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1 **Regional climate downscaling with prior statistical correction of the global climate**  
2 **forcing**

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9 **Abstract**

10 A novel climate downscaling methodology that attempts to correct climate simulation biases  
11 is proposed. By combining an advanced statistical bias correction method with a dynamical  
12 downscaling it constitutes a hybrid technique that yields nearly unbiased, high-resolution,  
13 physically consistent, three-dimensional fields that can be used for climate impact studies.  
14 The method is based on a prior statistical distribution correction of large-scale global climate  
15 model (GCM) 3-dimensional output fields to be taken as boundary forcing of a dynamical  
16 regional climate model (RCM). GCM fields are corrected using meteorological reanalyses.  
17 We evaluate this methodology over a decadal experiment. The improvement in terms of  
18 spatial and temporal variability is discussed against observations for a past period. The biases  
19 of the downscaled fields are much lower using this hybrid technique, up to a factor 4 for the  
20 mean temperature bias compared to the dynamical downscaling alone without prior bias  
21 correction. Precipitation biases are subsequently improved hence offering optimistic  
22 perspectives for climate impact studies.

23 **1 Introduction**

24 Global Climate Models (GCM) improved notably in their representation of the climate system  
25 over the past couple of decades (IPCC, 2007). Their design is focused on the global scale, and

26 their main scope consists in capturing the sensitivity of the global climate to changes in  
27 external natural and anthropogenic forcing. The fairly low resolution of such models does not  
28 allow for the detailed simulation of local atmospheric processes. In addition, the main focus  
29 being the global energy balance, coupled models may exhibit significant regional biases in  
30 important variables such as temperature or precipitation.

31 However, climate risk assessment requires horizontal resolution of the order of half a degree  
32 or below and unbiased projections, especially when it comes to meteorological extremes.  
33 More generally such information is required in order to design adaptation measures for which  
34 impact models (e.g., with regards to food safety, energy, water, air pollution), tuned on  
35 current climate observations, need to be applied to future climate projections. Such a  
36 requirement cannot be met by current raw GCM outputs.

37 The transformation of global model outputs into high spatial resolution products is referred to  
38 as climate downscaling. It can be divided into two broad types of approaches: statistical or  
39 dynamical downscaling. Statistical downscaling builds upon a prior knowledge of statistical  
40 relationships between the GCM and monitoring data. Statistical models representing those  
41 relationships are then applied over future time periods, without involving any additional  
42 physical modelling in addition to the GCM (Wilks and Wilby, 1999, Vrac et al., 2007,  
43 Semenov et al., 1998, Maraun et al., 2010). To downscale a global model in a dynamical way,  
44 one implements a Regional Climate Model (RCM) forced by the global fields at the  
45 boundaries (Giorgi et al., 2009, Laprise, 2008). Similarly to the GCM, the RCM provides a  
46 comprehensive physically-consistent representation of the climate system. However, GCM  
47 biases are conveyed to the RCM, and the latter can only compensate, or enhance, these flaws.  
48 In order to cope with these deficiencies, bias correction methods are often applied to RCM  
49 outputs prior to the implementation of an impact model (Christensen et al., 2008, Oettli et al.,  
50 2011). However this methodology suffers from several caveats. On the one hand, the fields

51 are generally corrected without considering spatial, temporal or inter-variable correlation. On  
52 the other hand, the bias correction requires high-resolution observations, generally not  
53 available on a grid, but rather at scattered locations. These problems could be at least partly  
54 avoided if most of the GCM biases were removed before the dynamical downscaling, an  
55 approach that we investigate in this article. A few studies investigated the possibility to  
56 correct large scale forcing prior to applying a mesoscale model (Rasmussen et al., 2012, Schär  
57 et al., 1996) but none of them achieved that with a downscaling technique that matches the  
58 whole range of the distribution to meteorological reanalyses.

59 We propose here an innovative downscaling methodology that combines both dynamical and  
60 statistical approaches, but in a different order compared to what is usually done. In a nutshell,  
61 our hybrid approach consists in applying a statistical correction of the GCM fields with  
62 respect to atmospheric reanalyses prior to performing a dynamical downscaling of these  
63 corrected fields. As such, this approach constitutes a hybrid climate downscaling technique  
64 building upon upstream statistical correction and downstream physical modelling.

65 Like any probabilistic downscaling technique, the upstream statistical correction may alter the  
66 integrity of the forcing fields by matching it to reanalyses. The main strength of our hybrid  
67 approach lies in the implementation of a mesoscale model after the probabilistic downscaling  
68 that guarantees the physical consistency of the resulting fields and hence constitutes an  
69 essential advantage for climate impact studies (Parry et al., 2007). Statistical downscaling that  
70 targets only a couple of surface variables has long been considered satisfactory for most  
71 climate impact studies (such as food safety or hydrological extremes). However other  
72 applications such as air quality modelling require physically-consistent 3D atmospheric fields.  
73 That is why regional air quality projection studies rely on raw RCM outputs, and our  
74 technique offers a unique perspective to derive unbiased, balanced, 3D forcing fields.

75 In section 2, the statistical and physical downscaling methodologies are presented. The  
76 evaluation results are given in section 3 on a test case for present day simulation. The  
77 application to future projections is left for upcoming studies.

## 78 **2 Methodology**

### 79 **2.1 Large scale climate model**

80 The large scale climate model that we use to demonstrate the efficiency of our hybrid  
81 statistical and dynamical technique is the coupled climate model IPSLcm (Institut Pierre  
82 Simon Laplace Coupled Model) GCM (Marti et al., 2010).

83 The simulations used here are obtained with the “low resolution” versions prepared for the  
84 CMIP5 (Climate Model Intercomparison Project) stream of the Intergovernmental Panel on  
85 Climate Change (IPCC). The meteorological fields are computed on a global 96x96 points  
86 grid with a horizontal resolution of 3.75 x 1.875 degrees and 39 vertical levels.

### 87 **2.2 Statistical downscaling**

88 The probabilistic downscaling methodology used here is the CDF-t (Cumulative Distribution  
89 Function transform) of (Michelangeli et al., 2009), based on a variant of the “quantile-  
90 matching” technique (Déqué, 2007). Quantile-matching consists in associating to a modelled  
91 value, the value in a control distribution (e.g. observations) that has the same probability. In  
92 other words, from a quantile in the CDF of the simulations, the corresponding quantile in the  
93 CDF of the control data (e.g. observations) is determined. By scaling the quantile-quantile  
94 relationship, the correction changes the shape of the distribution so that the events whose  
95 frequency (or probability) is systematically biased in the model are better captured.

96 While classical applications of quantile-matching consider that the CDF of the simulations is  
97 stationary in time (Maraun et al., 2010, Wilks and Wilby, 1999), the scope of CDF-t consists  
98 in expanding this technique for the case where the CDF of the simulations for the future has  
99 changed. This is done, first, by estimating the CDF of the corrected variable for the future

100 time period of interest (Michelangeli et al., 2009). Then, projections are obtained through a  
101 quantile-quantile technique between future uncorrected and corrected CDFs (Vrac et al.,  
102 2012). The methodology implemented here thus applies for future projections even though we  
103 decided to limit the scope of the present paper to historical periods in order to discuss its  
104 validation.

105 This CDF-t technique has been used successfully in the past to downscale climate models  
106 (Vrac et al., 2012, Flaounas et al., 2011, Michelangeli et al., 2009) but one should note the  
107 two major limitations of the approach. First, only the bulk CDF is matched, the temporal  
108 frequency and spatial patterns are not altered so that any flaw in the persistence or in the  
109 spatial distribution of the weather patterns is not improved. In addition, the major underlying  
110 hypothesis of the CDF-t downscaling is that, although the CDFs are not supposed to be  
111 stationary, the transformation  $T$  from model to observed variable CDFs is supposed to be  
112 valid under changed climate conditions, i.e. is supposed stationary in time. We emphasize that  
113 even though CDF-t is designed to be applied to future climate simulations, we decided to  
114 apply this technique in the present paper to a current period for validation purposes.

### 115 **2.3 Dynamical downscaling**

116 We use the Weather Research and Forecasting (Skamarock et al., 2008) mesoscale model to  
117 downscale the IPSLcm fields in a dynamical way. The spatial resolution is 50km and the  
118 domain covers the whole of Europe with 119x116 grid points. The setup is the same as that of  
119 (Menut et al., 2012) who present a detailed evaluation of the performance of the  
120 IPSLcm/WRF regional climate modelling suite. However no nudging was applied in the  
121 present case in order to evaluate the full effect of prior correction on dynamical downscaling.

### 122 **2.4 Experimental design**

123 We perform a CDF-t based correction of the large-scale input fields produced with the  
124 IPSLcm model so that corrected fields will be used for the dynamical downscaling.

125 Distributions are matched with those of reanalysed fields of the ERA-interim reanalysis.  
126 Unlike existing applications of CDF-t that perform a scaling of large-scale model outputs to  
127 point surface observations (Michelangeli et al., 2009) or gridded surface analyses (Flaounas et  
128 al., 2011) we scale several variables of the model to the whole 3D fields of the reanalysis.  
129 The correction is achieved at each GCM grid-point independently, where reanalysed fields  
130 were previously interpolated. There was no attempt to maintain the spatial consistency of the  
131 fields considering that (1) matched fields are coarse enough to avoid the introduction of high-  
132 frequency variability and (2) potential spurious features would vanish after having used the  
133 mesoscale model to downscale the corrected fields. For each variable and at each grid point,  
134 we extract the time series for the whole period to produce the two distributions (GCM and  
135 reanalysis) that will be matched. To account for seasonality, all training distributions are taken  
136 on a monthly basis. For 3D and surface temperature, the correction is performed  
137 independently for the 4 daily time steps to account for the diurnal cycle. Since we match the  
138 bulk distribution of the time series, there is no matching of sequences of event, on the  
139 contrary we maintain the temporal consistency of the input field.  
140 The correction is done for 3D zonal and meridional wind, 3D relative humidity, and 3D and  
141 surface (skin) temperature. Surface pressure and geopotential height are not matched in order  
142 to maintain flow consistency and quasi-geostrophy at the boundaries, but they are indirectly  
143 modified by the matching of the 3D temperature field. The hydrostatic balance of the  
144 corrected input field is recomputed before launching the mesoscale model in order to ensure  
145 physical consistency along the columns; by proceeding to an upward integration of the  
146 hydrostatic balance, corrections applied to the temperature field are conveyed to the  
147 geopotential height.  
148 The evaluation experiment consists of simulations over a 11-year period for the downscaling.  
149 The first year is considered as a spin-up period and it is thus discarded from the following

150 analysis. The last decade of the 20<sup>th</sup> century is chosen because of the full overlap between  
151 ERA-interim and IPCC historical simulations. This time period also allows comparing the  
152 efficiency of the methodology against observations. Two simulations are carried out, starting  
153 on 1 January 1989. The first one is done without applying the GCM correction prior to  
154 dynamical downscaling, while the second is done with application of the prior CDF-t  
155 approach. The two simulations are then compared to E-OBS data (Haylock et al., 2008) over  
156 the same time period. Since the focus of this study is not to validate the performance of the  
157 CFD-t itself directly applied to the GCM fields (as it was demonstrated before (Flaounas et  
158 al., 2011, Michelangeli et al., 2009, Vrac et al., 2012)), but the impact of CDF-t on the  
159 dynamical regional climate downscaling, it was unnecessary to implement a ‘leave-one-out’  
160 testing approach. The duration of the simulations (10 years) is too short to address the benefits  
161 for meteorological extremes; this aspect is left for future work while we focus here on average  
162 biases.

### 163 **3 Results**

164 The evaluation of the results is performed against the European Climate Gridded dataset (E-  
165 OBS) temperature and precipitation observations.

#### 166 **3.1 Surface temperature**

167 The bias of temperature averaged over the 10-year time period is given in Figure 1 for the  
168 reanalysis (ERA-i), the large-scale climate model (IPSLcm) and its statistically corrected  
169 version, the dynamically downscaled climate model (IPSLcm/WRF) and the hybrid  
170 statistical/dynamical downscaling (IPSLcm/CDF-t/WRF). For all the models the temperature  
171 is interpolated at 950hPa while the observations are provided at 2-m altitude. The  
172 discrepancies between E-OBS and ERA-i are confined to the outskirts of the domain where  
173 the gap filling procedure used in E-OBS has uncertainties as a result of the scarcity of the  
174 monitoring network. In addition, important differences are found over mountainous areas due



175 to lack of resolution and methodological differences. On average, the difference between  
176 ERA-i and the observations is -1.41K (standard deviation  $\sigma=2.03$ ) over the Western part of  
177 the domain (5W, 15E, 40N, 55N). Raw GCM temperatures exhibit a strong negative bias  
178 ( $-4.78\text{K}$ ,  $\sigma=0.6$ ), except over mountainous areas where the positive biases result from an  
179 artefact of the smooth orography. This strong negative bias of the low resolution version of  
180 the IPSLcm model was discussed before (Hourdin et al., 2012) and was improved in a more  
181 recent version of the model including a higher resolution (Cattiaux et al., 2012). This feature  
182 constitutes a somewhat good test case for the hybrid downscaling methodology presented  
183 here. The statistical correction is efficient at reducing the temperature bias of IPSLcm, the  
184 average bias of the corrected GCM is -1.36 ( $\sigma=2.07$ ) and its pattern resembles that of ERA-i.  
185 The negative bias of IPSLcm is amplified in the raw regional climate model simulations  
186 ( $-5.06\text{K}$ ,  $\sigma=1.49$ ), as was observed by (Menut et al., 2012). The dynamical downscaling  
187 does not constrain the distribution in any ways, and it appears that a negative feedback occurs  
188 here as the RCM increases the negative biases of forcing fields. On the contrary, the situation  
189 is better for the hybrid downscaling, the average bias is limited to -2.33K ( $\sigma=1.35$ ). The  
190 mesoscale still tends to cool down the GCM, and the average bias is larger than for the  
191 corrected version of IPSLcm since the compensation that occurred over high elevation terrain  
192 vanishes. Despite the reduction of the mean bias, it still exhibits a regional pattern with  
193 negative values in Western and Northern areas and positive values in Mediterranean areas.  
194 The overall negative bias is primarily found for low temperatures during winter and to a lesser  
195 extent for warm temperatures, even though a bias remains over the lowermost part of the  
196 distribution.

197 Seasonality has a strong impact, the mesoscale model tends to be warmer than the large scale  
198 forcing in winter (0.5 and 0.6K average bias for IPSLcm and IPSLcm/CDF-t, respectively)  
199 and colder in summer (-0.3 and -1.67K average bias for IPSLcm and IPSLcm/CDF-t,

200 respectively). The upstream statistical correction influences indirectly the atmospheric flow.  
201 This feature is confirmed with average sea-level pressure maps (not shown) that exhibit larger  
202 differences in winter than in summer, explaining this uneven influence on temperature of the  
203 bias correction over the year.

### 204 **3.2 Precipitation**

205 Beyond its relevance for climate impact studies, precipitation is an interesting variable to  
206 evaluate our methodology since, unlike temperature, this variable was not directly corrected  
207 by the prior statistical CDF-t method. The absolute differences between modelled and  
208 observed precipitations are provided on **Figure 2**.

209 The GCM exhibits an overestimation of precipitations throughout the domain. Only West-  
210 facing coastal areas have a deficit, presumably because of the too coarse resolution that is not  
211 able to capture the precipitation local maxima over the coastlines. The overestimation is less  
212 pronounced over mountainous areas because of a compensation of errors.

213 The dynamical downscaling of the raw GCM outputs yields an even stronger overestimation  
214 of the precipitation because of a negative feedback related to the low temperature bias. The  
215 deficit over coastlines and mountains is compensated by the higher resolution of the model.

216 It is only with the hybrid downscaling that the results are significantly improved. The model  
217 still exhibits an overestimation of precipitation but, over low-lying area of Western Europe,  
218 the bias is decreased by a factor of two. An excess is found over the Alps. Precipitation  
219 deficits are found around the Mediterranean, the spatial patterns of these deficits do not  
220 appear highly correlated to coastlines. It may thus be attributable to other uncorrected  
221 deficiencies such as weather regime frequencies rather than resolution issues.

222 The distribution of daily precipitation shows that the hybrid downscaling constitutes an  
223 improvement over the whole range of the distribution. Nevertheless, all the simulations still  
224 exhibit an overestimation of low precipitations and an underestimation of higher quantiles.

## 225 **4 Conclusion**

226 We propose an innovative climate downscaling methodology that combines state-of-the-art  
227 statistical and dynamical approaches. We apply a statistical correction to large-scale fields of  
228 a Global Climate Model (GCM) prior to a regional simulation. The statistical correction  
229 makes use of the Cumulative Distribution Function transformation (CDF-t) designed by  
230 (Michelangeli et al., 2009). The GCM field distributions are matched to those of reanalysed  
231 fields in order to apply a correction over the whole 3D domain for several variables. The  
232 corrected fields are then provided to a dynamical Regional Climate Model (RCM), so that we  
233 can produce bias-corrected, yet physically consistent, 3D fields at higher spatial resolution.

234 An application to present-day climate shows that the statistical upstream correction leads to a  
235 reduction of the surface temperature bias of a factor four in the regional climate simulation.

236 This improvement yields, in turn, a lower overestimation of precipitations.

237 The CDF-t upstream correction does not address yet spatial and temporal variability (climate  
238 modes, persistence and weather regimes), the technique remains sensitive to the choice of  
239 variables included in the correction and the location of the domain since the forcing is applied  
240 at the boundaries. The methodology carries some error compensation mechanisms whose  
241 effect is minimised thanks to the implementation of a dynamical downscaling in the lee of the  
242 statistical correction.

243 Nevertheless, considering the magnitude of the improvement in terms of mean bias we  
244 conclude that this innovative hybrid statistical/dynamical climate downscaling offers  
245 promising perspectives for climate impact studies requiring unbiased, balanced, high-  
246 resolution 3D fields.

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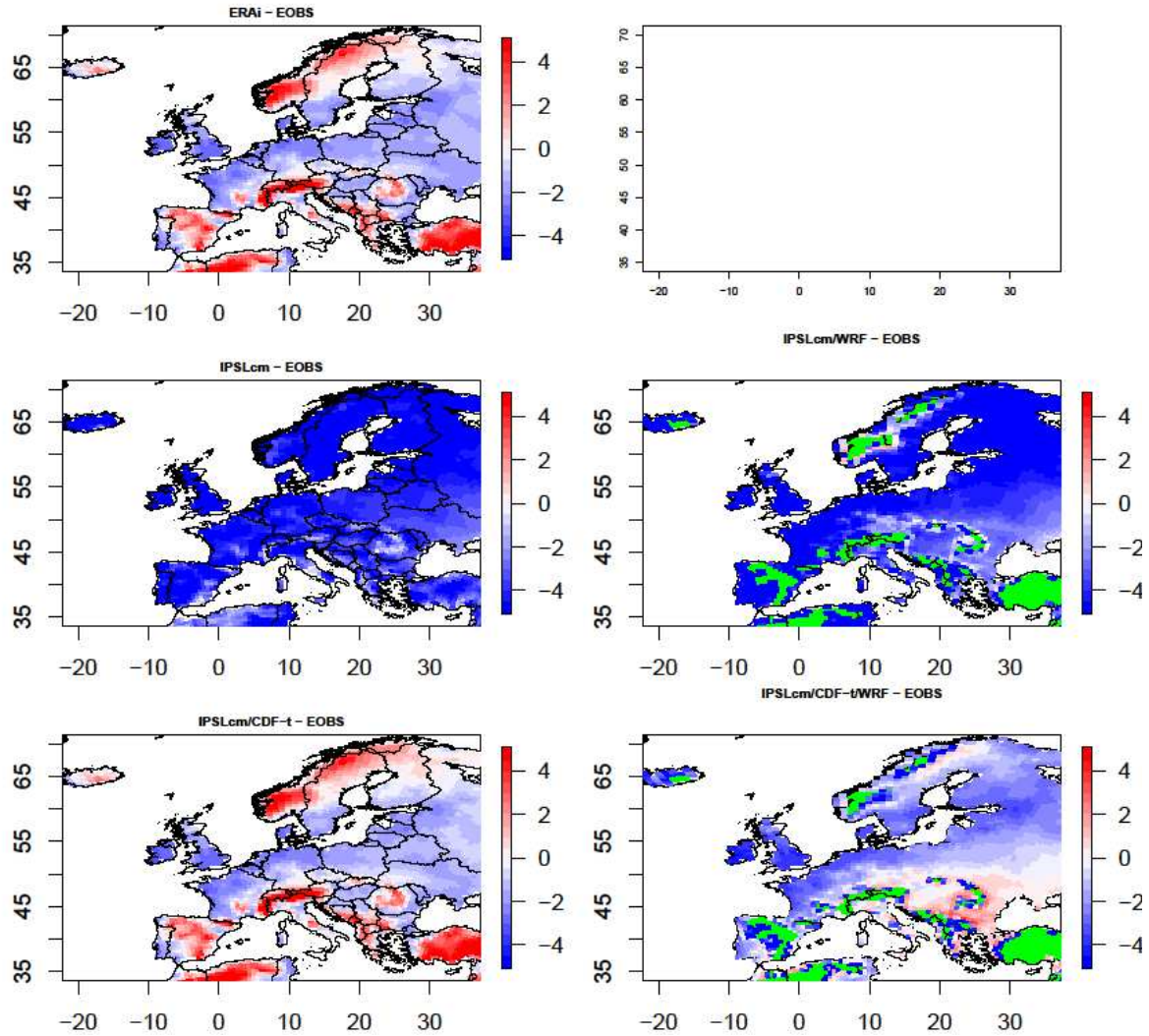
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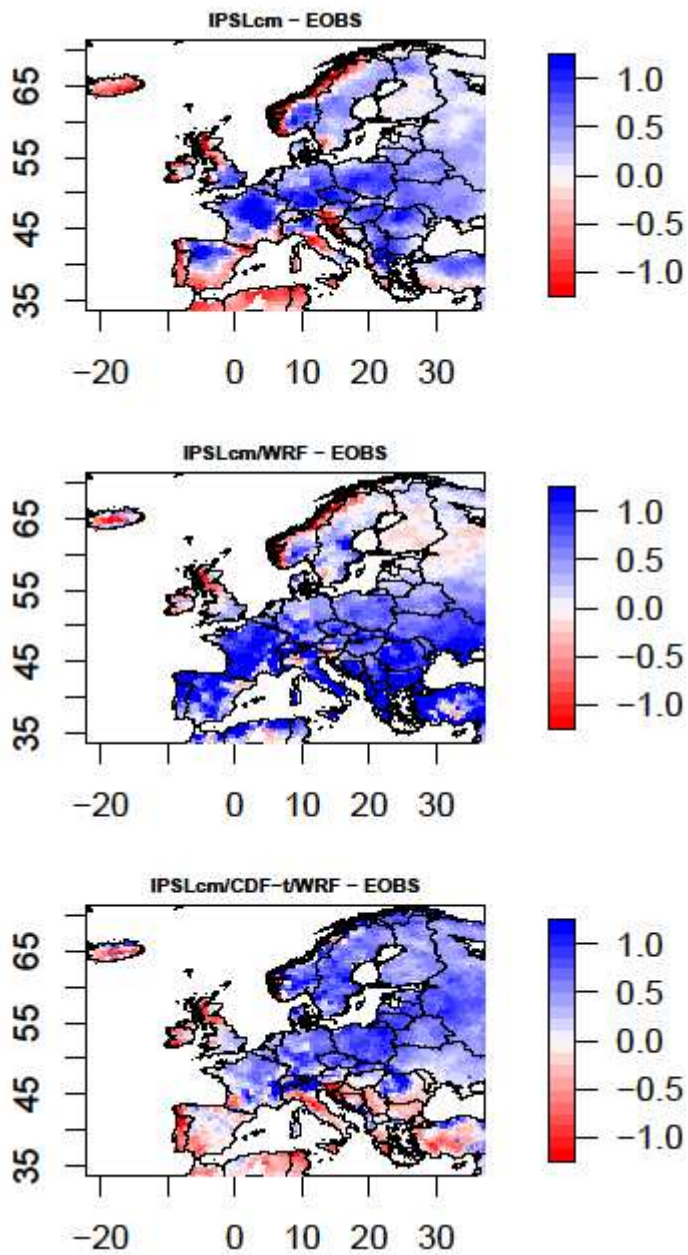
312 **Figures**



313

314 Figure 1 : Difference between the mean modelled 950hPa temperature and observed (E-OBS)  
 315 2-m temperature (K) over the 1990-1999 decade for ERA-interim, the GCM IPSLcm as well  
 316 as its corrected version and the RCM WRF driven by raw IPSLcm fields and by downscaled  
 317 IPSL fields corrected with the CDF-t technique. The green-shaded areas in the WRF field are  
 318 unavailable because located below the 950hPa level in the hybrid coordinates.

319



321

322 Figure 2 : Same as Figure 1 for the precipitations (mm/day) except that only the results of the

323 climate models are given and the colour scale is reversed.