Changes in the distribution of cold waves in France in the middle and end of the 21st century with IPSL-CM5 and CNRM-CM5 models

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Abstract: In this paper, a stochastic model is used to simulate daily minimum temperature time series coming from observations and two CMIP5 climate models (IPSL-CM5A-MR and CNRM-CM5) in order to analyze the changes in cold wave number and proportions under future climate conditions. The stochastic model allows computing 100 temperature time series for each different source (observation or climate model), and for 22 locations in France, which enables inferring the statistical significance of the changes. Two future time periods, near (around 2010 to 2060) and far future (around 2050 to 2100), and two RCPs (RCP4.5 and RCP8.5) are considered, while 3 different thresholds are used to identify cold waves: 0°C and the 10^{th} and 5^{th} percentiles of observed wintertime (December-January-February) daily minimum temperature distribution. The results show that both models project a significantly lower number of cold waves in the future, all durations considered, but the changes mainly concern the proportion of the longest cold waves (10 days and more). The decreases are higher with IPSL-CM5A-MR than with CNRM-CM5. The main driver of this change is the decreasing frequency of the observation based thresholds in the future, which is higher for IPSL-CM5-MR model because the impact of a higher mean is enhanced by a decrease in the variance.

Keywords: Climate change; cold waves; stochastic modelling

1. Introduction

In the climate change context, more and more studies are devoted to the evolution of extreme events, since those have a major impact on people, society and organizations. Among these events, temperature related ones, heat and cold waves, are of special concern for electricity companies, because they impact both electricity production and demand. Agriculture, road or rail management or health are other examples of impacted sectors. In 2012, IPCC devoted a special report to the assessment of this issue of climate change and extreme events: the Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX). Its main conclusions about temperature related extremes were that “it is very likely that there has been an overall decrease in the number of cold days and nights, and an overall increase in the number of warm days and nights, on the global scale” and “it is virtually certain that hot extremes will increase and cold extremes will decrease over

the 21st century with respect to the 1960-1990 climate". However, the same report also noted that fewer studies had been devoted to the analysis of cold or warm spells compared to those devoted to changes in the frequency and intensity of cold or warm days and nights. As a consequence, less robust conclusions could have been given for those events, and essentially concern warm events: "There is medium confidence that the length or number of warm spells, including heat waves, has increased since the middle of the 20th century". Nevertheless, the report stated that "it is very likely that the length, frequency and/or intensity of warm spells, including heat waves (defined with respect to present day climate) will increase over most land areas." Then, IPCC AR5 working group I report further supported those conclusions, in more strongly assessing the anthropogenic contribution to the observed changes. Furrer et al. (2010) and Wang et al. (2014) also have investigated the hot spell behavior by using extreme value theory. Cold waves are however an important issue for electricity management, especially in France where electrical heating is important.

In a recent set of papers, Sillmann et al. (2013) applied the climate extreme indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) to a large number of CMIP5 and CMIP3 simulations (Coupled Model Intercomparison Projects phases 5 and 3). Among these indices, CSDI represents cold spell duration, and their results show that CMIP5 models agree with ERA-40 and ERA-Interim re-analyses in representing a decreasing trend in the cold spell duration over the period 1948-2005. Part 1 is dedicated to model evaluation, then, in part 2, they found significant changes in CSDI over land in the end of the 21st century, with around 3.4 days less according to a RCP2.6 scenario, 3.9 days less for RCP4.5 and 4.2 days less for RCP8.5, the changes being coherent but weaker for CMIP3 models. At the European scale, De Vries et al. (2012) studied western European cold spells (where temperature falls below the 10th percentile of the winter daily mean temperature distribution) in current and future climate. They showed that most of the changes in cold spell statistics can be explained by changes in mean (increase) and variance (decrease) of the winter temperature distribution. This dominating role of the evolutions of mean and especially variance in the evolutions of temperature extremes had also been found by Parey et al (2010). Concerning France, Cattiaux et al. (2013a) first studied the link between hot and cold spells and the dynamic circulation and its reproduction by different versions and resolutions of the IPSL climate model. They found that the model version used for CMIP5 tends to improve the wintertime dynamics and the statistics of cold spells. In another paper, Cattiaux et al. (2013b) focused on changes in cold extremes over Europe in a pilot study using both French climate models (IPSL and CNRM) AMIP (Atmospheric Model Intercomparison Project) experiments.

Large decreases in the number of extremely cold days at the end in the 21st century are reported, mainly driven by non dynamical mechanisms. Peings et al. (2012) analyzed the representation of observed cold waves and their change at the end of the 21st century according to a RCP8.5 scenario with 13 CMIP5 models. They found that model biases mostly concern intensity rather than geographical extent and duration, and that these events will be less frequent at the end of the century, except for one model.

The present study aims at complementing these results by adopting a different point of view. We focus here on the local distributions of cold spells of different durations, from one single day to more than 15 consecutive days below a defined threshold. It is based on a set of high quality temperature time series provided by Météo-France and on the results of the French IPSL-CM5A-MR and CNRM-CM5 climate models run in the framework of CMIP5. Note that the version of IPSL model is different from that used in Peings et al (2012), who used the results of IPSL-CM5A-LR. Three different thresholds (one fixed, 0°C, and two percentile based, the 10th and 5th percentiles of the observed wintertime –December-January-February- temperature distribution), two future periods (around 2010 to 2060 and the end of the 21st century) and two climate change scenarios (RCP4.5 and RCP8.5) will be considered. The originality lies in the use of a stochastic model of temperature to bias correct and downscale the climate change simulations. Climate models are namely designed to faithfully simulate large scale features of the climate system and its circulations, as well as the main characteristics of the physical interactions, cycles and their possible evolutions under external forcing. However, they cannot precisely represent local weather and different downscaling techniques have been proposed in the literature to overcome this issue for impact studies (see Maraun et al. 2010 for a review). These techniques can be divided into statistical and dynamical approaches. Statistical methods are based on some identification of statistical relationships between large scale and local scale variables used to derive local information from the larger scale patterns given by the climate model. Dynamical methods consist in running a limited area climate model forced by the larger scale model at its boundaries in order to refine the simulation over a chosen small region. The approach used here is a statistical downscaling technique based on the use of a quite sophisticated stochastic model. This stochastic model allows moreover the simulation of a large number of equivalent temperature time series then used to evaluate the statistical significance of the obtained changes in proportions of cold spells of different duration. Furrer et al. (2010) also proposed a stochastic model, used by Wang et al. (2015) to study hot spell changes in China from CMIP5

simulations, but only hot spells are modelled, not the whole temperature time series as is the case here.

The considered time series, model simulations and the methodology will be described in section 2, and then section 3 will present the validation of the approach over the current climate period. Section 4 will be devoted to the analysis of the changes in the cold wave distribution in the near and far future according to RCP4.5 and RCP8.5 scenarios, before coming to the conclusion and discussion in section 5.

2. Data, models and methodology

2.1 Observation time series

In the framework of the French IMFREX project devoted to the impact of climate change on extreme events, Météo France developed a database of daily time series selected for their homogeneity over the longest possible period after a procedure of trend and metadata analysis dedicated to the detection of possible changes in the measurement conditions (Gibelin et al. 2014). These so-called SQRs (Série Quotidiennes de Référence, reference daily time series in French) constitute a robust database of observations over France to study climate change. A set of 39 of such temperature time series have been provided by Météo-France for this study, conducted in the framework of the French national research agency supported SECIF project (dedicated to the development of climate services for the French industries). Among this set of time series, 22 daily minimum temperature time series have been selected as the longest and most representative of different locations in France, as shown in Figure 1, and they cover periods between 1953 and 2011. However, since the historical simulations of the climate models end in 2005, the observation time series are considered over periods between their beginning year and 2005. Table 1 summarizes the observed time series periods considered. The selection aimed at attributing a single station to a climate model grid cell, and thus when stations are too close, only the longest one is selected.

2.2 Climate models

The CNRM-CM5 and IPSL-CM5A-MR coupled ocean atmosphere GCMs are described respectively in Voldoire et al. (2013) and Dufresne et al. (2012) and will just be briefly presented here. The atmospheric component of CNRM-CM5 is the spectral ARPEGE-Climat GCM with a T127 linear grid (256 x 128 grid points) with 31 vertical levels. The ISBA land surface model, the NEMO ocean model and the GELATO sea ice model are coupled to the atmospheric model through the AOSIS coupler. The atmospheric component of IPSL-CM5A-

MR is the LMDZ model which has a 144x143 regular grid and 39 vertical levels, and is coupled to the ORCHIDEE land surface scheme. The ocean model is the NEMO-OPA suites, which models interactions of ocean, sea ice and marine ecosystem. Ocean atmosphere coupling is done through the OASIS coupler. CNRM-CM5 and IPSL-CM5A-MR models have different physical parameterizations and only share a closely resembling radiative scheme.

For each model, the historical simulation, covering period 1950-2005, and two scenario runs, RCP4.5 and RCP8.5, covering period 2006-2100 are considered. For current climate, model simulations are considered over the exact same period as that of the corresponding observation time series. For example, for an observation time series spanning the period 1954-2005, the model historical simulation is considered for years 1954 to 2005. Two future periods are then considered, one ending in 2060 and the other ending in 2100, the length being chosen identical to the observation time series length for convenience. Thus, again, for an observation time series covering 1954-2005, the first future period is 2009-2060 and the second one 2049-2100.

2.3 Stochastic temperature model

As stated before, a stochastic temperature model is used to bias correct and downscale the temperature time series provided by the climate models. This temperature generator is designed to realistically reproduce temperature extremes, and potentially simulate larger extremes than observed. It is a stochastic Functional Seasonal Heteroscedastic Auto Regressive model used to simulate the stochastic part of the process after the deterministic parts, trends and seasonalities in the mean and the variance, have been removed. It has namely been found from analyses of a large number of different temperature time series that once trends and seasonalities in the mean and the variance have been removed, no trends can be identified in the other moments (up to moment 4), the auto-correlations and in the extremes of the residuals (Hoang 2010). However, some seasonality remains in the other moments and in the auto-correlations, but not really in the extremes. Thus the stochastic model simulates Z(t), where

$$Z(t) = \frac{X(t) - S_m(t) - m(t)}{S_v(t)\, s(t)} \quad (1)$$

with X(t) the observed temperature time series, $S_m(t)$ the seasonality of the mean, m(t) the trend in mean, $S_v(t)$ the seasonality of the standard deviation, and s(t) the trend in standard deviation. This corresponds to a standardization based on two deterministic parts of mean and standard deviation (seasonality and trend) rather than on their constant value estimated over

the whole time period. The seasonalities are identified as trigonometric polynomials of the form

$$\theta_0 + \sum_{i=1}^{p} (\theta_{i,1} \cos\frac{2i\pi t}{365} + \theta_{i,2} \sin\frac{2i\pi t}{365}) \quad (2)$$

where the order p is chosen according to an Akaike criterion. The non parametric trends are estimated by LOESS with an optimal smoothing parameter obtained through a modified partitioned cross-validation technique (Hoang 2010; Dacunha-Castelle et al. 2015; Parey et al. 2014). Then, Z(t) is modeled as:

$$Z(t) = b(t)Z(t-1) + a(t, Z(t-1))\varepsilon_t \quad (3)$$

With

$$b(t) = \theta_0 + \sum_{j=1}^{p_1} (\theta_{j,1} \cos\frac{2j\pi t}{365} + \theta_{j,2} \sin\frac{2j\pi t}{365}) \quad (4)$$

p_1 being again chosen according to an Akaike criterion, and a is the conditional standard deviation, obtained from the conditional variance a^2 estimated as:

$$a^2(t, Z(t-1)) = (\hat{r}_2 - t)(t - \hat{r}_1) \sum_{k=0}^{5} \sum_{j=1}^{p_2} (\alpha_{1,k}^j \cos\frac{2j\pi t}{365} + \alpha_{2,k}^j \sin\frac{2j\pi t}{365}) Z(t-1)^k \quad (5)$$

under constraints for its first derivatives at the boundaries:

$$(a^2)'(r_1) = \frac{2b(r_1)}{1 - 1/\xi_1} \text{ and } (a^2)'(r_2) = \frac{2b(r_2)}{1 - 1/\xi_2}, \; a^2(t, Z(t-1)) > 0 \forall t \quad (6)$$

and p_2 chosen by Akaike criterion. Extreme value distributions for temperature are known as bounded, thus the simulation of the residuals Z(t) has to support this behavior and Z(t) is defined over an interval $[r_1,r_2]$. r_1 and r_2 correspond to the estimated bounds of the extreme value distributions for the left and right tails of Z(t). The constraints for the derivatives of the conditional variance are meant to force it to reach zero at the boundaries. The details and mathematical justifications for these choices can be found in Dacunha-Castelle et al. (2015).

The bounds r_1 and r_2 are estimated by application of the extreme value theory to the Z(t) time-series obtained from the observations, and ξ_1 and ξ_2 are the shape parameters estimated for the lower and upper tail by fitting a Generalized Extreme Value distribution to the block maxima (as the extremes of Z(t) are stationary, a block length of 73 days is used in order to select a sufficient number of maxima to more reliably fit the distribution). ε_t is the random part and is defined as a truncated normal distribution whose truncation depends on the value of Z(t-1).

Then a simulation of the initial temperature time series is obtained by re-introducing the estimated deterministic parts.

The stochastic model is fitted to the residuals obtained from the observed time series, and then, seasonalities and trends coming either from the observations or from the climate model time series are used to reconstruct temperature time-series from the simulated residual time series. In this study, 100 simulations of the residuals for each of the 22 observed temperature time series have been considered.

2.4 Simulated temperature time series

As stated before, for each location 100 time series of the residuals Z(t), after removing trends and seasonalities, are computed. The ability of the model to reproduce the observed behavior of Z(t) has been checked in Hoang (2010), Dacunha-Castelle et al. (2015) and Parey et al. (2014), thus, from these, 100 temperature time series coherent with the observed one are obtained by reintroducing trends and seasonalities. For climate model temperature time series, potential biases have first to be investigated. Seasonality is the first estimated deterministic part, and trend is identified from the time series of anomalies from the seasonality. The same procedure is applied to observed and model temperature time series, and when comparing the obtained seasonalities and trends, it appears that most of the model bias is embedded in the seasonality identification, while trends are then more coherent with the observed ones. Figure 2 illustrates this point for the station of Cannes, in the south of France. Thus, the reconstructed temperature time series for present climate are built by adding (multiplying by for standard deviation) observed seasonalities and climate model trends to the simulated residuals Z(t). Then, for future time periods, seasonalities are obtained by adding the modeled difference in seasonality of the mean between future and present period for the seasonality in the mean, and multiplying by the ratio of future period standard deviation seasonality to present period one for the seasonality of the standard deviation:

$S_{mf} = S_{mo} + (S_{mm2} - S_{mm1})$; $S_{vf} = S_{vo} * S_{vm2}/S_{vm1}$ with S_m denoting seasonality of the mean, S_v seasonality of the standard deviation, and subscripts f, o, m1 and m2 denoting respectively future period, observation, model present period and model future period. Figure 3 illustrates such a reconstruction for the same station of Cannes.

2.5 Cold waves

Cold waves are defined here as cold spells with one or more consecutive days with daily minimum temperature below a chosen low threshold. In this study, three thresholds are considered: a fix threshold, 0°C, and two low percentiles: the 10^{th} and 5^{th} percentiles of the

observed wintertime daily minimum temperature distribution over the observation period. Winter is the climatological winter covering the months of December, January and February (DJF).

3. Validation for present period

3.1 Climate and stochastic models performances

In a first step, the repartitions of all identified cold spells for each station between different durations are compared for observation and climate model present period simulations. As climate models have biases, the thresholds used to define cold waves are chosen as the corresponding percentiles of the climate model time series. Thus, the fixed 0°C threshold is not 0°C for the models, but the value corresponding in the model time series to the percentile of 0°C in the observations. The 5^{th} and 10^{th} percentile of wintertime temperature correspond similarly to different temperature values in the model runs and in the observations. The comparisons show that generally, both climate models tend to produce fewer 1-day events and more 2 days and more ones than observed, and may have difficulties to reproduce very long cold spells. The stochastic model generally leads to a better reproduction of the proportion of long events, but tends to overestimate that of 1-day ones. Figure 4 illustrates this behavior for the station of Tomblaine and the 10^{th} percentile threshold. It can be noticed that the stochastic model is able to produce long cold waves in some simulations, even though none has been observed (14 days or >15 days in Figure 4 right panel). With a more extreme threshold like the 5^{th} percentile of wintertime temperature, the climate and stochastic models both have difficulties to produce a similar proportion of very long events as observed, although the stochastic model again sometimes succeeds in producing some among the 100 simulations, even though none have been observed.

Besides, using the stochastic model allows inferring significance for the observed changes with the computation of the 95% confidence interval for the distributions obtained from the 100 simulations of each proportion of cold spell duration. Figure 5 illustrates the mean number of cold waves per year for the 0°C threshold, all durations gathered, for the different considered locations in France. Black circles indicate the stations for which the simulated mean number is significantly different from the observed one (the observed number does not fall inside the 95% confidence interval of simulated numbers). These discrepancies are mainly due to the previously mentioned tendency to produce much more 1-day events than observed, whereas the proportions of longer cold spells are more faithfully represented. Then, the

repartitions of cold spells computed from the stochastic simulations for the current period reconstructed with observed seasonalities and trends or observed seasonalities and climate model trends are very similar, as can be seen in Figure 6 for Tomblaine and the longest cold spells.

3.2 Use in the climate change context

In order to check the ability of the suggested methodology to be used in the climate change context, a cross-validation has been conducted for one location. The temperature time series of Champhol, observed over period 1954 and 2005, has been split into two periods of equal length: 1954-1979 and 1980-2005 (26 years each). The stochastic model has been calibrated over the first period, and 100 simulations have been made. Then, the minimum temperature time series for the second period has been reconstructed using first period seasonalities corrected using climate model seasonality differences between both periods and climate model trends for the second period, following the suggested methodology for future climate. Figure 7 shows that the obtained proportions of cold spells are similar to that which would have been obtained by using observed period 2 seasonalities and trends. Figure 7 is for the 10^{th} percentile threshold but this holds true for all used thresholds. This result gives confidence in the use of this methodology to derive bias corrected future temperature time series.

4. Future changes in cold waves number and repartitions

4.1 Cold waves number

Then, the changes projected for the future are analyzed, considering the same observation based thresholds for the present and future periods. In line with all previous studies on the subject, the mean number of cold spells per year, all durations considered, decreases whichever the future time period, RCP scenario or threshold chosen for the identification. For the nearest future period until 2060, both scenarios not surprisingly give relatively similar results for both models, but IPSL-CM5A-MR model generally projects larger decreases than CNRM-CM5: around 1 to 5 less episodes per year for 0°C, up to 2 less for the 5^{th} percentile and around 2 to 3 less for the 10^{th} percentile with IPSL-CM5A-MR and around 1 to 4 less episodes per year for 0°C, 1 (more rarely 2) less for the 5^{th} percentile and 1 to 2 less for the 10^{th} percentile with CNRM-CM5. The decreases are larger for the far future period with generally one to 2 events less than for the nearest period. Figure 8 illustrates these results for

the 10th percentile threshold and each model and both near and far future periods for RCP4.5. The black circles denote significant changes and show that all changes are significant.

4.2 Cold waves repartitions

We just saw that the mean number of excursions under the different thresholds, whatever their lengths, is projected to decrease in the future. Now, let's go further and see how the repartition among the different event durations is changed. Among this lower total number of cold spells, in the nearest future period, only the proportion of the longest events (15 days and more for 0°C, 10 days and more for the 5th percentile and 11 to 12 days or more for the 10th percentile) significantly decreases, and once again, more according to IPSL-CM5A-MR model than according to CNRM-CM5 model. The results are again similar for both RCPs until 2060, although a little bit higher for RCP8.5. For the end of the century, the picture looks similar but the significant decreases concern all stations and begin for shorter events. Here, the impact is larger with RCP8.5 than with RCP4.5, IPSL-CM5A-MR giving again a stronger response than CNRM-CM5. Significant decreases in proportions concern events during 5 days and more for 0°C, 8 days or more (4 days at some locations) for the 5th percentile and 10 days or more (again, less for less cold places) for the 10th percentile. Figure 9 illustrates these results for the period until 2100, both models and scenarios and for the 5th percentile threshold.

4.3 Role of observation based threshold in the changes

Previous results are obtained with the same threshold for the identification of cold waves for present and future periods. However, due to climate change, these thresholds become rarer in both future periods than nowadays. In order to identify the impact of this change on previous results, the cold spell repartitions have been estimated again from the stochastic simulations of the observations, but using as thresholds the values corresponding to the previously defined threshold location in future wintertime temperature distributions. Thus, the observation based 5th and 10th threshold for example correspond to 2nd to 4th and 5th to 8th percentile for the nearest period, around 1st and 2nd to 4th percentile for the late period, depending on the model scenario and location. They thus lie in the farthest tail of the distribution, which could largely explain the observed changes in number and repartitions of cold waves. When using such threshold for the observations and comparing to the previously obtained results for the future periods, we can observe that they generally look very similar, confirming the upmost role played by this threshold change in the obtained results. Figure 10 illustrates this comparison

for the late period (late 2040s to 2100), RCP4.5 and the current period 5th percentile of wintertime temperature distribution as threshold. Significant changes appear for similar cold spell lengths, the differences rarely exceeding one or 2 days. For one station and IPSL-CM5-MR, a difference of 4 days can be noticed (circled in red in Figure 9): the significant decrease is found from 13 days with the observation based threshold and 9 days with the future one. After checking, it appears that the simulations do not produce 9-day cold spells with the future threshold, but produce a similar (even slightly higher) proportion of 10-day ones, and then, for the longest spells, the results are coherent. As the 10-day spells do not change, the coherent decrease is rather for 11 days and more and then, the results can be considered as similar. The reason for this absence of 9-day spells will have to be further investigated, but the proportion become very small for such lengths and a small change, induced by different trends, can induce such a result. It seems then that the dynamic of cold spells does not change much in the future, and the frequency of current cold waves decreases because current cold temperatures become less frequent. Now let us compare the threshold shifts given by each climate model. As an example, Figure 11 illustrates them for the station of Boulogne sur mer, in the north of France: for IPSL-CM5-MR, due to both mean increase and variance decrease (or location and scale of the distribution), the observation based 5th percentile of wintertime temperature distribution (around -5°C for this station), becomes a 0.5th percentile in the future. Such a decrease in the variance is not projected by CNRM-CM5, and the 5th percentile of observation distribution becomes a 1.5th percentile of the future wintertime distribution. Both mean and variance change impact the percentile change, and the difference in variance change explains why the impact is found higher with IPSL-CM5-MR than with CNRM-CM5. Cold spell length decreases in the future mainly because the frequency of current thresholds decreases, and this decrease is linked to both mean and variance changes. It must be recalled here that when the threshold becomes rarer, the climate and the stochastic models both have difficulties to produce long cold waves, which could artificially intensify the identified impact.

5 Conclusion and discussion

In this study, a stochastic temperature generator has been used to bias correct and downscale climate simulation results and analyze the future changes in cold waves number and repartition. Cold waves are defined as consecutive days (from 1 single day to more than 15 days) with daily minimum temperature below different thresholds: 0°C or the 10th and 5th

percentiles of observed wintertime daily minimum temperature distribution. For future period, two climate model simulations have been considered, one according to RCP8.5 scenario and the other according to RCP4.5, with only two climate models used in the framework of the CMIP5 exercise: CNRM-CM5 and IPSL-CM5A-MR. The main outcomes are the following:

- Using the stochastic model allows both simulating some very long events, even though none have been observed, and inferring the significance of changes by use of the confidence intervals derived from 100 simulations for each period
- In agreement with all previous studies, a significant decrease in the number of cold spells is found in the future, whichever the future period, model or scenario
- Among these fewer cold waves, the decreasing essentially concerns the longest ones, with smaller differences for the nearest future period, whichever the scenario, and with CNRM-CM5 model
- The main driver of the changes is the threshold shift: observation based thresholds are rarer in the future due to climate warming
- For IPSL-CM5-MR, the variance decrease add to the mean increase to make current thresholds even rarer in the future, which explains the highest impact found with this model

The fact that in winter, variance decreases when mean increases, has already been evidenced in Parey et al. 2010. However, the present study shows that two different models may have a different behavior in this respect, the decrease in temperature variance being much lower for CNRM-CM5 than for IPSL-CM5A-MR. This study should thus be extended to the consideration of more climate models. It could be interesting to apply the same methodology to heat waves too, in order to compare the impacts. Schoetter et al. 2015 also found that for heat waves, the main driver is the threshold shift, and considering the respective roles of shift and broadening of the distributions, found no significant change in variance, and thus, a dominating role for the mean change, whereas here the variance change seems to play a more important role for cold spells. One advantage of the methodology used here is the decomposition of the signal between 2 deterministic parts, seasonality and trend, both for mean and variance, and a stochastic signal. Academic tests will be done with prescribed changes in the different deterministic components in order to quantify their respective roles in the change of extreme temperature events. In parallel, suggestions and tests are under way to improve the stochastic model in order to fix its tendency to produce too much single day events and too few very long ones, especially when the threshold is extreme (typically lower than the 5^{th} percentile).

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500 **Tables**

Number	Location	Period
1	Château Gaillard	1953-2005
2	Cannes	1959-2005
3	Chateaubernard	1953-2005
4	Farges en Septaine	1953-2005
5	Saint Cast le Guildo	1955-2005
6	Besançon	1959-2005
7	Montélimar	1959-2005
8	Champol	1954-2005
9	Guipavas	1958-2005
10	Beaucouze	1955-2005
11	Auderville	1955-2005
12	Courcy	1959-2005
13	Saint Dizier	1959-2005
14	Tomblaine	1959-2005
15	Augny	1959-2005
16	Boulogne sur mer	1955-2005
17	Epinoy	1955-2005
18	Strasbourg	1959-2005
19	Mont Saint Vincent	1953-2005
20	Sainte Adresse	1955-2005
21	Vélizy Villacoublais	1954-2005
22	Saint Georges la Baulche	1954-2005

501 Table 1: list of the observed time series locations with their observation period considered for
502 present climate
503

Figures

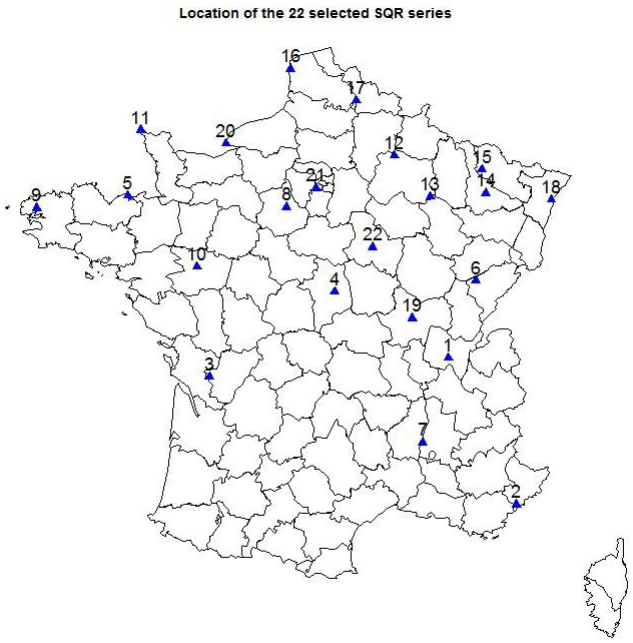
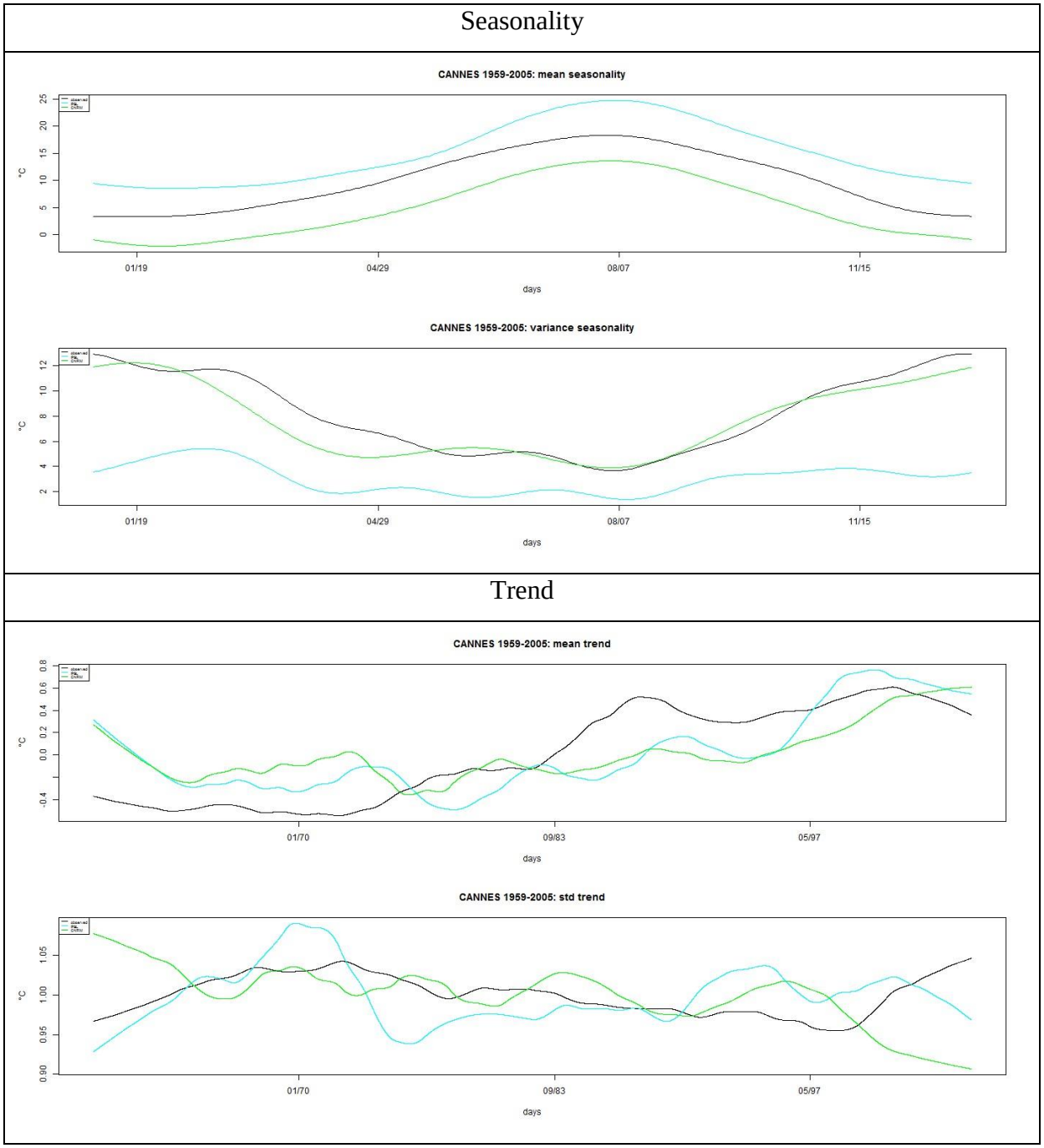


Figure 1: location of the 22 selected daily minimum temperature time series; the numbers refer to table 1 for the location identification

509



510 Figure 2: seasonality (top panel: mean top and variance bottom) and trend (bottom panel:
511 mean top and variance bottom) of the observed (black curves), IPSL-CM5A-MR (cyan) and
512 CNRM-CM5 (green) daily minimum temperature time series for Cannes, in the south of
513 France

514

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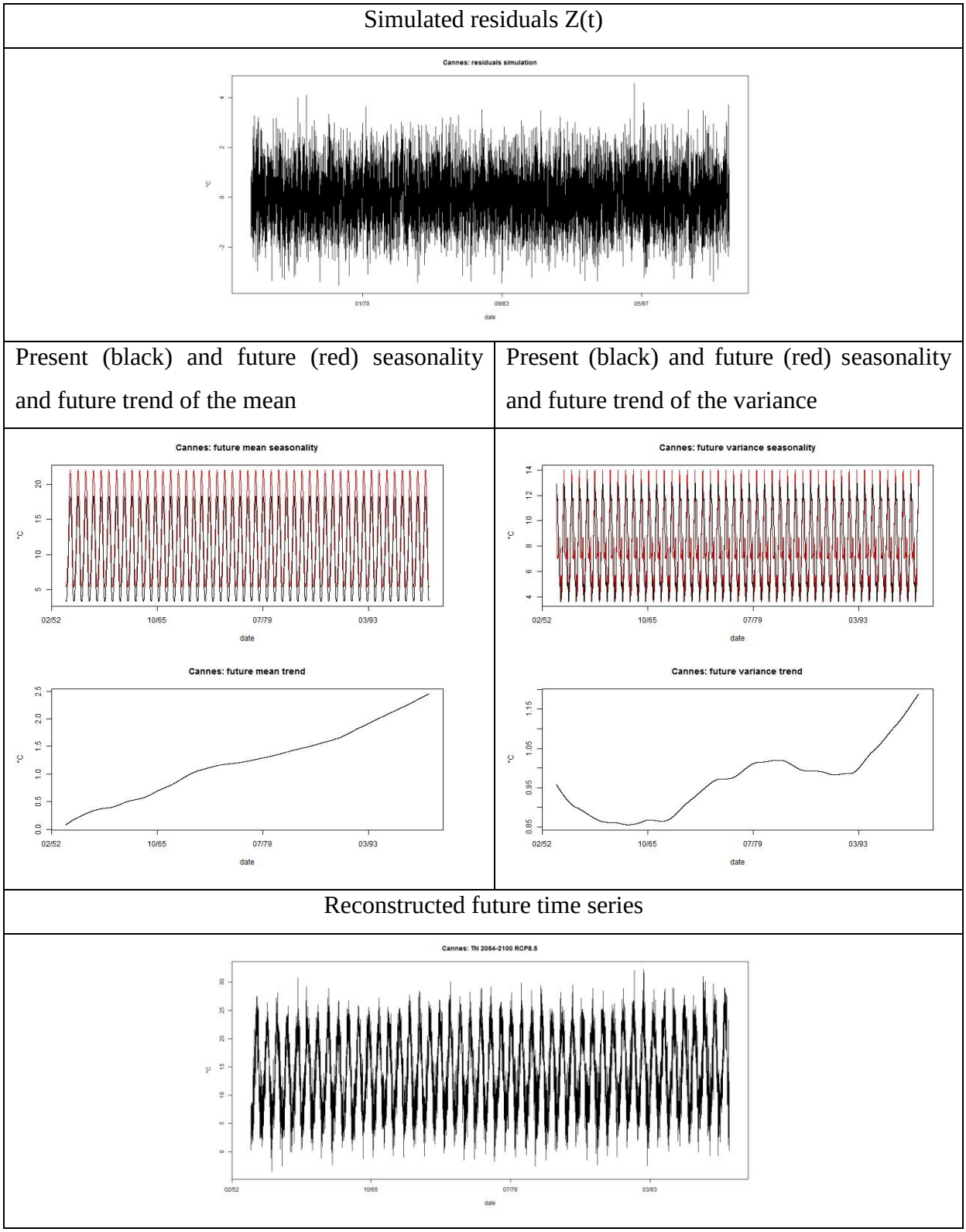
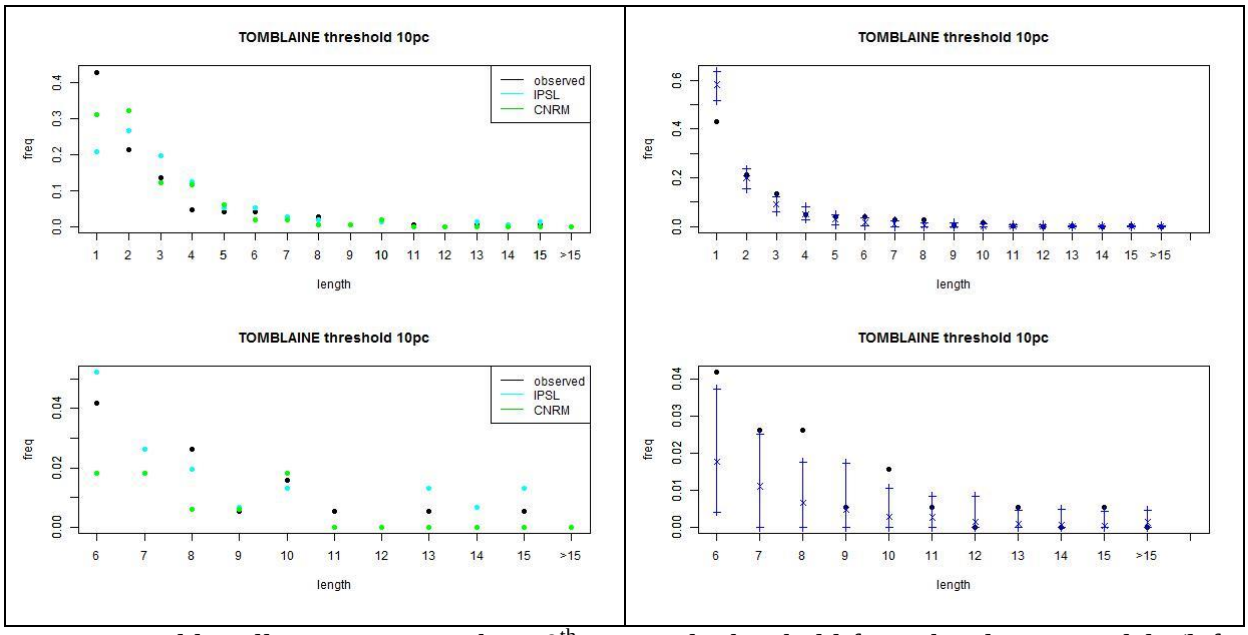


516 Figure 3: reconstruction of a future daily minimum temperature time series (bottom panel)
517 from the simulated residuals (top panel), the future seasonalities and trends (middle panel, for
518 seasonality: black = present, red = future) for the mean (left panel) and the variance (right
519 panel)



520 Figure 4: cold spells repartition with a 10th percentile threshold from the climate models (left
521 panel: observation in black, IPSL-CM5A-MR in cyan and CNRM-CM5 in green) and with
522 the stochastic model (right panel: observation in black, distribution for the 100 simulations in
523 blue: x mean and + 2.5 and 97.5 percentiles) for the station of Tomblaine. Top plots represent
524 all cold wave lengths while bottom plots zoom on the longest ones (6 days and more)
525

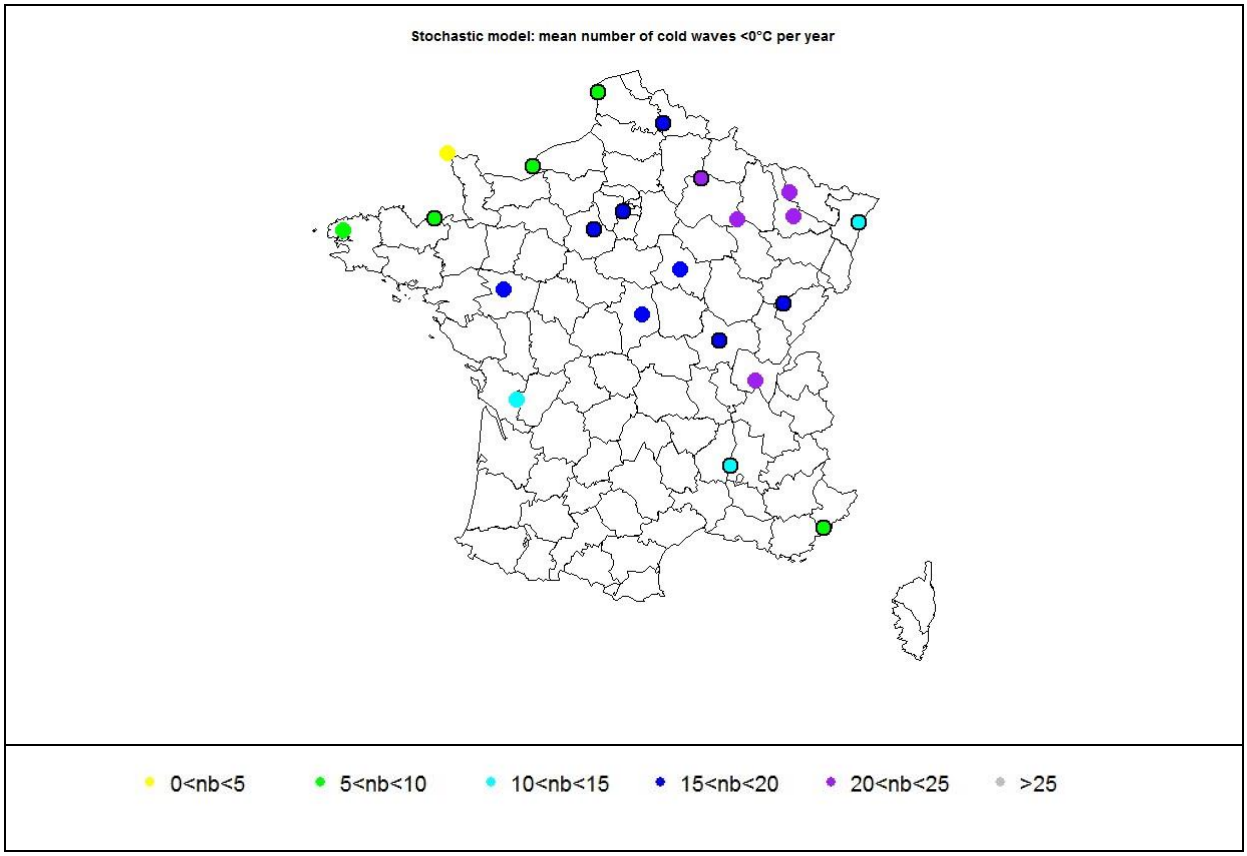


Figure 5: mean number of observed cold spells per year with 0°C threshold. Black circling denotes the locations where the observed number does not fall inside the 95% confidence interval of the stochastic simulations

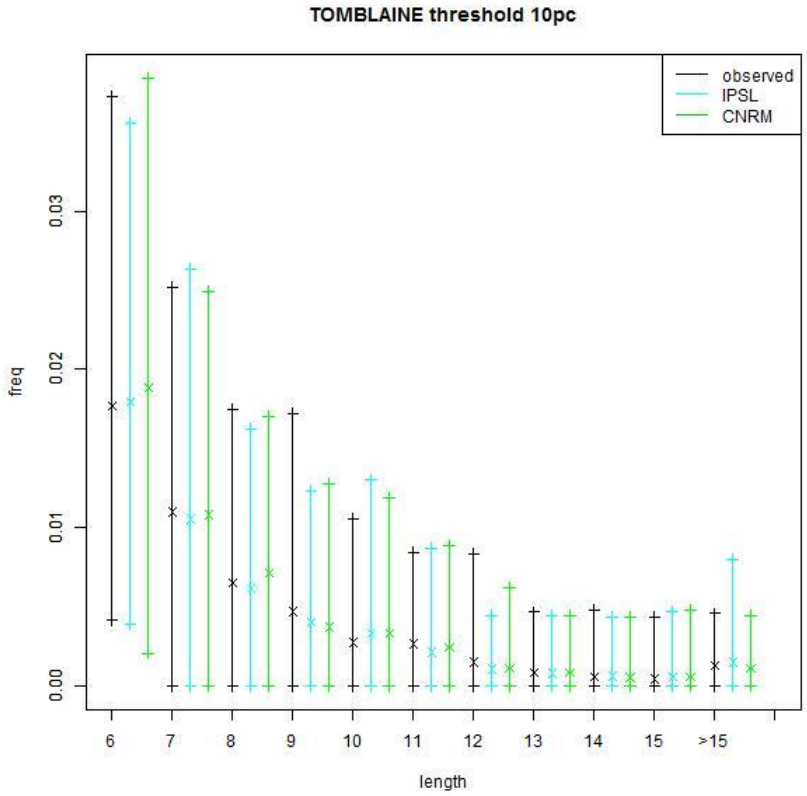


Figure 6: distributions of proportions of the longest cold waves (6 days and more) obtained with the stochastic model for the station of Tomblaine from the observations (simulated residuals + observed seasonalities and trends, black), and from IPSL-CM5A-MR (blue) and CNRM-CM5 (green) (simulated residuals + observed seasonalities and model trends). Cross is for the mean value, and start and end of the segments are the 2.5 and 97.5 percentiles of the distribution obtained from the 100 simulations

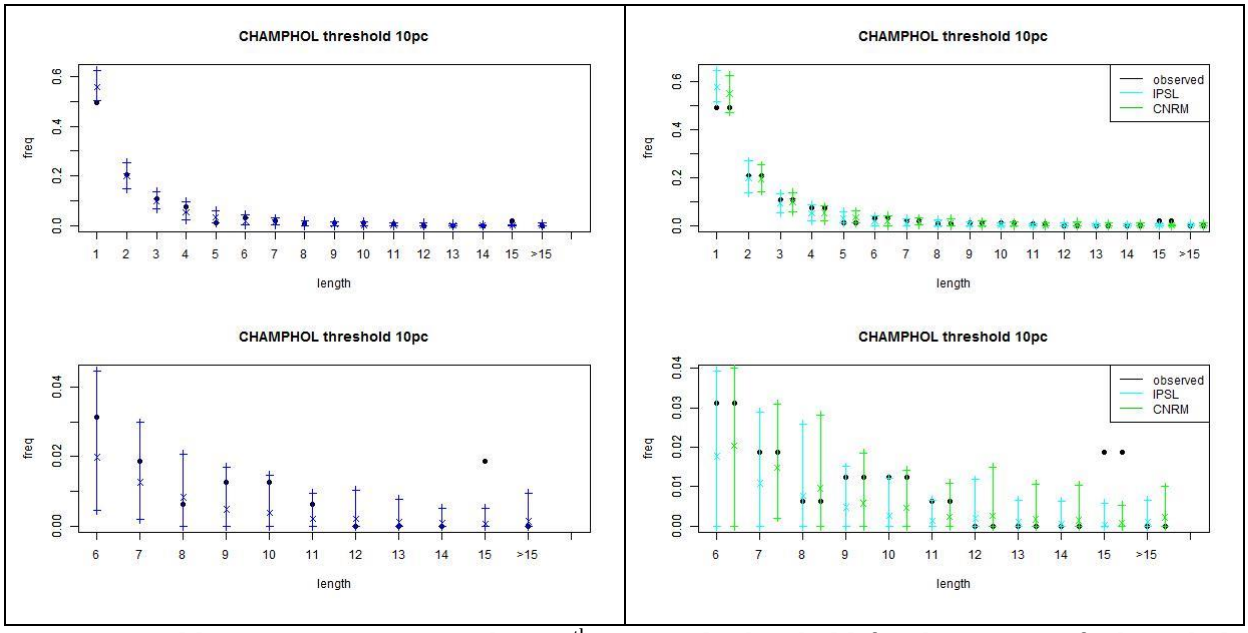


Figure 7: cold waves repartition with a 10th percentile threshold for the station of Champhol over period 1980-2005 as given by direct fitting of the stochastic model on the observations (left panel) or by reconstruction using climate model trends and seasonality increments (right panel, IPSL-CM5A-MR in cyan and CNRM-CM5 in green) and stochastic model fitted over period 1954-1979. Black points are for observed proportions while each bar represents the distribution of the 100 simulations (x for mean and + for 2.5 and 97.5 percentiles). Top plots represent all cold wave lengths while bottom plots zoom on the longest ones (6 days and more)

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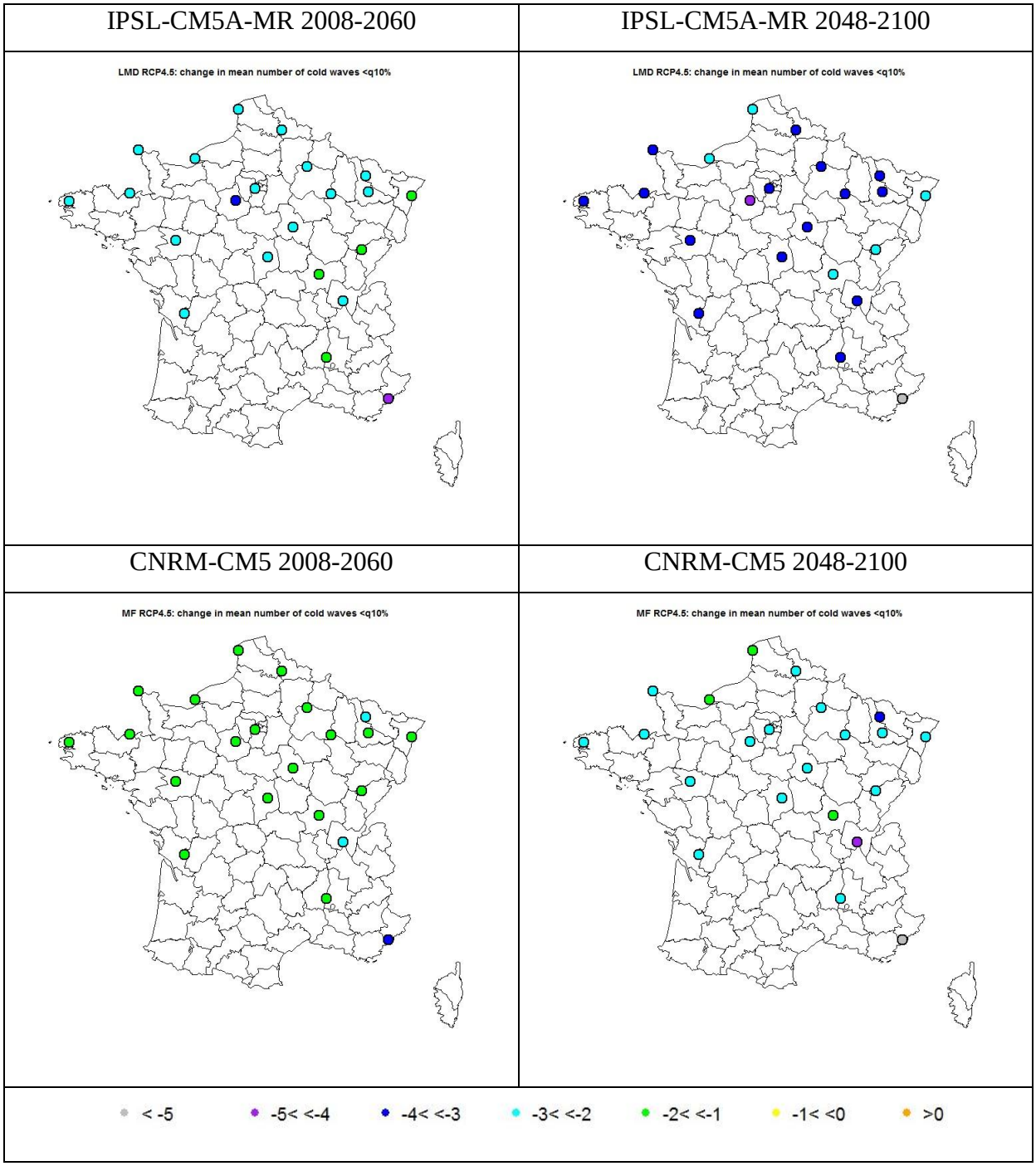

562 Figure 8: change in the mean annual number of cold waves of all duration for the near (ending
563 in 2060, left panel) and far (ending in 2100, right panel) future periods with IPSL-CM5A-MR
564 (top plots) and CNRM-CM5 (bottom plots) models with RCP4.5 with the 10^{th} percentile
565 threshold

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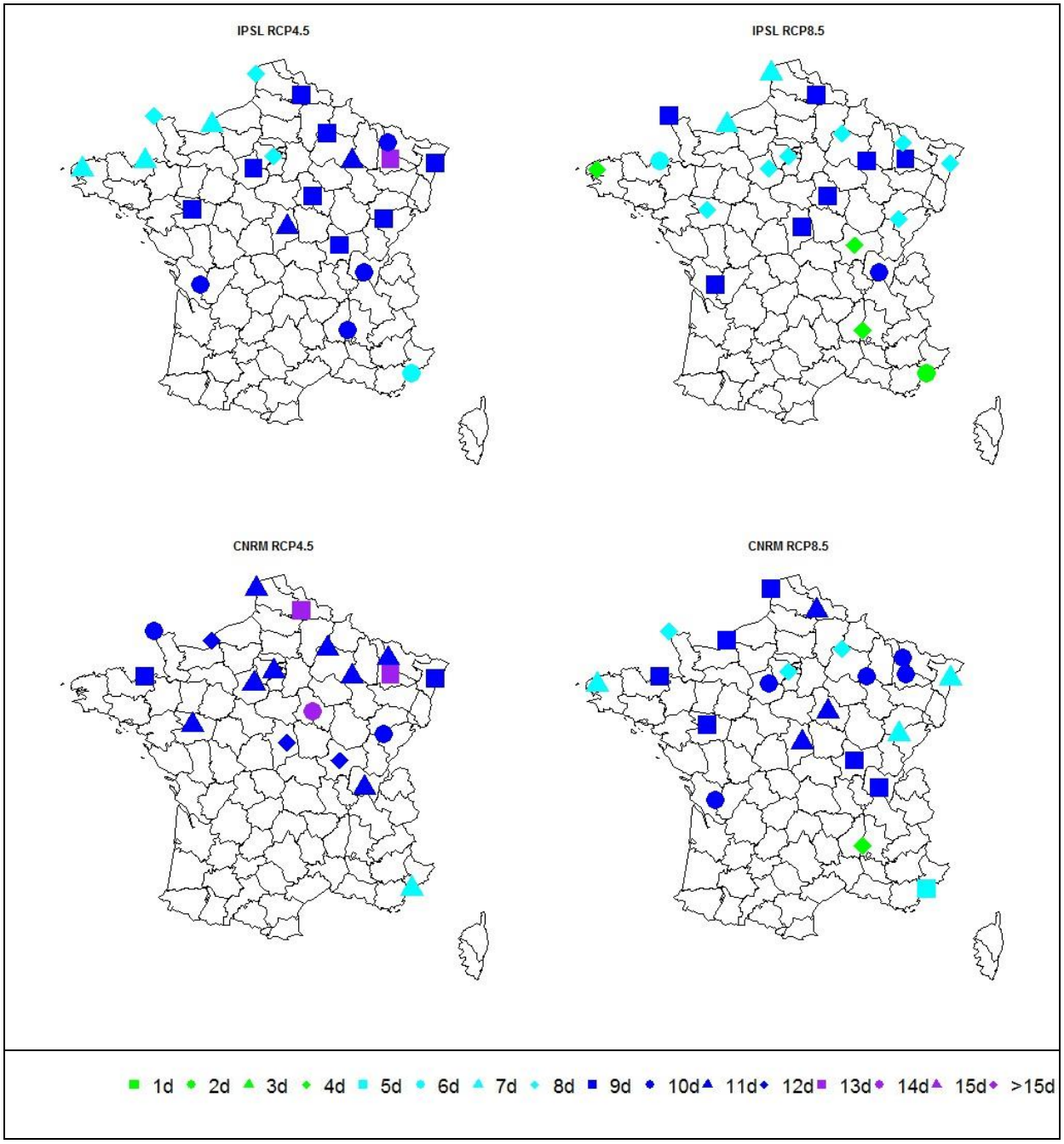

Figure 9: length from which the proportion significantly changes from the observed proportion for future period ending in 2100 according to IPSL-CM5A-MR (top) and CNRM-CM5 (bottom) models with RCP4.5 (left panels) and RCP8.5 (right panels) with the 5th percentile threshold

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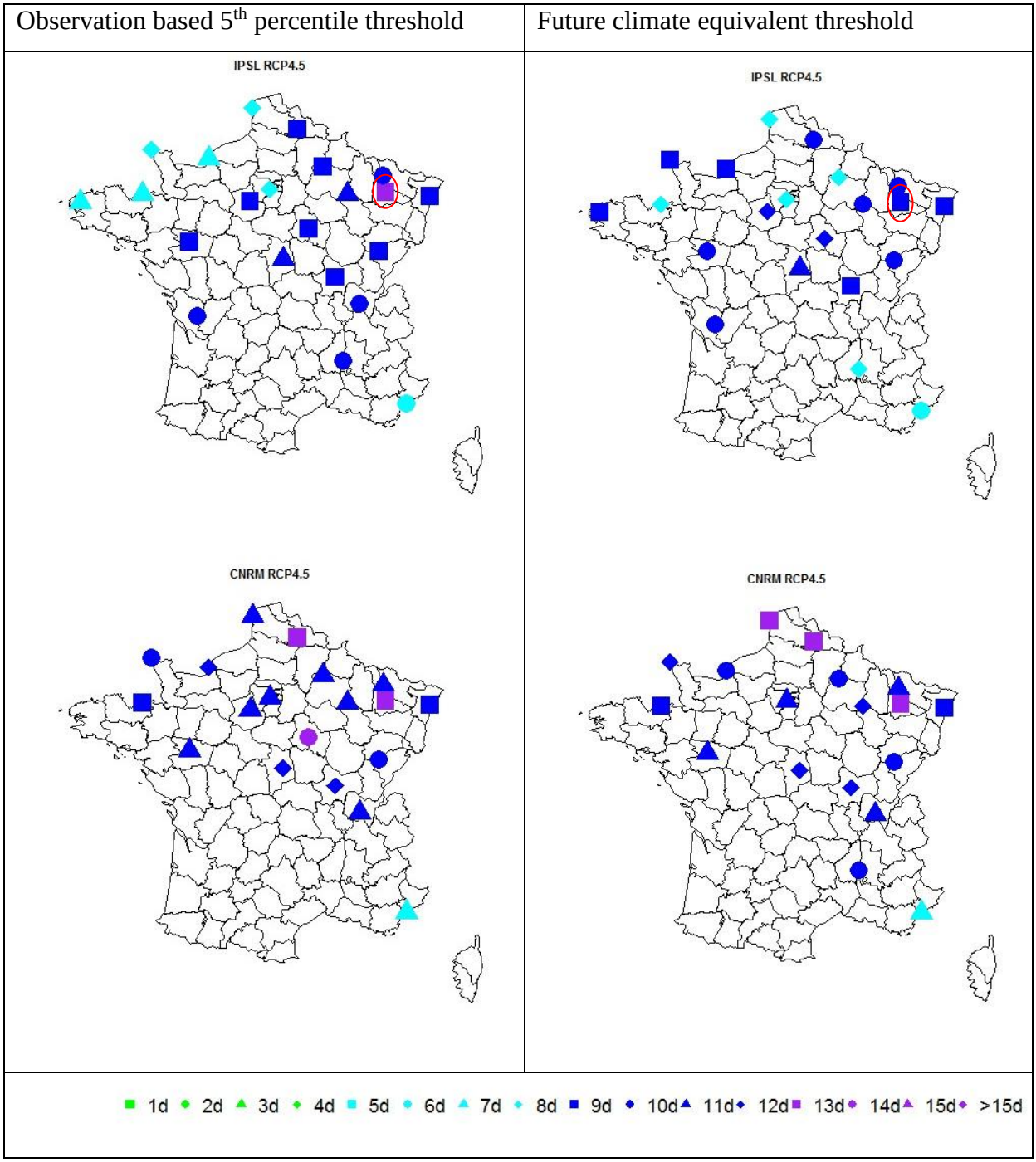

574 Figure 10: length from which changes in proportions of cold waves are significant from the
575 observation based stochastic simulations with the observation based 5th percentile threshold
576 (left panel) and a threshold corresponding to the rank of this observation based 5th percentile
577 threshold in the far future (ending in 2100) wintertime temperature distribution (right panel).
578 Red circling isolates the station of Tomblaine which is further discussed

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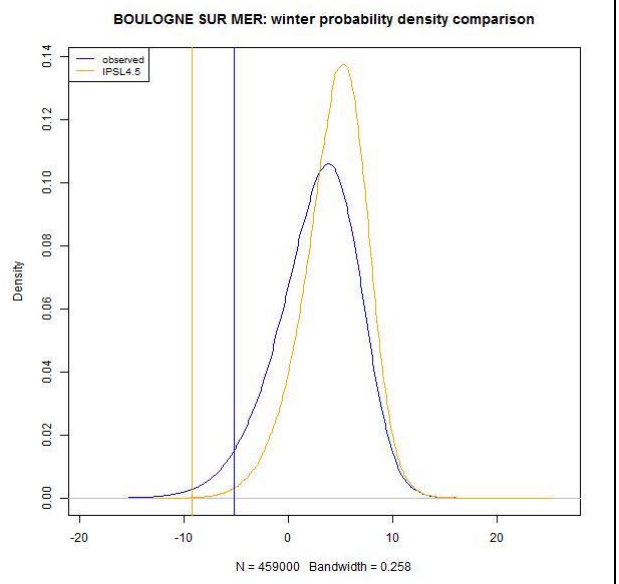
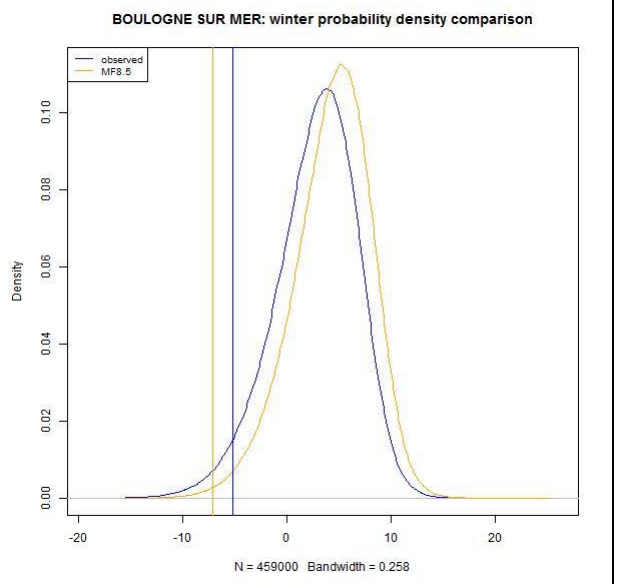
IPSL-CM5A-MR	CNRM-CM5
	

582 Figure 11: probability density function of the wintertime daily minimum temperature
583 according to the observations (blue curve) and climate model far future period with RCP4.5
584 (orange curve) with IPSL-CM5A-MR (left panel) and CNRM-CM5 (right panel). The blue
585 line is for the observation based 5th percentile threshold and the orange one for its equivalent
586 percentile in the future distribution