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Space-time interpolation of daily air temperatures

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Abstract

We propose a model to describe the mean function as well as the spatio-temporal covariance structure of 15 years of both maximum and minimum daily temperature data from 190 stations throughout the region of Catalonia (Spain), with daily data covering the period 1994-2008. Our aim is threefold: (a) estimation of the long-term trend of maximum and minimum temperatures; (b) assessing the spatial and temporal variability of temperatures, and (c) interpolation of the spatial temperatures at any given time.

Long-term trend, annual harmonics and winds were considered as explanatory variables of the mean function. The parameters associated with these variables were allowed to vary between stations and within each year. We controlled temporal autocorrelation by means of ARMA models. For the spatial covariance structure we used the Matérn family of covariance functions and a nugget term. Spatio-temporal models were built as Bayesian hierarchical models with two stages following the integrated nested place Laplace approximation (INLA) for Bayesian inference. For the final model estimation we used a two-stage approach, in which we first assumed the stations were spatially independent, and then we modeled the spatio-temporal covariance using the interim posterior from the residuals of the model in the first-stage as prior distributions of replications of a spatial process. We allowed all spatial parameters to also vary with time.

Keywords: Average temperature; Integrated nested Laplace approximation; Spatial variability; Spatio-temporal covariance; Two-stage Bayesian approach.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC), in its fourth and final evaluation report (IPCC, 2007a), pointed out several long-term changes in climate at global and regional scales. These changes have a higher probability of being associated with an anthropic activity.

Climate change refers to any significant change in measures of climate, such as temperature, precipitation and other weather patterns, that lasts for decades or longer. Consensus exists among scientists that the world's climate is changing, with more precipitation and weather extremes. Potential effects of this climate change are likely to include stronger and longer heat waves, more frequent heavy precipitation events, extreme weather events and increased air pollution (IWGCCH, 2010).

During the last years, efforts have focused on addressing how environmental changes can affect people's health. The more direct health effects of climate change can include injuries and illnesses from severe weather and heat exposure, increases in disease caused by allergies, respiratory problems, illnesses carried by insects or water and threats to the safety and availability of food and water supplies (IPCC, 2007b; IWGCCH, 2010).

Throughout the world, the prevalence of some diseases and other threats to human health depend largely on local climate, and particularly on local temperature. Climate-related disturbances in ecological systems can indirectly impact the incidence of serious infectious diseases, while extreme temperatures can lead directly to loss of life (IWGCCH, 2010). Many studies have shown that increases in average temperature may lead to more extreme heat waves during the summer, while producing less extreme cold spells during the winter. Higher temperatures, in combination with favorable rainfall patterns, could prolong disease transmission seasons in some locations where certain diseases already exist. In other locations, climate change will decrease transmission via reductions in rainfall or temperatures that are too high for transmission. Thus, temperature and humidity levels must be sufficient for certain disease-carrying vectors, such as ticks that carry Lyme disease, to thrive (National Research Council, 2001; IPCC, 2007b).

Additionally, temperature changes are expected to contribute to air quality and health problems. In fact, respiratory disorders may be exacerbated by warming-induced increases in the frequency of smog events and particulate air pollution (Schwartz and Randall, 2003). Sunlight and high temperatures, combined with other pollutants such as nitrogen oxides and volatile organic compounds, can cause ground-level ozone to increase. This increment can damage lung tissue, and is especially harmful for those with asthma and other chronic lung diseases. For other pollutants, the effects of climate change or weather are less studied and results vary by region. However, it seems clear that warm temperatures can increase air and water pollution, which in turn harm human health (McMichael *et al.*, 2003; Schwartz and Randall, 2003).

Studying the local global climate change is a pressing challenge for public environmental and health agencies. The problem is broad and complex. However results are needed to respond to the challenges of global climate change (IWGCCH, 2010). The discovery of a significant trend towards an increase or decrease in the average values of a particular climatic element becomes a first symptom of climate change. The long-term evolution of the average temperature in a known time interval is considered a useful indicator that is easy to understand (Meteorological Service of Catalonia, 2010).

Motivated by these clear facts concerning the air temperature as an important climatic element, we analyze in this paper the spatio-temporal behavior of daily air temperatures in the Catalonian region of Spain. We propose a model to describe the mean function as well as the spatio-temporal covariance structure of 15 years of both maximum and minimum daily temperature data from 190 stations throughout the region of Catalonia (Spain, see Figure 1), with daily data covering the period 1994-2008. Our aim is threefold: (a) estimation of the long-term trend of maximum and minimum temperatures; (b) assessing the spatial and temporal variability of temperatures, and (c) interpolation of the spatial temperatures at any given time.

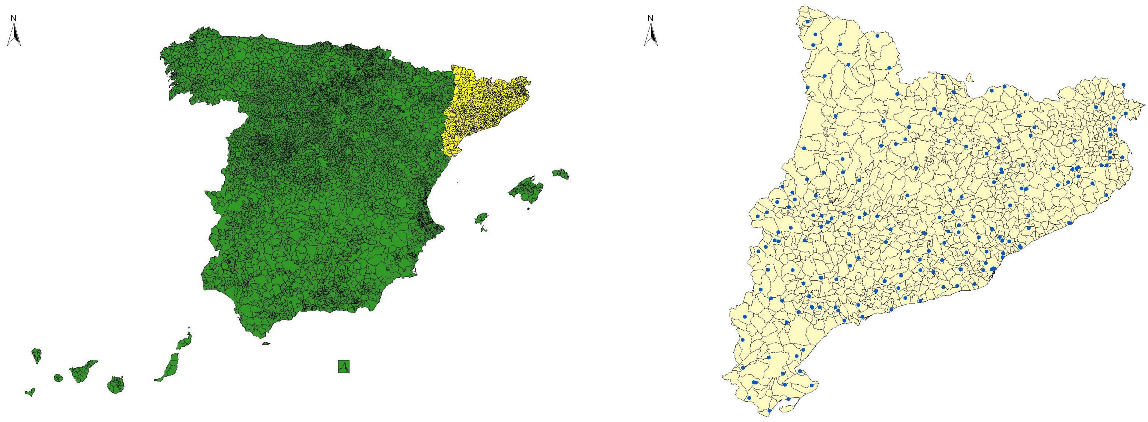

Figure 1: Situation of Catalonia region within Spain (*left*), and stations (in dotted points) with daily temperature data during 1994-2008 (*right*)

There are now many published research papers on interpolation of temperatures (Chessa and Delitala, 1997; Courault and Monestiez, 1999; Ninyerola *et al.*, 2000; Degaetano and Belcher, 2006; Stahl *et al.*, 2006, amongst many others). According to Stahl *et al.* (2006), schemes for spatial interpolation of air temperature vary in relation to three aspects: (1) the approach to adjusting for elevation, (2) the model used for characterizing the spatial variation of air temperature, and (3) the method of choosing prediction points. Most of them do not take into account the temporal dimension of the data. However, Luo *et al.* (1998) use a method that borrows information both across space and time. In fact, they could be considered a precedent of the related literature on spatio-temporal modeling of meteorological data (Haslett and Raftery, 1989; Huerta *et al.*, 2004; Lund *et al.*, 2006).

The statistical approach used in this paper is similar to the one used in Im *et al.* (2009), which, in turn, was similar to Li *et al.* (1999) to model particulate matter in Vancouver (Canada). Three important differences can be found in our work. First, unlike Im *et al.* (2009), and to get closer to reality, we allowed all parameters associated with the explanatory variables of the mean function of the temperature process to vary between stations and over time. Likewise, we allowed the ARMA models used to control autocorrelation to vary between stations, and the spatial parameters of our model to vary with time. Second, we followed a Bayesian approach and not a frequentist one, like in Im *et al.* (2009). Third, these authors estimate their model in three consecutive stages, using the residuals from the previous step as dependent variable. We however used a 2-stage approach. In the first stage, we assumed the stations were spatially independent and modeled the mean function of daily average temperature controlling for possible temporal autocorrelation. In the second stage, we modeled the spatio-temporal covariance using the interim posterior from the residuals of the model in the first stage as prior distributions of replications of a spatial process.

The plan of the paper is as follows. Section 2 presents the data set motivating this paper together with a description of the statistical strategy followed to model the data set in space and time. The Bayesian approach together with the INLA technique are discussed further in this Section. The results are commented in detail in Section 3. The paper ends with some final conclusions and discussion of the results.

2. Methods

2.1. Data set

Meteorological data, recorded daily for the period 1 January 1994 to 31 December 2008, from 190 stations throughout the region of Catalonia (Spain), were provided by the Weather Area (Meteorological Service of Catalonia) (see Figure 1). We had maximum and minimum temperatures, and wind (average wind speed and predominant direction) measurements for each station. The altitude and the spatial coordinates for each station were also considered.

2.2. Modeling strategy

The spatio-temporal process defining the daily temperature was specified following Im *et al.* (2009)

$$
\begin{aligned}
Y_{it} &= X_{it}^{'}\beta_{it} + \frac{\Phi_i(B)}{\Theta_i(B)}\varepsilon_{it} \\
cov\left(\varepsilon_{it}, \varepsilon_{i't}\right) &= \mathrm{M}\left(\left|i - i'\right|, r_t^2\sigma_t^2, \rho_t, \delta_t\right) + \left(1 - r_t^2\right)\sigma_t^2 I\left(i = i'\right)
\end{aligned} \tag{1}
$$

where Y_{it} denotes either the maximum or minimum temperature on day t (in our case, from 1 January 1994 to 31 December 2008) at station i with $i = 1, 2, \ldots, 190$. X_{it} contains the explanatory variables, while β is the unknown parameter vector associated to the explanatory variables. $\frac{\Phi_i(B)}{\Theta_i(B)}$ denotes the ARMA model, and ε_{it} stands for the innovations at each station on day t.

In particular, we included as explanatory variables of the mean function a long-term trend ($trend = 1, \ldots, 5479$, where 1 corresponded to 1 January 1994 and 5479 to 31 December 2008), annual harmonics $\cos(2\pi n\ trend/365)$ and $\sin(2\pi n\ trend/365)$, with $n = 1, 1.5, 2, 2.5, 3$ corresponding to periods $12, 8, 6, 4.8, 4$ months, respectively, and daily measurements of wind at each station, indeed a variable measuring the interaction between the average wind speed and the predominant direction -using a categorical variable capturing 8 sectors of the wind rose-. We considered more complicated forms than the linear approximation for the long-term trend, but these did not improve enough the goodness-of-fit of the models (perhaps because we already included in the model a 12-month period harmonic). In this sense, we preferred the parsimony of our approach to the complexity of the others.

The vector β of all parameters associated with the explanatory variables was allowed to vary between stations and with each year (this is the reason of the sub indexes in the parameters in (1)).

Meteorological conditions that may persist from one day to another can influence air temperature, leading to temporal correlation (Im *et al.*, 2009). We controlled this autocorrelation by means of ARMA models of the form

$$\frac{\Phi_i(B)}{\Theta_i(B)} = \frac{1 - \phi_{1i}B - \phi_{2i}B^2 - ... - \phi_{pi}B^p}{1 - \upsilon_{1i}B - \upsilon_{2i}B^2 - ... - \upsilon_{qi}B^q} \tag{2}$$

where $\Phi_i(B)$ denotes the autoregressive (AR) component of order p; $\Theta_i(B)$ stands for the moving average (MA) component of order q; B is the backshift operator (i.e. $B^i X_t = X_{t-i}$), and finally ϕ and υ define the unknown AR and MA parameters, respectively. Note that again we allowed the parameters of the ARMA models to vary between stations (see the corresponding subindexes). In fact, we initially estimated ARMA(2,2) for all the stations, and according to the statistical significance of the parameters, the models were simplified.

For the spatial covariance structure we used the Matérn family of covariance functions and a nugget term, for a fixed t over each station i. In (1), M is the Matérn function (Stein, 1999), $\sigma_t^2 I$ denotes the *sill* (the total variance of the innovation process) at time t, $r_t^2\sigma_t^2$ is the variance of the spatially correlation portion of the process, $\left(1 - r_t^2\right)\sigma_t^2$ corresponds to the *nugget* (the variability for a given station), ρ_t is the *range* of the process (the size of the region where the process was significantly correlated), and finally δ_t is the smoothness degree of the process (we particularly tried $\delta_t = 1, 2, 3$, as we cover the most common and practical possibilities).

2.3. Estimation

The integrated nested Laplace approximation (INLA) for Bayesian inference

Spatio-temporal models were built as Bayesian hierarchical models with two stages (Schrödle and Held, 2010). The first stage was the observational model $\pi(y\,|x)$, where y denotes the vector of observations and x the vector of all Gaussian variables following a Gaussian Markov random field (GMRF). The second stage was given by the set of hyperparameters θ and their respective prior distribution $\pi(\theta)$.

Given data y for each component x_i of x, the marginal posterior density of the GMRF, $\pi(x_i\,|y)$, can be written as,

$$\pi(x_i\,|y) = \int_\theta \pi(x_i\,|\theta, y)\,\pi(\theta\,|y)\,d\theta \tag{3}$$

Assuming that the precision matrix of the Gaussian field is sparse, the integrated nested Laplace approximation (INLA) for Bayesian inference (Rue *et al.*, 2009) build a nested approximation of (3). In particular, we can use the approximation by a finite sum

$$\tilde{\pi}(x_i\,|y) = \sum_k \tilde{\pi}(x_i\,|\theta_k, y)\,\tilde{\pi}(\theta_k\,|y)\,\Delta_k \tag{4}$$

with $\tilde{\pi}(x_i|\theta,y)$ and $\tilde{\pi}(\theta|y)$ denoting approximations of $\pi(x_i|\theta,y)$ and $\pi(\theta|y)$, respectively. The posterior marginal $\pi(\theta|y)$ of the hyperparameters is approximated using a Laplace approximation (Tierney and Kadane, 1986)

$$\tilde{\pi}(\theta|y) \propto \frac{\pi(x,\theta,y)}{\tilde{\pi}_G(x|\theta,y)}|x = x^*(\theta) \tag{5}$$

where the denominator $\tilde{\pi}_G(x|\theta,y)$ denotes the Gaussian approximation of $\pi(x|\theta,y)$ and $x^*(\theta)$ is the mode of the full conditional distribution $\pi(x|\theta,y)$ (Rue and Held, 2005).

According to Rue *et al.* (2009), it is sufficient to numerically explore this approximate posterior density using suitable support points θ_k, denoted as Δ_k.

In this paper, we defined these points in the h-dimensional space, using the strategy called central composite design (*CCD*). Centre points were augmented with a group of star points which allowed the estimation of the curvature of $\tilde{\pi}(\theta|y)$ (Rue *et al.*, 2009).

To approximate the first component of (4), we used a simplified Laplace approximation, less expensive from a computational point of view with only a slight loss of accuracy (Rue *et al.*, 2009; Martino and Rue, 2010).

Estimation strategy

Following the INLA approach, we specified the Matérn model for the latent Gaussian field (R-INLA, 2010) (subscripts were omitted for simplicity without loss of generality)

$$Corr(d) \propto (\kappa d)^{\delta}\, \mathrm{K}_{\delta}(\kappa d) \qquad \alpha = \delta + d/2 \tag{6}$$

where d denotes the spatial distance, K_{δ} defines the modified Bessel function, and δ sets the smoothness degree of the process. The range r was defined as $r = \sqrt{8}/\kappa$.

The hyperparameters of the model were the range and the precision parameter τ (the marginal variance of the latent field was $1/\tau$). Prior distributions were assigned to the log of the hyperparameters. In particular, Gamma distributions with parameters (i.e. shape and scale parameters) equal to 1 were considered. The smoothness parameter, δ, however, was considered a fixed parameter. As previously mentioned, we tried $\delta = 1, 2, 3$. In particular, δ was chosen to minimize the value of DIC (Spiegelhalter *et al.*, 2002)

$$DIC = D(\bar{\theta}) + 2p_D \tag{7}$$

where $D(\bar{\theta})$ denotes the deviance (defined as $D(\theta) = -2\log L(data|\theta)$, and where $L(.)$ denotes the (frequentist) likelihood function, and θ the parameters) evaluated at the posterior mean of the parameters, and p_D is the 'effective number of parameters' (which measures the complexity of the model), and is given by

$$p_D = E_{\theta|y}\left[D\right] - D\left(E_{\theta|y}\left[\theta\right]\right) = \bar{D} - D\left(\bar{\theta}\right) \tag{8}$$

with $\bar{D}$ denoting the posterior mean of standardized deviance.

The Matérn correlation function was built on a regular 200×200 lattice, covering the whole territory of Catalonia, corresponding to a cell of *1,207.31* m (height) $\times$ *1,226.65* m (base) (*1.481* km^2).

For the final model estimation we used a two-stage approach. In the first stage, we assumed the stations were spatially independent and we modeled the mean function of daily average temperatures controlling for possible temporal autocorrelation. In the second stage we modeled the spatio-temporal covariance, using the interim posterior from the residuals of the model (average within each cell) in the first stage as prior distributions of replications of a spatial process. For this second part we could realistically assume that the precision matrix of the Gaussian field was sparse (Rue and Held, 2005; Rue *et al.*, 2009). We allowed all spatial parameters to also vary with time.

3. Results

The analyses shown in this paper were carried out with the *R* freeware Statistical Package (version 2.11.1) (R Development Core Team, 2010) and the R-INLA package (R-INLA, 2010). The total number of measuring stations was 190 which recorded daily maximum and minimum temperatures during the study period 1994-2008.

The daily maximum temperature increased until 2003, decreasing thereafter (Figures 2 and 3). Note, however, that from 2003 onwards the variability of the daily maximum temperature increased dramatically, up to 15.26% each year, on average (Figure 3). This increase in the variability was also present in the daily minimum temperatures, although less important (8.76% on the average) and not so clear (Figures 2 and 3). Apparently, there was a decrease in daily minimum temperatures, much more important from 2003 onwards.

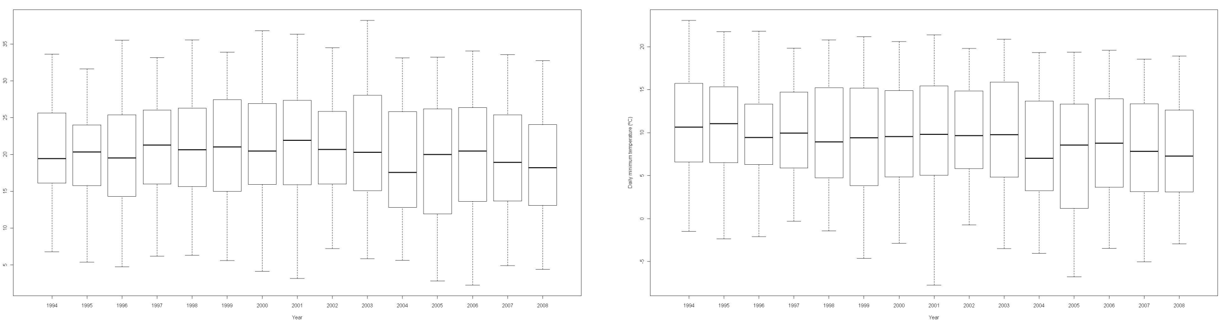

Figure 2: Boxplots by year of daily maximum (*left*) and minimum (*right*) temperatures in 190 stations in Catalonia for the period 1994-2008

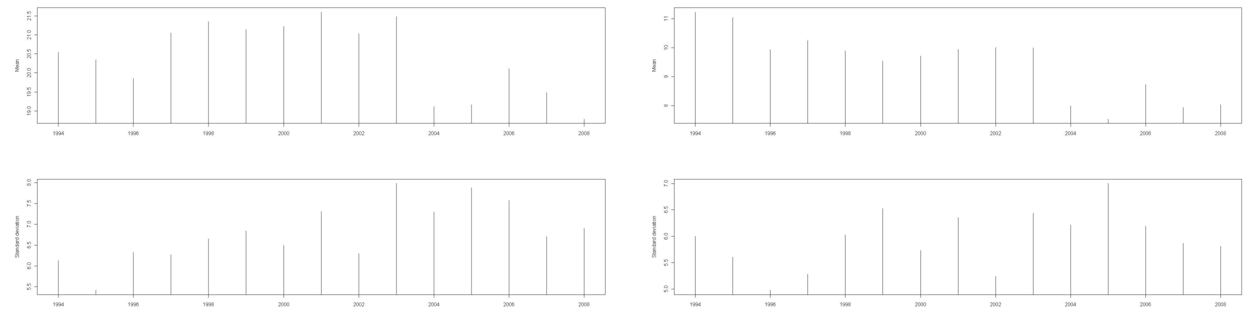

Figure 3: Annual averages and standard deviations of daily maximum (*left*) and minimum (*right*) temperatures in the 190 stations

With respect to the trend estimation in model (1), with daily maximum temperature as dependent variable, in 152 out of the 190 stations (80.0% of all the stations) the coefficient of the long-period trend was statistically significant at the 95% confidence level (i.e., the 95% credible interval did not contain the zero). In the case of daily minimum temperature, in 161 out of the 190 stations (84.7% of all the stations) the 95% credible interval of the coefficient of the long-period trend did not contain the zero.

All coefficients were 'averaged' using a linear mixed model, considering the station as grouping variable and the intercept as the random effect. In the model we allowed a within-group heteroscedasticity structure, with the standard errors of the coefficients as fixed variance weights. On 'average' the estimated coefficient for the long-period trend was equal to 2.109e-05, with a 95% credible interval (1.066e-05, 3.153e-05), for the maximum temperature, and a coefficient of 7.987e-05, with a 95% credible interval (1.446e-05,14.528e-05), for the minimum temperature.

These increases, however, were not homogeneous. First, the estimated daily variation in temperature depended on the latitude for both, maximum and minimum temperatures (Figure 4). In both cases the parametric coefficient of the relationship between (estimated) daily variation in temperature and latitude (in a generalized additive model with a Gaussian family and identity link) was statistically significant ($p<0.001$) but it was not the case for the smooth terms ($p>0.1$). The slope of the linear relationship was negative for maximum temperatures (-2.155e-05) but positive, clearly deeper (8.035e-05), for minimum temperatures (Figure 4). The estimated daily variation in temperature, however, did not depend on longitude or on altitude.

Estimated variation in daily temperature was not homogeneous in time either (Figure 5). Increases were only clear for the period 2004-2006 for maximum temperatures (median variation between 1994 and 2003, -0.036%, and 1.755% between 2004 and 2006), and for the period 2002-2006 when considering minimum temperatures (0.003% of median variation between 1994 and 2001, 1.349% between 2002 and 2006). Note also that the estimated variation was not homogeneous amongst months (Figure 6): (a) positive from April to September with

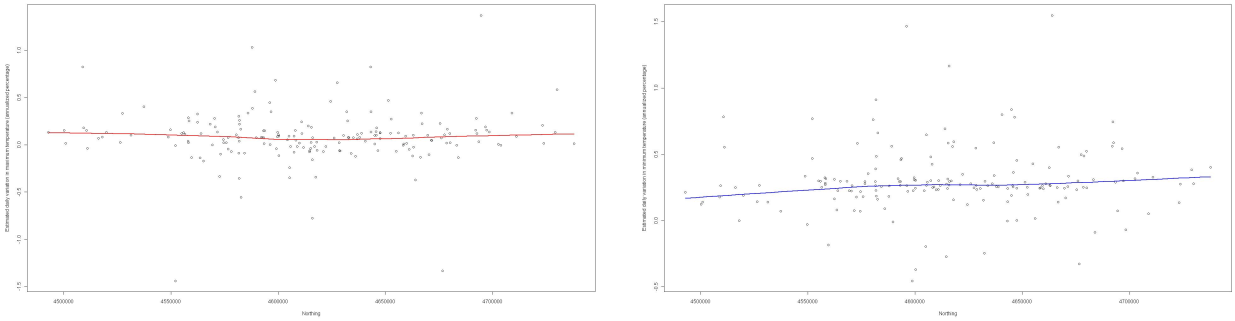

Figure 4: Estimated daily variation by latitude (annualized percentage) in maximum (*left*) and minimum (*right*) temperatures during the period 1994-2008

maximum temperatures (June, with a median increase of 12.74%, followed by May, with 11.89%, were the months with maximum increases and December, with -8.54%, and February, with -8.44%, were those months with the maximum decrease), and (b) positive from May to October with minimum temperatures (in this case it was July, with a median increase of 9.13%, and August, with 8.74%, the months with a maximum increase; and January, with -4.57%, February, with -4.11%, and December, with -3.98%, the months with the minimum variation).

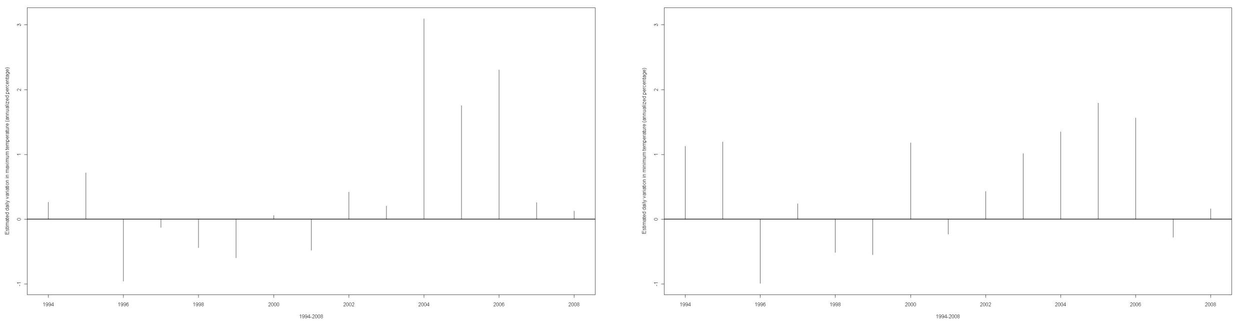

Figure 5: Estimated daily variation by year (annualized percentage) in maximum (*left*) and minimum (*right*) temperatures during the period 1994-2008

The coefficients associated with the harmonics were all also statistically significant. In addition, the temporal structure in form of ARMA models was the following. Note that we allowed the parameters of the ARMA models to vary between stations, and we initially estimated ARMA(2,2) for all the stations, and according to the statistical significance of the parameters, the models were simplified. We estimated an ARMA(2,1) model, i.e. $\frac{(1-\phi_1 B - \phi_2 B^2)}{(1-\upsilon_1 B)}$, with parameters ('averaged' as explained above) $\phi_1 = 0.68155$, $\phi_2 = -0.05743$, and $\upsilon_1 = -0.18330$, in 167 stations when considering maximum temperatures, and $\phi_1 = 0.32882$, $\phi_2 = 0.10523$,

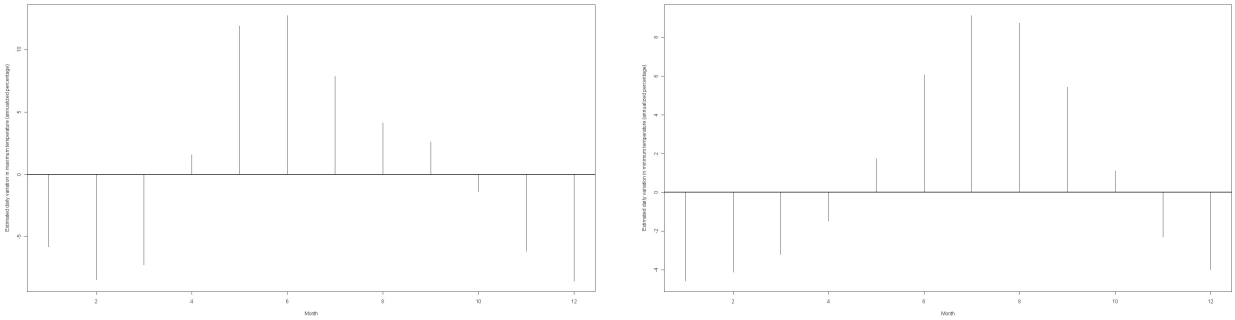

Figure 6: Estimated daily variation by month (annualized percentage) in maximum (*left*) and minimum (*right*) temperatures during the period 1994-2008

and $\upsilon_1 = 0.28255$ in 150 stations when using minimum temperatures. ARMA(1,1) models, i.e. $\frac{(1-\phi_1 B)}{(1-\upsilon_i B)}$, with parameters $\phi_1 = 0.48699$ and $\upsilon_1 = -0.01194$, were fitted in 19 stations for maximum temperatures, and in 14 stations for minimum temperatures with parameters $\phi_1 = 0.55320$ and $\upsilon_1 = 0.11454$. An AR(1) model, i.e. $(1 - \phi_{1i}B)$, with parameter $\phi_1 = 0.46448$ was fitted to 3 stations for maximum temperatures, and with $\phi_1 = 0.64679$ in 21 stations for minimum temperatures. Finally, a MA(1) model, i.e. $(1 - \upsilon_1 B)$, was fitted with parameter $\upsilon_1 = 0.41032$ in 1 station for maximum temperatures, and with $\upsilon_1 = 0.48629$ in 5 stations when considering minimum temperatures.

With respect to the estimation of the spatial bit of the model in (1), the value of the smoothness parameter δ that minimized DIC was equal to *2* for both maximum and minimum temperatures. The median estimated *sill* was (weighted average on time) *0.342* (first quartile *0.139*, third quartile *1.753*) for maximum temperatures, and it was *0.339* (first quartile *0.147*, third quartile *1.239*) for minimum temperatures. For both maximum and minimum temperatures, the median estimated *range* was *7,941* m (first quartile *7,908* m, third quartile *12,310* m). Finally, the median estimated *nugget* was practically negligible (*1.272e-12* for maximum temperatures, and *1.642e-12* for minimum temperatures).

Note that both the median and the variability of *sill* increased from 2004 onwards. In the case of maximum temperatures it increased from *0.2015* on average for the period 1994-2003 to *2.2579* for the period 2004-2008 (Figure 7), and from *0.1939* to *1.7047*, respectively, in the case of minimum temperatures (Figure 7).

In Figures 8 and 9 the septiles of the distribution of the interpolated standardized residuals (weighted average according to the temporal variation) are shown. In the case of maximum temperatures there was an increment of both the variability and the size of the residuals from the period 1994-2003 to 2004-2008. Note also that there was a movement of the upper septiles to the northeast and the south, from the west central and, in a lesser extent, the east central. The opposite behavior was found for minimum temperatures, i.e a slight decrease of both, the variability and the size of the residuals from the period 1994-2002 to 2003-2008, and a movement of the upper septiles to the north and the southeast, from the east and, in a lesser extent, the west central were found.

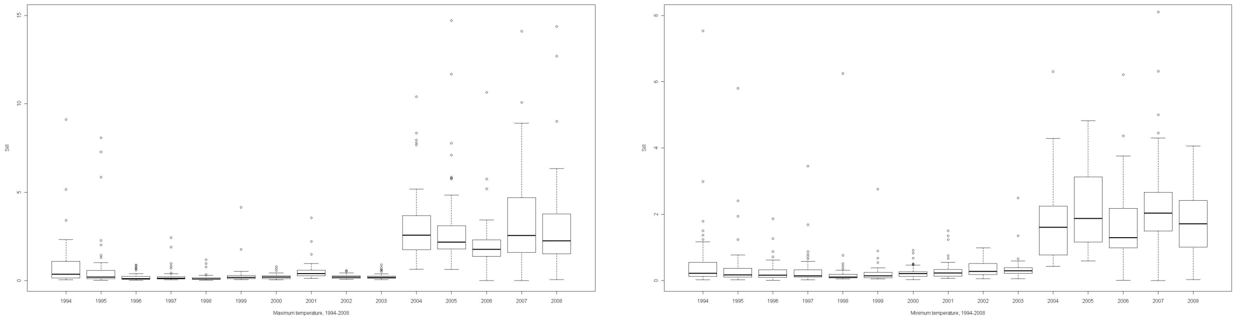

Figure 7: Estimated sill by year. Maximum (*left plot*) and minimum (*right plot*) temperatures

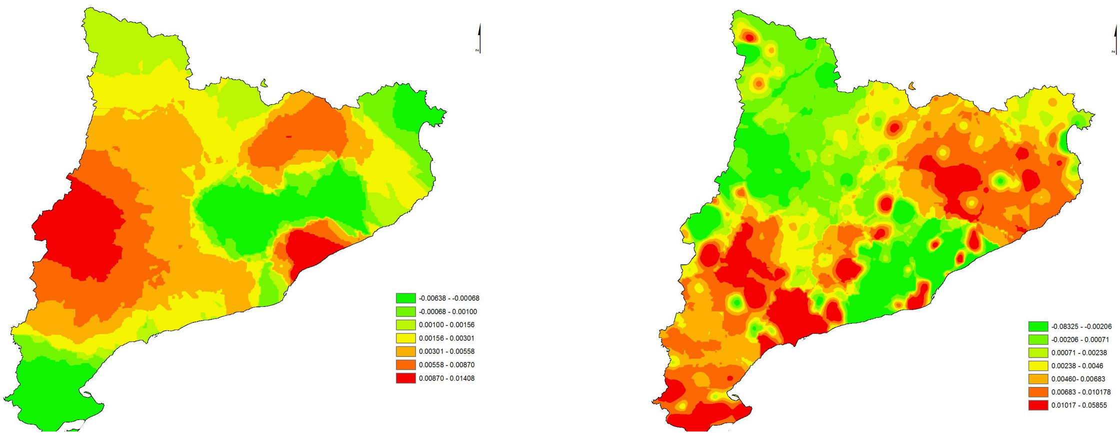

Figure 8: Standardized residuals for the maximum temperature for the period 1994-2003 (*left plot*), and for the period 2004-2008 (*right plot*)

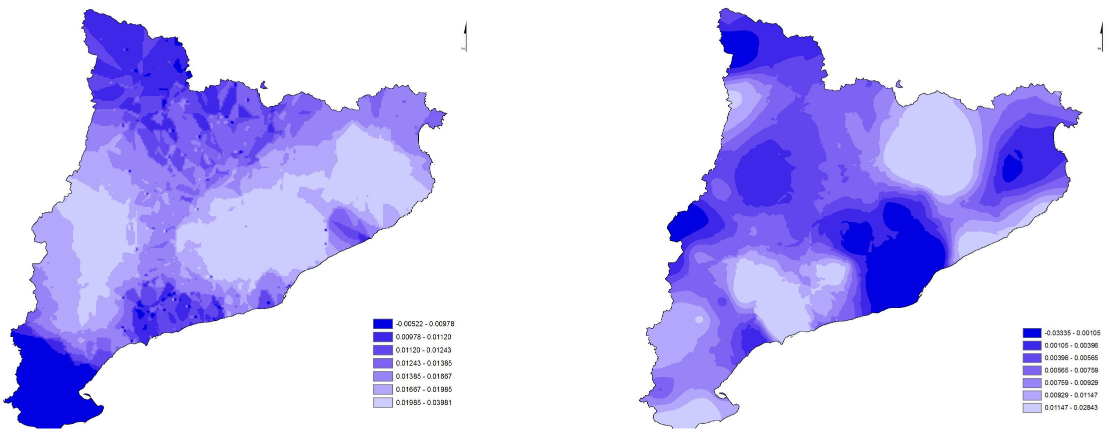

Figure 9: Standardized residuals for the minimum temperature for the period 1994-2002 (*left plot*), and for the period 2003-2008 (*right plot*)

4. Conclusions and discussion

Considering a model to describe the mean function as well as the spatio-temporal covariance structure of 15 years of daily maximum and minimum temperature data from 190 stations throughout Catalonia (Spain), with daily data covering the period 1994-2008, we have estimated a slight increase in daily maximum temperature (0.773% annualized on average) and a more significant increase in minimum temperature (2.960% annualized on average). These values correspond to a 15-year increase of 0.159^{o}C (95% credible interval 0.080^{o}C, 0.242^{o}C) in maximum temperature, and an increase of 0.332^{o}C (95% credible interval 0.008^{o}C, 0.635^{o}C) in minimum temperature.

For 60 years of daily temperature data from a subset of 16 stations in Catalonia (during the period 1950-2009), the Meteorological Service of Catalonia (2010) estimated a 10-year increase of 0.26^{o}C for the maximum temperature (in the range of 0.17^{o}C – 0.34^o C, depending on the station) and of 0.17^{o}C (range 0.09^{o}C – 0.23^{o}C) for the minimum temperature. There were three differences with respect to our approach. First, the Meteorological Service of Catalonia (2010) estimated the long term trend for each station independently, without taking into account the spatial dimension of the data. Second, for the sub-period 1990-2009, they estimated a 10-year increase of 0.52^{o}C (range 0.07^{o}C - 0.90^{o}C) for the maximum temperature, and 0.37^{o}C (range 0.05^{o}C – 0.64^{o}C) for the minimum temperature. Finally, in their analysis they included the year 2009 (in the 16 stations they analyzed, 2009 was the third warmest year since 1950 - together with 1997 and, just after 2006 and 2003 - with an anomaly of 1.05^{o}C with respect to the climate average). In fact, they pointed out that positive trends obtained were slightly more pronounced, due to the warm character of 2009.

The increases we estimated were not homogeneous, both for time and space. Increases were only clear for the period 2004-2006 in maximum temperature, and for 2002-2006 in minimum temperature. In fact, considering only these periods, the increases we estimated practically matched those showed by the Meteorological Service of Catalonia (2010). Furthermore, in our case, the estimated variation was not homogeneous amongst months: positive from April to September in maximum temperature, and from May to October in minimum temperature. These variations were very similar to those obtained from the Meteorological Service of Catalonia (2010). We also found that the estimated daily variation in temperature depended on the latitude for both, the maximum and minimum temperature. The slope of the relationship was negative for the maximum temperature (-2.155e-05), and positive and clearly deeper (8.035e-05) for the minimum temperature. The Meteorological Service of Catalonia (2010) did not find spatial differences in the temporal variations of the stations they analyzed. It is very likely that the differences with respect to our work and the smaller number of stations they analyzed could explain this discrepancy.

5. Conflicts of Interest

There are no conflicts of interest for any of the authors. All authors disclose any financial and personal relationships with other people or organizations that could inappropriately influence and/or bias their work.

6. Acknowledgements

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