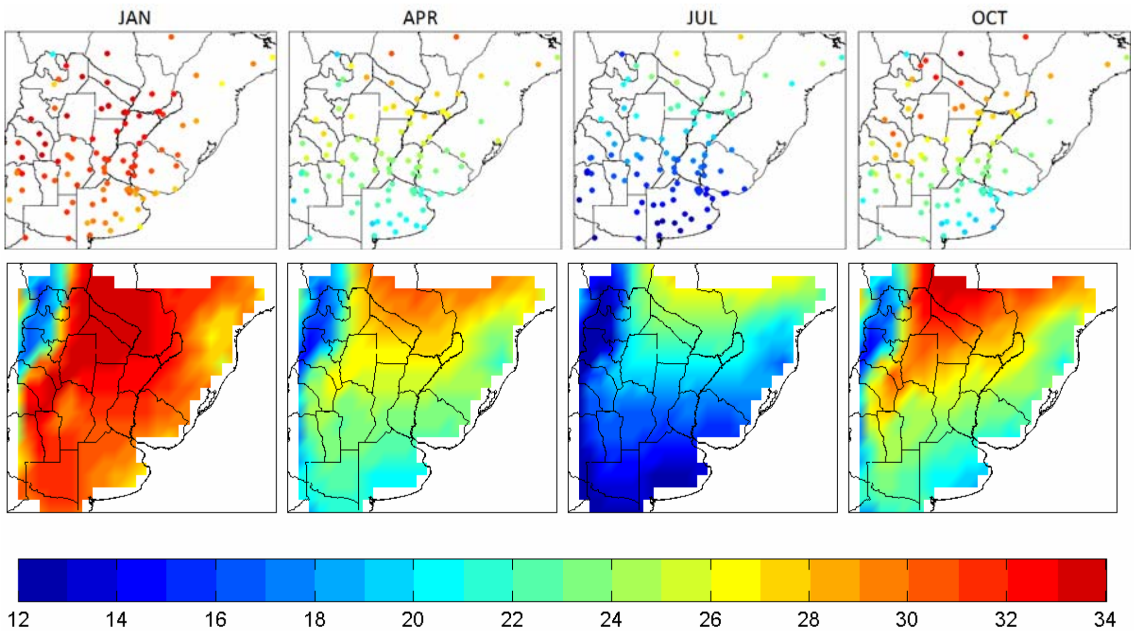

Figure 4. Mean maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

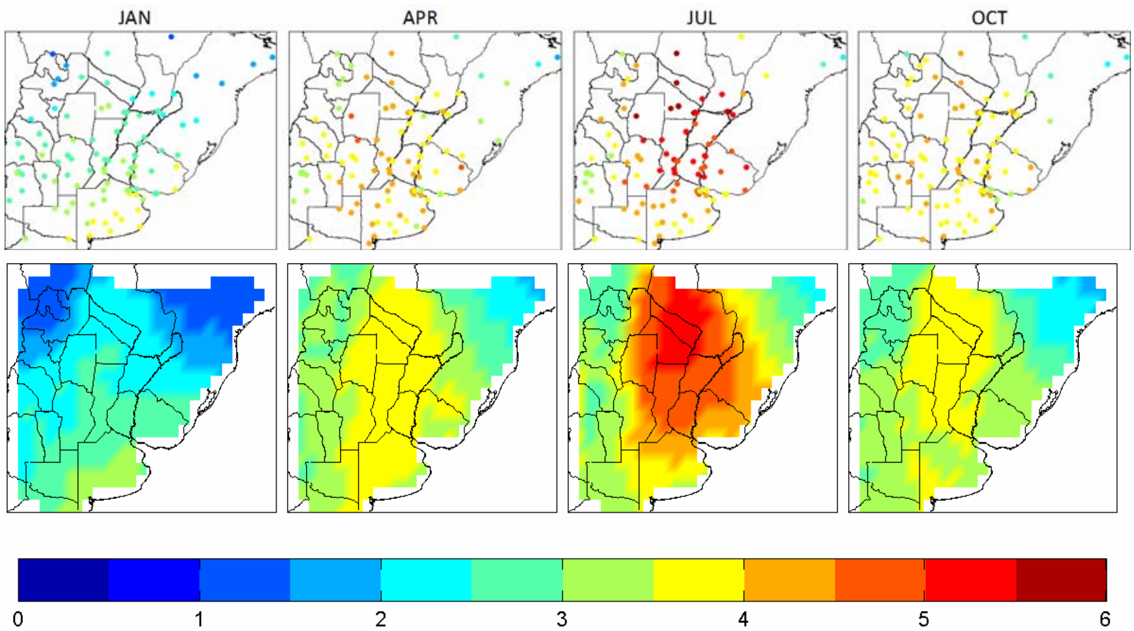

Figure 5. Standard deviation of minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

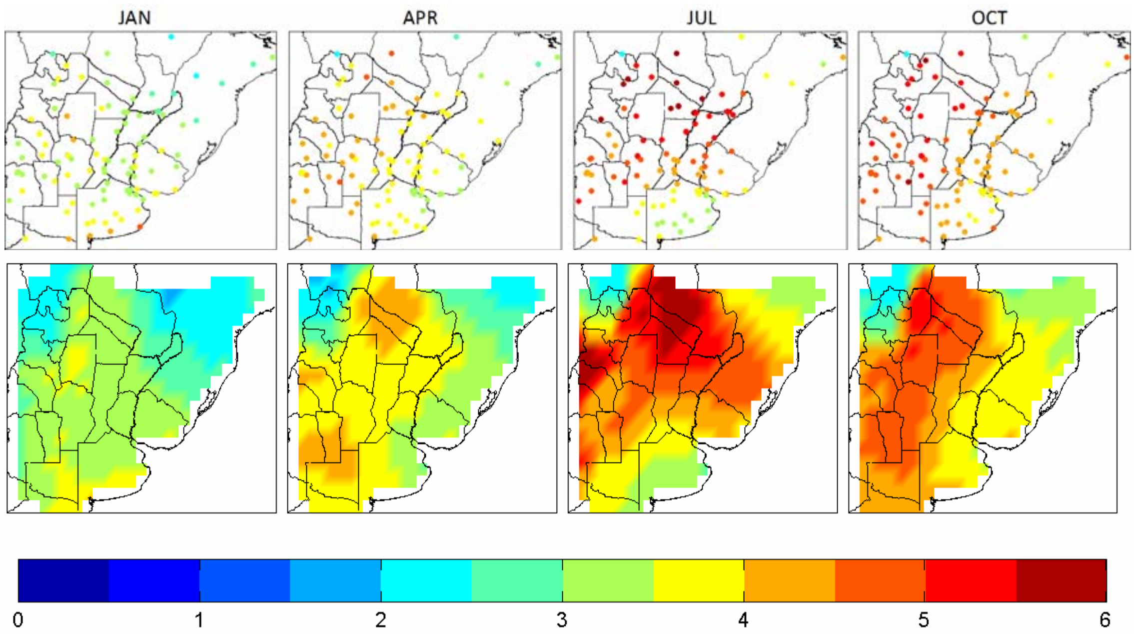

Figure 6. Standard deviation of maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 1ºx1º.

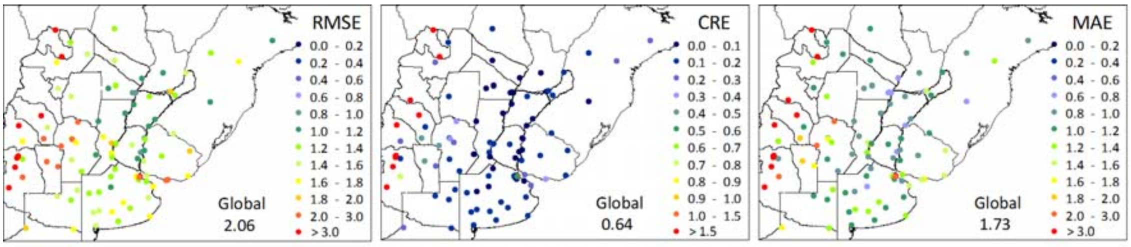

Figure 7. Skill scores for minimum temperature. Global values calculated as average over the whole region are indicated in the figure. Gridded data resolution is 1ºx1º.

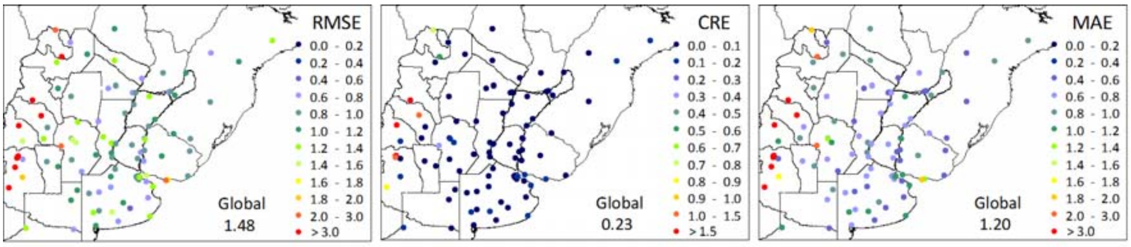

Figure 8. As in figure 7, for maximum temperature.

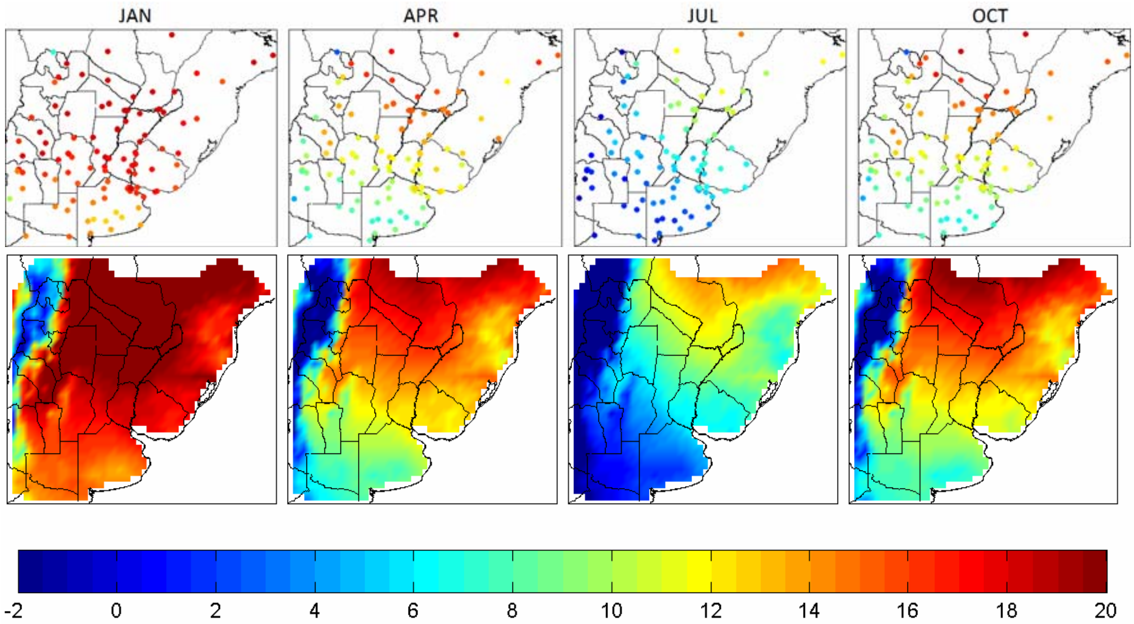

Figure 9. Mean minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

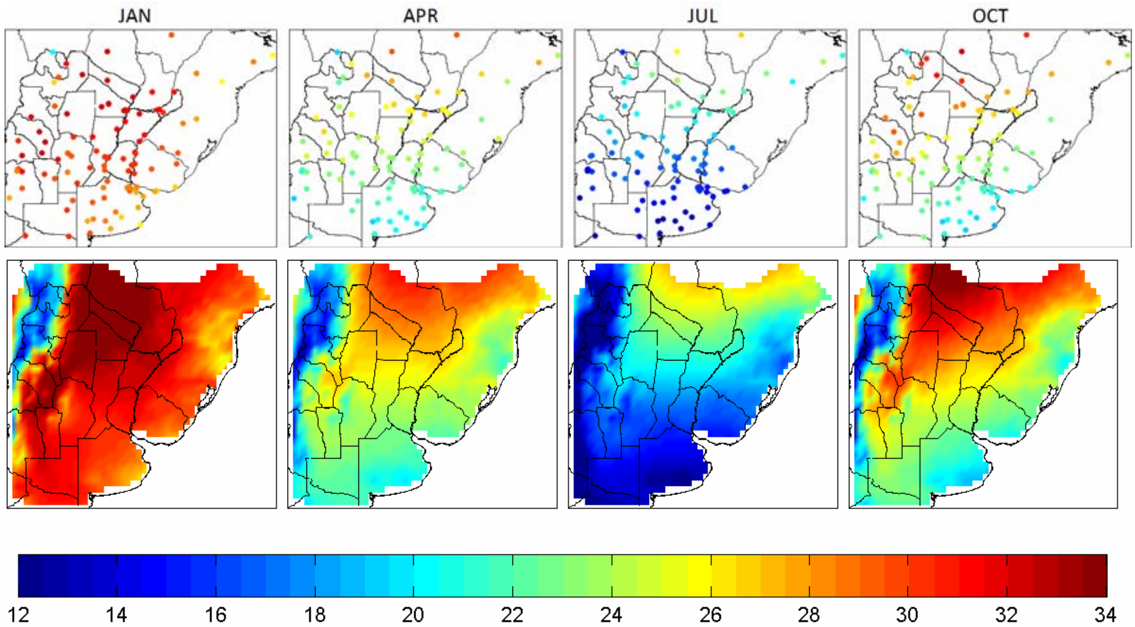

Figure 10. Mean maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

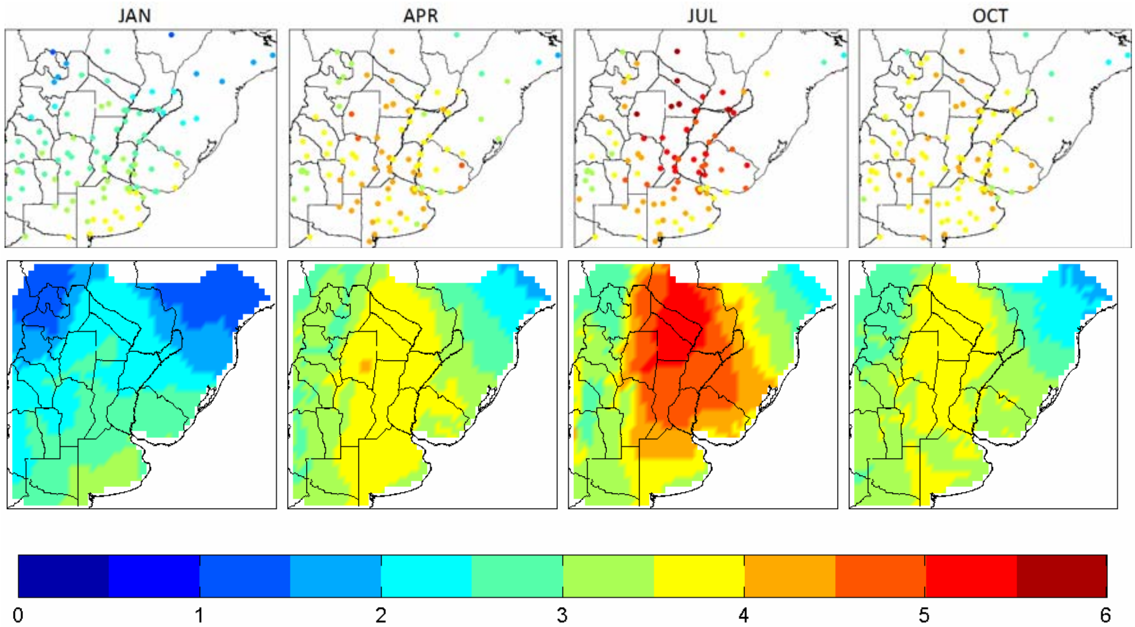

Figure 11. Standard deviation of minimum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

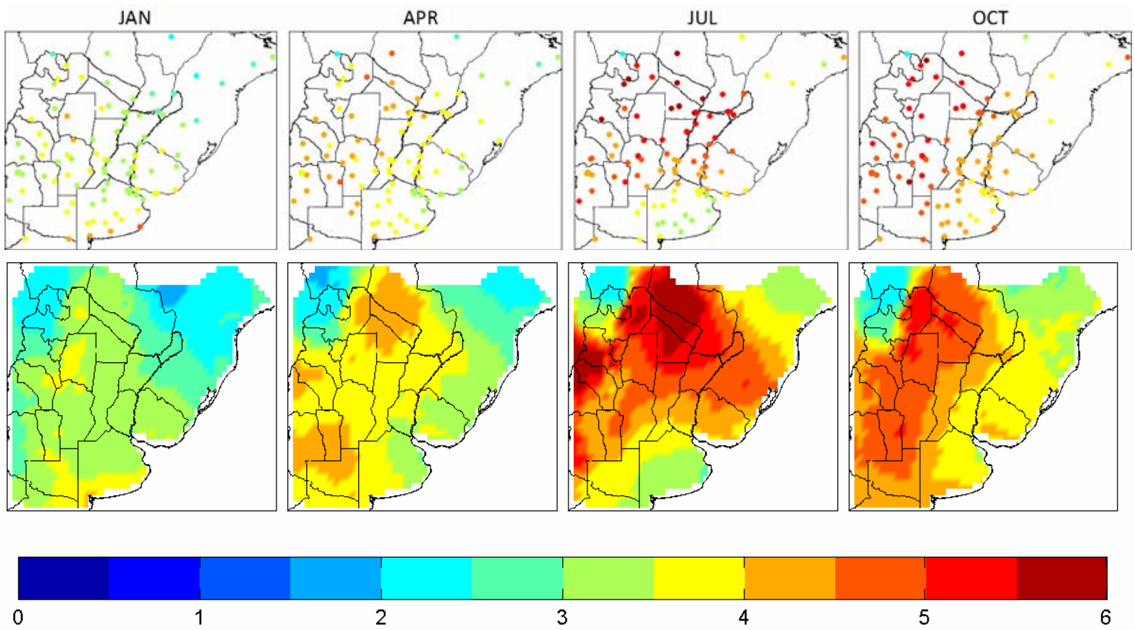

Figure 12. Standard deviation of maximum temperature (ºC) at station points (*upper panels*) and grid boxes *(lower panels)* for January, April, July and October 1961-2000. Color scale is the same for both datasets. Gridded data resolution is 0.5ºx0.5º.

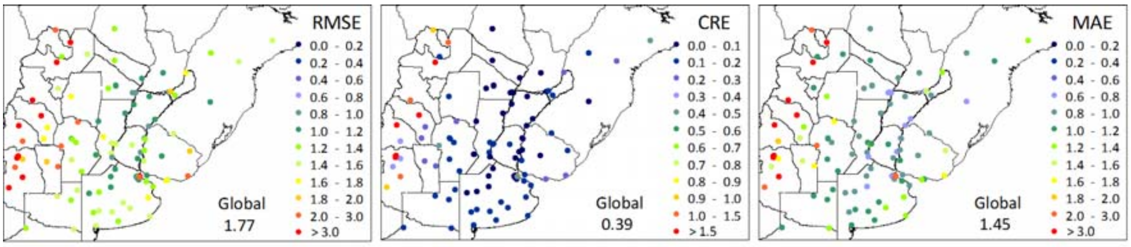

Figure 13. Skill scores for minimum temperature for the higher resolution version. Global values calculated as average over the whole region are indicated in the figure. Gridded data resolution is 0.5ºx0.5º.

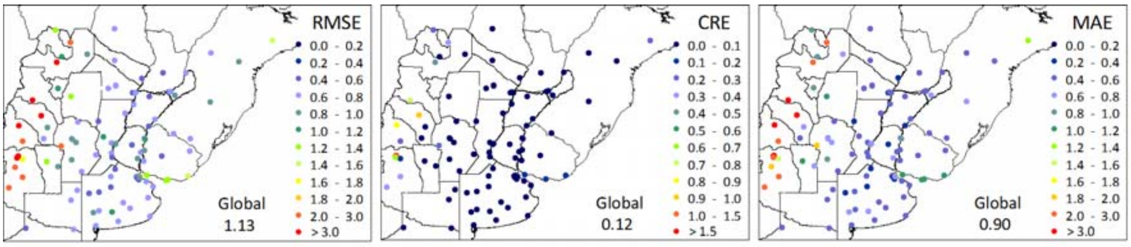

Figure 14. As in figure 13, for maximum temperature.

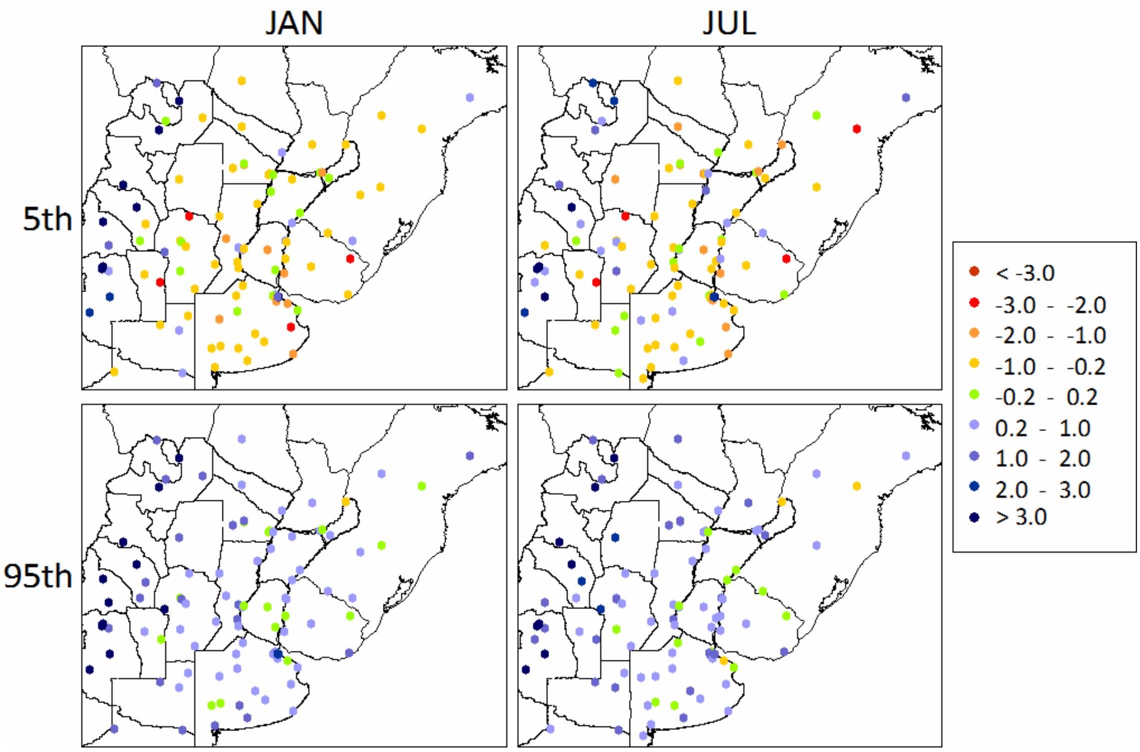

Figure 15. Difference between (*upper panels*) 5th percentile calculated on station data and nearest grid box for (*left*) January and (*right*) July for minimum temperature. (*lower panels*) Same as before, for 95th percentile. Negative values indicate overestimation of the interpolated values.

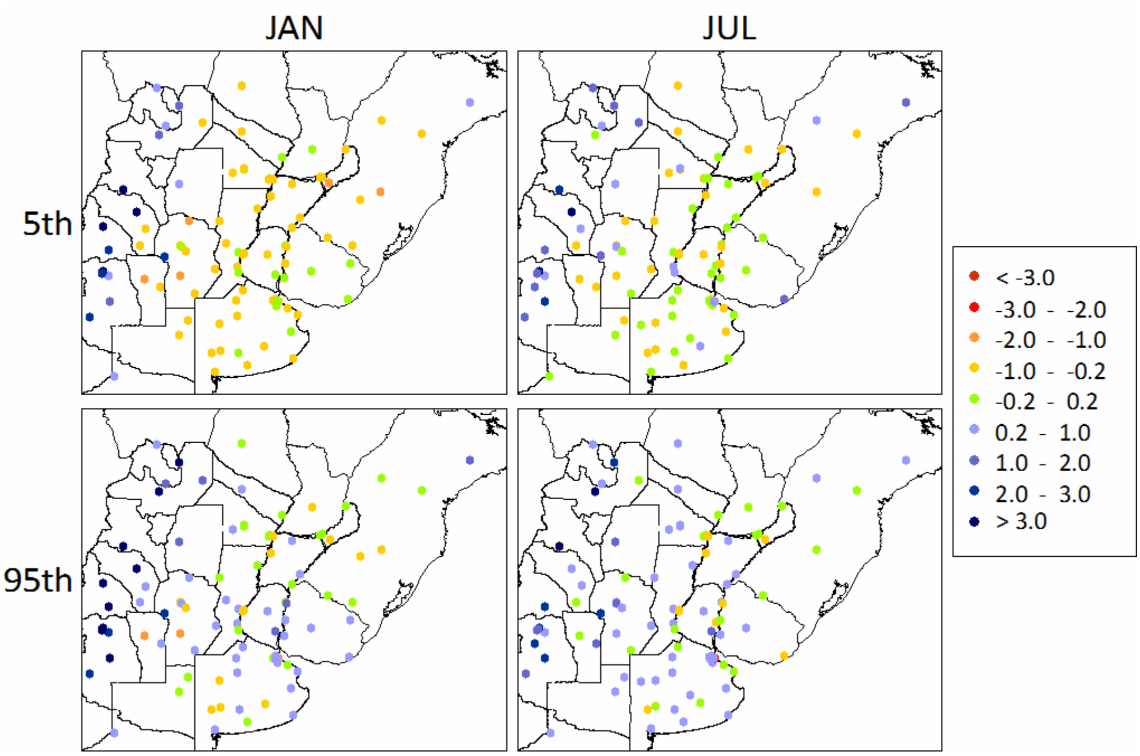

Figure 16. As in Figure 16, for maximum temperature.

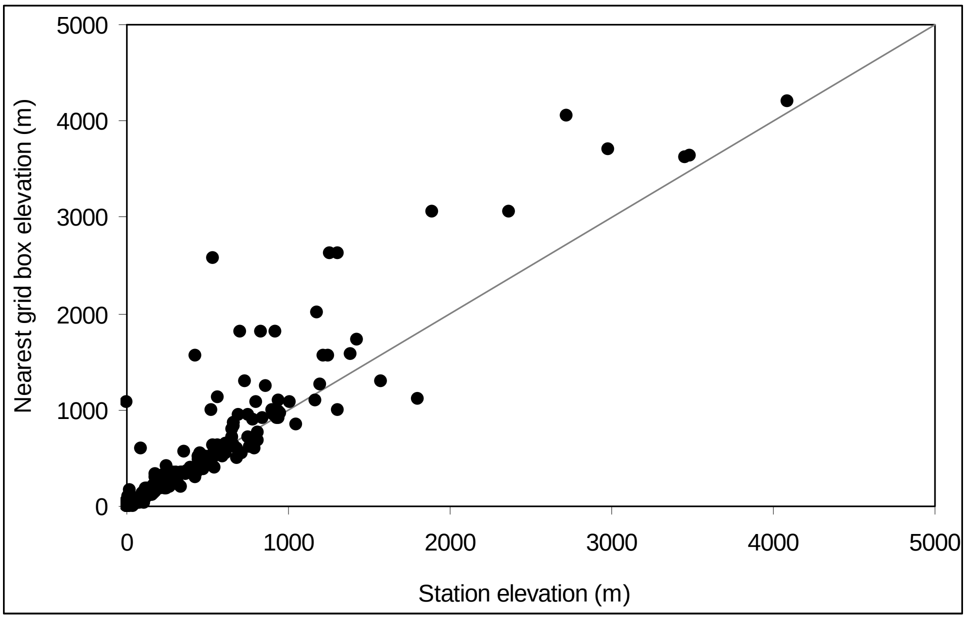

Figure 17. Station elevation (in meters) versus nearest grid box elevation (in meters) for all stations used in this study.

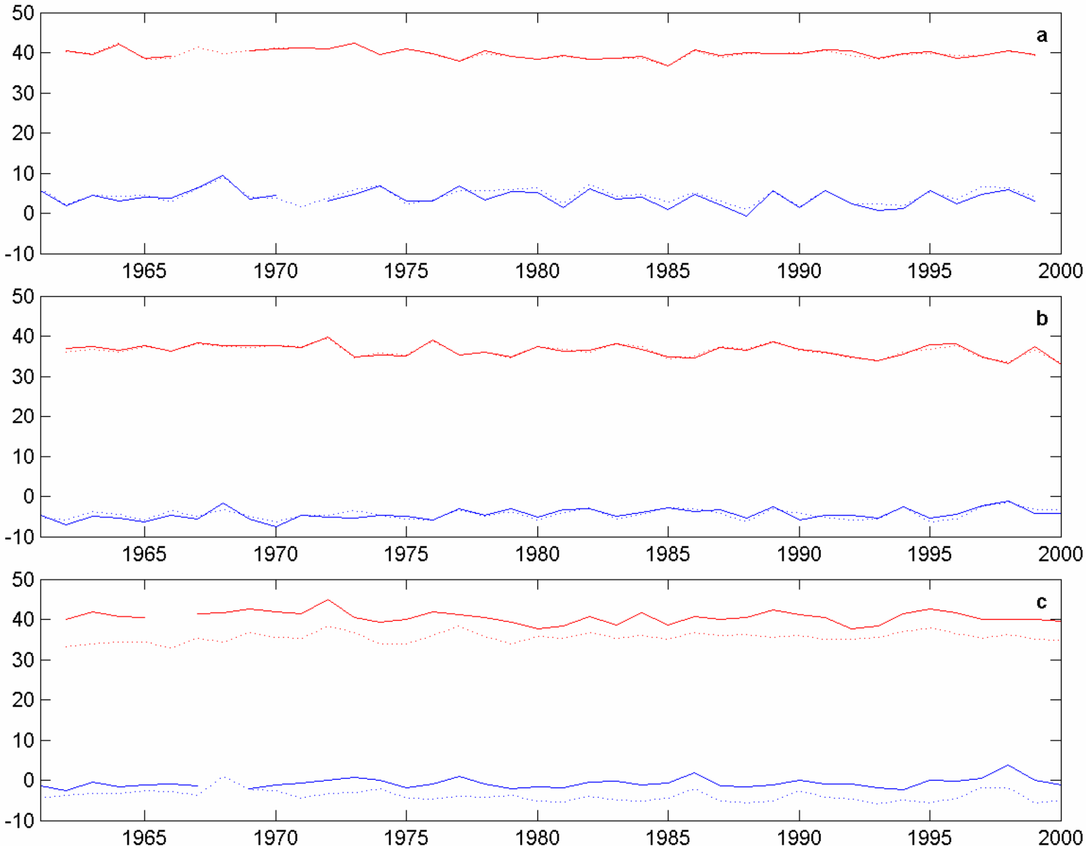

Figure 18. 95th percentile of summer (DJF) maximum temperature (*red*) and 5th percentile of winter (JJA) minimum temperature (*blue*) at three different locations (*solid line*): (*a*) 22.02S, 60.6W, 181m, (*b*) 36.57S, 64.27W, 191m and (*c*) 29.38S, 66.82W, 429m and their nearest grid box (*dotted line*).

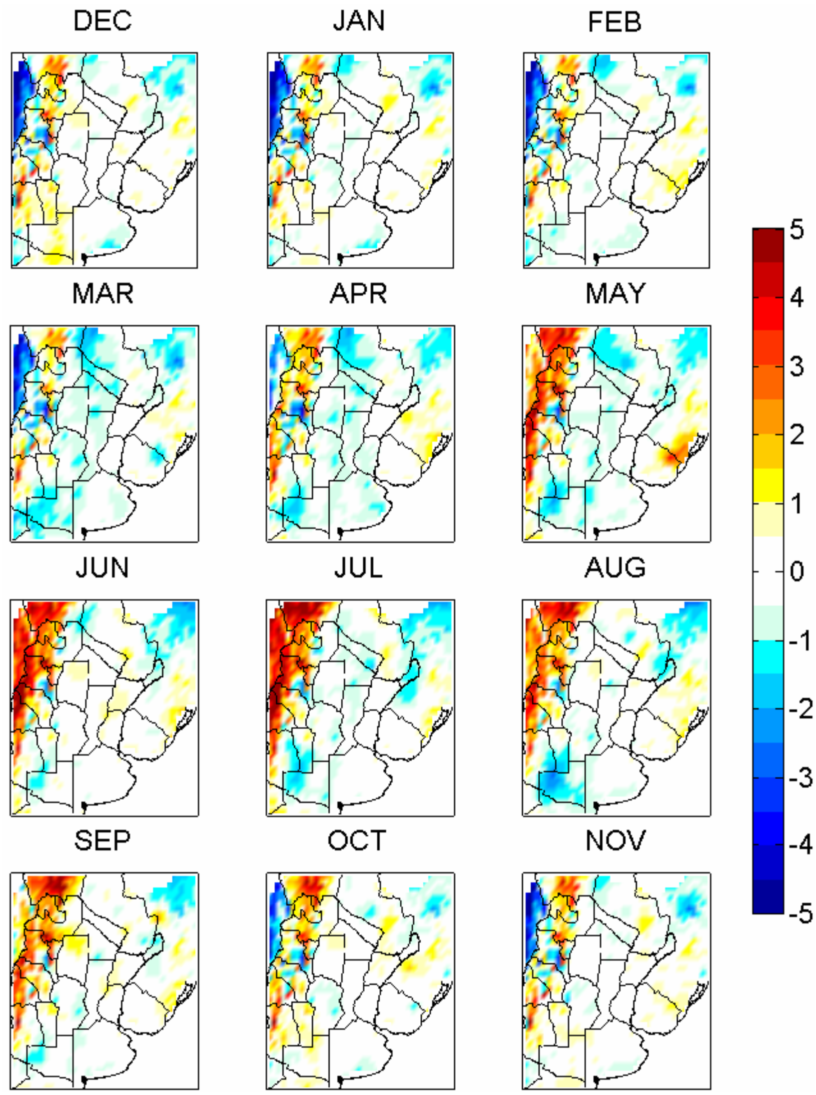

Figure 19. Monthly differences (in ºC) between CRU dataset and the gridded dataset presented in this study for minimum temperature. Negative values indicate that CRU has minor values.

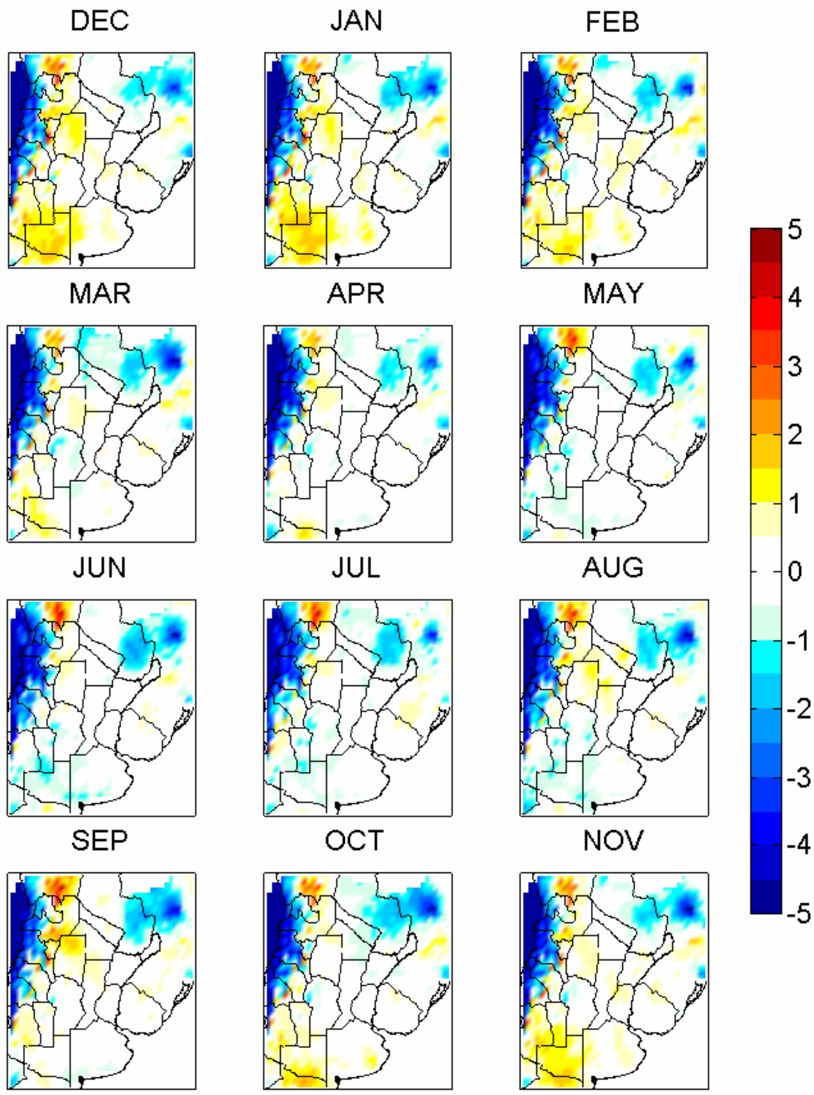

Figure 20. As in Fig. 18, for maximum temperature.