

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

Sylvie Parey, Thi Thu Huong Hoang

► To cite this version:

Sylvie Parey, Thi Thu Huong Hoang. 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. Climate Dynamics, 2015, 47 (3-4), pp.879-893. 10.1007/s00382-015-2877-6 . hal-01569003

HAL Id: hal-01569003 https://hal.science/hal-01569003

Submitted on 26 Jul 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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

3 CM5 and CNRM-CM5 models

4 S. Parey, T.T.H. Hoang

- 5 EDF/R&D 6, quai Watier 78 401 Chatou Cedex France
- 6 Tel : 33 1 30 87 76 14
- 7 Fax : 33 1 30 87 71 08
- 8 <u>sylvie.parey@edf.fr</u>
- 9

10 Abstract: In this paper, a stochastic model is used to simulate daily minimum temperature time series 11 coming from observations and two CMIP5 climate models (IPSL-CM5A-MR and CNRM-CM5) in 12 order to analyze the changes in cold wave number and proportions under future climate conditions. 13 The stochastic model allows computing 100 temperature time series for each different source 14 (observation or climate model), and for 22 locations in France, which enables inferring the statistical 15 significance of the changes. Two future time periods, near (around 2010 to 2060) and far future 16 (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 10th and 5th percentiles of observed wintertime 17 18 (December-January-February) daily minimum temperature distribution. The results show that both 19 models project a significantly lower number of cold waves in the future, all durations considered, but 20 the changes mainly concern the proportion of the longest cold waves (10 days and more). The 21 decreases are higher with IPSL-CM5A-MR than with CNRM-CM5. The main driver of this change is 22 the decreasing frequency of the observation based thresholds in the future, which is higher for IPSL-23 CM5-MR model because the impact of a higher mean is enhanced by a decrease in the variance.

24 Keywords: Climate change; cold waves; stochastic modelling

25

26 **1. Introduction**

27 In the climate change context, more and more studies are devoted to the evolution of extreme 28 events, since those have a major impact on people, society and organizations. Among these 29 events, temperature related ones, heat and cold waves, are of special concern for electricity 30 companies, because they impact both electricity production and demand. Agriculture, road or 31 rail management or health are other examples of impacted sectors. In 2012, IPCC devoted a 32 special report to the assessment of this issue of climate change and extreme events: the 33 Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate 34 Change Adaptation (SREX). Its main conclusions about temperature related extremes were 35 that "it is very likely that there has been an overall decrease in the number of cold days and 36 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 37

38 the 21st century with respect to the 1960-1990 climate". However, the same report also noted 39 that fewer studies had been devoted to the analysis of cold or warm spells compared to those 40 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 41 42 concern warm events: "There is medium confidence that the length or number of warm spells, 43 including heat waves, has increased since the middle of the 20th century". Nevertheless, the 44 report stated that "it is very likely that the length, frequency and/or intensity of warm spells, 45 including heat waves (defined with respect to present day climate) will increase over most 46 land areas." Then, IPCC AR5 working group I report further supported those conclusions, in 47 more strongly assessing the anthropogenic contribution to the observed changes. Furrer et al. 48 (2010) and Wang et al. (2014) also have investigated the hot spell behavior by using extreme 49 value theory. Cold waves are however an important issue for electricity management, 50 especially in France where electrical heating is important.

51 In a recent set of papers, Sillmann et al. (2013) applied the climate extreme indices defined by 52 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). 53 54 Among these indices, CSDI represents cold spell duration, and their results show that CMIP5 55 models agree with ERA-40 and ERA-Interim re-analyses in representing a decreasing trend in 56 the cold spell duration over the period 1948-2005. Part 1 is dedicated to model evaluation, 57 then, in part 2, they found significant changes in CSDI over land in the end of the 21st century, 58 with around 3.4 days less according to a RCP2.6 scenario, 3.9 days less for RCP4.5 and 4.2 59 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 60 temperature falls below the 10th percentile of the winter daily mean temperature distribution) 61 62 in current and future climate. They showed that most of the changes in cold spell statistics can 63 be explained by changes in mean (increase) and variance (decrease) of the winter temperature 64 distribution. This dominating role of the evolutions of mean and especially variance in the 65 evolutions of temperature extremes had also been found by Parey et al (2010). Concerning 66 France, Cattiaux et al. (2013a) first studied the link between hot and cold spells and the 67 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 68 69 wintertime dynamics and the statistics of cold spells. In another paper, Cattiaux et al. (2013b) 70 focused on changes in cold extremes over Europe in a pilot study using both French climate 71 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.

78 The present study aims at complementing these results by adopting a different point of view. 79 We focus here on the local distributions of cold spells of different durations, from one single 80 day to more than 15 consecutive days below a defined threshold. It is based on a set of high 81 quality temperature time series provided by Météo-France and on the results of the French 82 IPSL-CM5A-MR and CNRM-CM5 climate models run in the framework of CMIP5. Note 83 that the version of IPSL model is different from that used in Peings et al (2012), who used the 84 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-85 86 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 87 88 originality lies in the use of a stochastic model of temperature to bias correct and downscale 89 the climate change simulations. Climate models are namely designed to faithfully simulate 90 large scale features of the climate system and its circulations, as well as the main 91 characteristics of the physical interactions, cycles and their possible evolutions under external 92 forcing. However, they cannot precisely represent local weather and different downscaling 93 techniques have been proposed in the literature to overcome this issue for impact studies (see 94 Maraun et al. 2010 for a review). These techniques can be divided into statistical and 95 dynamical approaches. Statistical methods are based on some identification of statistical 96 relationships between large scale and local scale variables used to derive local information 97 from the larger scale patterns given by the climate model. Dynamical methods consist in 98 running a limited area climate model forced by the larger scale model at its boundaries in 99 order to refine the simulation over a chosen small region. The approach used here is a 100 statistical downscaling technique based on the use of a quite sophisticated stochastic model. 101 This stochastic model allows moreover the simulation of a large number of equivalent 102 temperature time series then used to evaluate the statistical significance of the obtained 103 changes in proportions of cold spells of different duration. Furrer et al. (2010) also proposed a 104 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 thecase here.

107 The considered time series, model simulations and the methodology will be described in 108 section 2, and then section 3 will present the validation of the approach over the current 109 climate period. Section 4 will be devoted to the analysis of the changes in the cold wave 110 distribution in the near and far future according to RCP4.5 and RCP8.5 scenarios, before 111 coming to the conclusion and discussion in section 5.

112

113 **2. Data, models and methodology**

114 **2.1 Observation time series**

115 In the framework of the French IMFREX project devoted to the impact of climate change on 116 extreme events, Météo France developed a database of daily time series selected for their 117 homogeneity over the longest possible period after a procedure of trend and metadata analysis 118 dedicated to the detection of possible changes in the measurement conditions (Gibelin et al. 119 2014). These so-called SQRs (Série Quotidiennes de Référence, reference daily time series in 120 French) constitute a robust database of observations over France to study climate change. A 121 set of 39 of such temperature time series have been provided by Météo-France for this study, 122 conducted in the framework of the French national research agency supported SECIF project 123 (dedicated to the development of climate services for the French industries). Among this set 124 of time series, 22 daily minimum temperature time series have been selected as the longest 125 and most representative of different locations in France, as shown in Figure 1, and they cover 126 periods between 1953 and 2011. However, since the historical simulations of the climate 127 models end in 2005, the observation time series are considered over periods between their 128 beginning year and 2005. Table 1 summarizes the observed time series periods considered. 129 The selection aimed at attributing a single station to a climate model grid cell, and thus when 130 stations are too close, only the longest one is selected.

131 **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.

144 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 145 146 simulations are considered over the exact same period as that of the corresponding 147 observation time series. For example, for an observation time series spanning the period 1954-148 2005, the model historical simulation is considered for years 1954 to 2005. Two future 149 periods are then considered, one ending in 2060 and the other ending in 2100, the length 150 being chosen identical to the observation time series length for convenience. Thus, again, for 151 an observation time series covering 1954-2005, the first future period is 2009-2060 and the 152 second one 2049-2100.

153 **2.3 Stochastic temperature model**

154 As stated before, a stochastic temperature model is used to bias correct and downscale the 155 temperature time series provided by the climate models. This temperature generator is 156 designed to realistically reproduce temperature extremes, and potentially simulate larger 157 extremes than observed. It is a stochastic Functional Seasonal Heteroscedastic Auto 158 Regressive model used to simulate the stochastic part of the process after the deterministic 159 parts, trends and seasonalities in the mean and the variance, have been removed. It has namely 160 been found from analyses of a large number of different temperature time series that once 161 trends and seasonalities in the mean and the variance have been removed, no trends can be 162 identified in the other moments (up to moment 4), the auto-correlations and in the extremes of 163 the residuals (Hoang 2010). However, some seasonality remains in the other moments and in 164 the auto-correlations, but not really in the extremes. Thus the stochastic model simulates Z(t),

165 where
$$Z(t) = \frac{X(t) - S_m(t) - m(t)}{S_v(t)^{s(t)}}$$
 (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 theform

172
$$\theta_0 + \sum_{i=1}^p \left(\theta_{i,1} \cos \frac{2i\pi t}{365} + \theta_{i,2} \sin \frac{2i\pi t}{365}\right)$$
(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:

177
$$Z(t) = b(t)Z(t-1) + a(t, Z(t-1))\varepsilon_t$$
(3)

178 With

179
$$b(t) = \theta_0 + \sum_{j=1}^{p_1} \left(\theta_{j,1} \cos \frac{2j\pi t}{365} + \theta_{j,2} \sin \frac{2j\pi t}{365}\right)$$
(4)

180 p₁ being again chosen according to an Akaike criterion, and a is the conditional standard
 181 deviation, obtained from the conditional variance a² estimated as:

182
$$a^{2}(t, Z(t-1)) = (\hat{r}_{2} - t)(t - \hat{r}_{1}) \sum_{k=0}^{5} \sum_{j=1}^{p_{2}} (\alpha_{1,k}^{j} \cos \frac{2j\pi}{365} + \alpha_{2,k}^{j} \sin \frac{2j\pi}{365}) Z(t-1)^{k}$$
(5)

183 under constraints for its first derivatives at the boundaries:

(6)

184
$$(a^2)'(r_1) = \frac{2b(r_1)}{1 - \frac{1}{\xi_1}} \text{ and } (a^2)'(r_2) = \frac{2b(r_2)}{1 - \frac{1}{\xi_2}}, \ a^2(t, Z(t-1)) > 0 \forall t$$

185

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) timeseries 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). 198 Then a simulation of the initial temperature time series is obtained by re-introducing the 199 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.

205 **2.4 Simulated temperature time series**

206 As stated before, for each location 100 time series of the residuals Z(t), after removing trends 207 and seasonalities, are computed. The ability of the model to reproduce the observed behavior 208 of Z(t) has been checked in Hoang (2010), Dacunha-Castelle et al. (2015) and Parey et al. 209 (2014), thus, from these, 100 temperature time series coherent with the observed one are 210 obtained by reintroducing trends and seasonalities. For climate model temperature time series, 211 potential biases have first to be investigated. Seasonality is the first estimated deterministic 212 part, and trend is identified from the time series of anomalies from the seasonality. The same 213 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 214 215 seasonality identification, while trends are then more coherent with the observed ones. Figure 216 2 illustrates this point for the station of Cannes, in the south of France. Thus, the reconstructed 217 temperature time series for present climate are built by adding (multiplying by for standard 218 deviation) observed seasonalities and climate model trends to the simulated residuals Z(t). 219 Then, for future time periods, seasonalities are obtained by adding the modeled difference in 220 seasonality of the mean between future and present period for the seasonality in the mean, and 221 multiplying by the ratio of future period standard deviation seasonality to present period one 222 for the seasonality of the standard deviation:

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

227 **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 10th and 5th 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).

234

3. Validation for present period

236 **3.1 Climate and stochastic models performances**

237 In a first step, the repartitions of all identified cold spells for each station between different 238 durations are compared for observation and climate model present period simulations. As 239 climate models have biases, the thresholds used to define cold waves are chosen as the 240 corresponding percentiles of the climate model time series. Thus, the fixed 0°C threshold is 241 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 5th and 10th percentile of wintertime temperature correspond 242 243 similarly to different temperature values in the model runs and in the observations. The 244 comparisons show that generally, both climate models tend to produce fewer 1-day events and 245 more 2 days and more ones than observed, and may have difficulties to reproduce very long 246 cold spells. The stochastic model generally leads to a better reproduction of the proportion of 247 long events, but tends to overestimate that of 1-day ones. Figure 4 illustrates this behavior for 248 the station of Tomblaine and the 10th percentile threshold. It can be noticed that the stochastic 249 model is able to produce long cold waves in some simulations, even though none has been 250 observed (14 days or >15 days in Figure 4 right panel). With a more extreme threshold like the 5th percentile of wintertime temperature, the climate and stochastic models both have 251 252 difficulties to produce a similar proportion of very long events as observed, although the 253 stochastic model again sometimes succeeds in producing some among the 100 simulations, 254 even though none have been observed.

255 Besides, using the stochastic model allows inferring significance for the observed changes 256 with the computation of the 95% confidence interval for the distributions obtained from the 257 100 simulations of each proportion of cold spell duration. Figure 5 illustrates the mean 258 number of cold waves per year for the 0°C threshold, all durations gathered, for the different 259 considered locations in France. Black circles indicate the stations for which the simulated 260 mean number is significantly different from the observed one (the observed number does not 261 fall inside the 95% confidence interval of simulated numbers). These discrepancies are mainly 262 due to the previously mentioned tendency to produce much more 1-day events than observed, 263 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

269 In order to check the ability of the suggested methodology to be used in the climate change 270 context, a cross-validation has been conducted for one location. The temperature time series 271 of Champhol, observed over period 1954 and 2005, has been split into two periods of equal 272 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 273 274 time series for the second period has been reconstructed using first period seasonalities 275 corrected using climate model seasonality differences between both periods and climate 276 model trends for the second period, following the suggested methodology for future climate. 277 Figure 7 shows that the obtained proportions of cold spells are similar to that which would 278 have been obtained by using observed period 2 seasonalities and trends. Figure 7 is for the 279 10th percentile threshold but this holds true for all used thresholds. This result gives 280 confidence in the use of this methodology to derive bias corrected future temperature time 281 series.

282

283 **4.** Future changes in cold waves number and repartitions

284

4.1 Cold waves number

286 Then, the changes projected for the future are analyzed, considering the same observation 287 based thresholds for the present and future periods. In line with all previous studies on the 288 subject, the mean number of cold spells per year, all durations considered, decreases 289 whichever the future time period, RCP scenario or threshold chosen for the identification. For 290 the nearest future period until 2060, both scenarios not surprisingly give relatively similar 291 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 5th percentile 292 293 and around 2 to 3 less for the 10th percentile with IPSL-CM5A-MR and around 1 to 4 less 294 episodes per year for 0°C, 1 (more rarely 2) less for the 5th percentile and 1 to 2 less for the 295 10th percentile with CNRM-CM5. The decreases are larger for the far future period with 296 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.
- 298 The black circles denote significant changes and show that all changes are significant.
- 299

300 4.2 Cold waves repartitions

301 We just saw that the mean number of excursions under the different thresholds, whatever their 302 lengths, is projected to decrease in the future. Now, let's go further and see how the 303 repartition among the different event durations is changed. Among this lower total number of 304 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 305 percentile) significantly decreases, and once again, more according to IPSL-CM5A-MR 306 307 model than according to CNRM-CM5 model. The results are again similar for both RCPs 308 until 2060, although a little bit higher for RCP8.5. For the end of the century, the picture looks 309 similar but the significant decreases concern all stations and begin for shorter events. Here, 310 the impact is larger with RCP8.5 than with RCP4.5, IPSL-CM5A-MR giving again a stronger 311 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 10 312 days or more (again, less for less cold places) for the 10th percentile. Figure 9 illustrates these 313 results for the period until 2100, both models and scenarios and for the 5th percentile 314 315 threshold.

316

4.3 Role of observation based threshold in the changes

318 Previous results are obtained with the same threshold for the identification of cold waves for 319 present and future periods. However, due to climate change, these thresholds become rarer in 320 both future periods than nowadays. In order to identify the impact of this change on previous 321 results, the cold spell repartitions have been estimated again from the stochastic simulations 322 of the observations, but using as thresholds the values corresponding to the previously defined 323 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 324 nearest period, around 1st and 2nd to 4th percentile for the late period, depending on the model 325 326 scenario and location. They thus lie in the farthest tail of the distribution, which could largely 327 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 328 329 periods, we can observe that they generally look very similar, confirming the upmost role 330 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 331 332 wintertime temperature distribution as threshold. Significant changes appear for similar cold 333 spell lengths, the differences rarely exceeding one or 2 days. For one station and IPSL-CM5-334 MR, a difference of 4 days can be noticed (circled in red in Figure 9): the significant decrease 335 is found from 13 days with the observation based threshold and 9 days with the future one. 336 After checking, it appears that the simulations do not produce 9-day cold spells with the 337 future threshold, but produce a similar (even slightly higher) proportion of 10-day ones, and 338 then, for the longest spells, the results are coherent. As the 10-day spells do not change, the 339 coherent decrease is rather for 11 days and more and then, the results can be considered as 340 similar. The reason for this absence of 9-day spells will have to be further investigated, but 341 the proportion become very small for such lengths and a small change, induced by different 342 trends, can induce such a result. It seems then that the dynamic of cold spells does not change 343 much in the future, and the frequency of current cold waves decreases because current cold 344 temperatures become less frequent. Now let us compare the threshold shifts given by each 345 climate model. As an example, Figure 11 illustrates them for the station of Boulogne sur mer, 346 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 347 temperature distribution (around -5°C for this station), becomes a 0.5th percentile in the future. 348 Such a decrease in the variance is not projected by CNRM-CM5, and the 5th percentile of 349 observation distribution becomes a 1.5th percentile of the future wintertime distribution. Both 350 351 mean and variance change impact the percentile change, and the difference in variance change 352 explains why the impact is found higher with IPSL-CM5-MR than with CNRM-CM5. Cold 353 spell length decreases in the future mainly because the frequency of current thresholds 354 decreases, and this decrease is linked to both mean and variance changes. It must be recalled 355 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 356 357 impact.

358

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 364 percentiles of observed wintertime daily minimum temperature distribution. For future period, 365 two climate model simulations have been considered, one according to RCP8.5 scenario and 366 the other according to RCP4.5, with only two climate models used in the framework of the 367 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
- 378 379

380

- 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

381 The fact that in winter, variance decreases when mean increases, has already been evidenced 382 in Parey et al. 2010. However, the present study shows that two different models may have a 383 different behavior in this respect, the decrease in temperature variance being much lower for 384 CNRM-CM5 than for IPSL-CM5A-MR. This study should thus be extended to the 385 consideration of more climate models. It could be interesting to apply the same methodology 386 to heat waves too, in order to compare the impacts. Schoetter et al. 2015 also found that for 387 heat waves, the main driver is the threshold shift, and considering the respective roles of shift 388 and broadening of the distributions, found no significant change in variance, and thus, a 389 dominating role for the mean change, whereas here the variance change seems to play a more 390 important role for cold spells. One advantage of the methodology used here is the 391 decomposition of the signal between 2 deterministic parts, seasonality and trend, both for 392 mean and variance, and a stochastic signal. Academic tests will be done with prescribed 393 changes in the different deterministic components in order to quantify their respective roles in 394 the change of extreme temperature events. In parallel, suggestions and tests are under way to 395 improve the stochastic model in order to fix its tendency to produce too much single day 396 events and too few very long ones, especially when the threshold is extreme (typically lower 397 than the 5th percentile).

Acknowledgment: This work is supported by the SECIF project from the French National Research Agency
 (ANR). Special thanks to S. Denvil (IPSL) for providing the CMIP5 simulations, to Paul-Antoine Michelangeli
 (EDF/R&D) for preparing and managing the EDF climate model results database, and to G. Gayraud (Météo France) for providing the SQR temperature time series.

403

404 6 References

405 Cattiaux J., Douville H., Ribes A., Chauvin F., Plante C. (2013): Towards a better
406 understanding of changes in wintertime cold extremes over Europe: a pilot study with CNRM
407 and IPSL atmospheric models. Climate Dynamics, Volume 40, Issue 9, pp 2433-2445 doi
408 10.1007/s00382-012-1436-7

- 409 Cattiaux J., Quesada B., Arakélian A., Codron F., Vautard R., Yiou P. (2013) : North-Atlantic
- 410 dynamics and European Temperature Extremes in the IPSL model: sensitivity to atmospheric
- 411 resolution. Climate Dynamics, Volume 40, Issue 9, pp 2293-2310 doi 10.1007/s00382-012-
- 412 1529-3
- 413 Dacunha-Castelle D., Hoang T.T.H., Parey S. (2015): Modeling of air temperatures:
- 414 preprocessing and trends, reduced stationary process, extremes, simulation, Journal de la
- 415 Société Française de Statistique, volume 156, No1, pp 138-168
- 416 de Vries H, Haarsma RJ, Hazeleger W (2012) Western European cold spells in current and
- 417 future climate. Geophys Res Lett 39:L04706. doi:10.1029/2011GL050665
- 418 Dufresne J-L, Foujols M-A, Denvil S., Caubel A., Marti O., Aumont O, Balkanski Y, Bekki
- 419 S., Bellenger H, Benshila R, Bony S, Bopp L, Braconnot P, Brockmann P, Cadule P, Cheruy
- 420 F, Codron F, Cozic A, Cugnet D, de Noblet N, Duvel J-P, Ethé C, Fairhead L, Fichefet T,
- 421 Flavoni S, Friedlingstein P, Grandpeix J-Y, Guez L, Guilyardi E, Hauglustaine D, Hourdin F,
- 422 Idelkadi A, Ghattas J, Joussaume S, Kageyama M, Krinner G, Labetoulle S, Lahellec A,
- 423 Lefebvre M-P, Lefevre F, Levy C, Li Z. X, Lloyd J, Lott F, Madec G, Mancip M, Marchand
- 424 M, Masson S, Meurdesoif Y, Mignot J, Musat I, Parouty S, Polcher J, Rio C, Schulz M,
- 425 Swingedouw D, Szopa S, Talandier C, Terray P, Viovy N, Vuichard N (2013): Climate
- 426 change projections using the IPSL-CM5 Earth System Model: from CMIP3 to CMIP5,
- 427 Climate Dynamics Volume 40, Issue 9, pp 2123-2165
- 428 Furrer, E. M., R. W. Katz, M. D. Walter, and R. Furrer (2010): Statistical modeling of hot
- 429 spells and heat waves. Climate Research, 43, pp 191–205.
- 430 IPCC (2012): Managing the Risks of Extreme Events and Disasters to Advance Climate
- 431 Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental

- 432 Panel on Climate Change, Cambridge University Press, Cambridge, UK, and New York, NY,
- 433 USA, 582 pp.
- 434 IPCC (2013): Climate Change 2013: The Physical Science Basis. Contribution of Working
- 435 Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change
- 436 [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia,
- 437 V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom
- 438 and New York, NY, USA, 1535 pp, doi:10.1017/CBO9781107415324.
- 439 Gibelin AL, Dubuisson B, Corre L, Deaux N, Jourdain S, Laval L, Piquemal JM, Mestre O,
- 440 Dennetière D, Desmidt S, Tamburini A (2014): Evolution de la température en France depuis
- 441 les années 1950 : Constitution d'un nouveau jeu de séries homogénéisées de référence, La
- 442 Météorologie, 87, 45-53, DOI : 10.4267/2042/54336
- Hoang, T. T. H. (2010), Modélisation de séries chronologiques non stationnaires, non
 linéaires: application à la définition des tendances sur la moyenne, la variabilité et les
 extrêmes de la température de l'air en Europe, PhD thesis work (written in English),
 http://www.tel.archivesouvertes.fr/tel-00531549/fr/
- 447 Maraun D, Wetterhall F, Ireson AM, Chandler RE and others (2010): Precipitation
- 448 downscaling under climate change: recent developments to bridge the gap between dynamical
- 449 models and the end user. Rev Geophys 48: RG3003, doi: 10.1029/2009RG000314
- 450 Parey, S., D. Dacunha-Castelle, and T. T. H. Hoang (2010): Mean and variance evolutions of
- the hot and cold temperatures in Europe, Climate Dynamics, Volume 34, pp 345–369.
- 452 Parey, S., T. T. H. Hoang, and D. Dacunha-Castelle (2013): The importance of mean and
- 453 variance in predicting changes in temperature extremes, J. Geophys. Res., 118, 8285–8296,
 454 *doi:*10.1002/jgrd.50629
- 455 Parey S., Hoang T.T.H., Dacunha-Castelle D. (2014): Validation of a stochastic temperature
- 456 generator focusing on extremes and an example of use for climate change, Climate Research,
- 457 Vol. 59, pp 61–75
- 458 Peings Y., Cattiaux J., Douville H. (2013): Evaluation and response of winter cold spells over
- 459 western Europe in CMIP5 models. Climate Dynamics, Volume 41, pp 3025-3037, doi
 460 10.1007/s00382-012-1565-z
- 461 Schoetter R., Cattiaux J., Douville H. (2015): Changes of western European heat wave
- 462 characteristics projected by the CMIP5 ensemble. Climate Dynamics, Volume 45, Issue 5, pp463 1601-1616
- 464 Sillmann J., Kharin V.V., Zhang X., Zwiers S.W. and Bronaugh D. (2013): Climate extremes
- 465 indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate.

466	Journal of Geophysical Research: Atmospheres, volume 118, pp 1716–1733,		
467	doi:10.1002/jgrd.50203		
468	Sillmann J., Kharin V.V., Zhang X., Zwiers S.W. and Bronaugh D. (2013): Climate extremes		
469	indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. Journal of		
470	Geophysical Research: Atmospheres, volume 118, pp 2473–2493, doi:10.1002/jgrd.50188		
471	Voldoire A, Sanchez-Gomez E, Salas y Melia D, Decharme B, Cassou C, Senesi S, Valcke S,		
472	Beau I, Alias A et al (2013) The CNRM-CM5.1 global climate model: description and basic		
473	evaluation. Climate Dynamics, Volume 40, Issue 9, pp 2091-2121, doi:10.1007/s00382-011-		
474	1259-у		
475	Wang, W., W. Zhou, Y. Li, and X. D. Wang (2014): Statistical modeling and CMIP5		
476	simulations of hot spell changes in China. Climate Dynamics, volume 44, pp 2859-2872.		
477			
478			
479			
480			
481			
482			
483			
484			
485			
486			
487			
488			
489			
490			
491			
492			
493			
494			
495			
496			
497			
498			
499			

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

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

present climate

504 **Figures**



505
506 Figure 1: location of the 22 selected daily minimum temperature time series; the numbers
507 refer to table 1 for the location identification
508



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



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



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



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

TOMBLAINE threshold 10pc



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 551 over period 1980-2005 as given by direct fitting of the stochastic model on the observations 552 553 (left panel) or by reconstruction using climate model trends and seasonality increments (right 554 panel, IPSL-CM5A-MR in cyan and CNRM-CM5 in green) and stochastic model fitted over 555 period 1954-1979. Black points are for observed proportions while each bar represents the 556 distribution of the 100 simulations (x for mean and + for 2.5 and 97.5 percentiles). Top plots 557 represent all cold wave lengths while bottom plots zoom on the longest ones (6 days and 558 more)





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





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 CNRMCM5 (bottom) models with RCP4.5 (left panels) and RCP8.5 (right panels) with the 5th
percentile threshold



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

- 579
- 580



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