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2 **Comparing correction methods of RCM outputs for improving crop impact projections in** 3 **the Iberian Peninsula for 21st century**

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18

19 **Abstract**

20

21 Assessment of climate change impacts on crops in regions of complex orography such as the
22 Iberian Peninsula (IP) requires climate model output which is able to describe accurately the
23 observed climate. The high resolution of output provided by Regional Climate Models (RCMs)
24 is expected to be a suitable tool to describe regional and local climatic features, although their
25 simulation results may still present biases. For these reasons, we compared several post-
26 processing methods to correct or reduce the biases of RCM simulations from the ENSEMBLES
27 project for the IP. The bias-corrected datasets were also evaluated in terms of their applicability
28 and consequences in improving the results of a crop model to simulate maize growth and
29 development at two IP locations, using this crop as a reference for summer cropping systems in
30 the region. The use of bias-corrected climate runs improved crop phenology and yield
31 simulation overall and reduced the inter-model variability and thus the uncertainty. The number
32 of observational stations underlying each reference observational dataset used to correct the bias
33 affected the correction performance. Although no single technique showed to be the best one,
34 some methods proved to be more adequate for small initial biases, while others were useful
35 when initial biases were so large as to prevent data application for impact studies. An initial
36 evaluation of the climate data, the bias correction/reduction method and the consequences for
37 impact assessment would be needed to design the most robust, reduced uncertainty ensemble for
38 a specific combination of location, crop, and crop management.

39

40 **Keywords**

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42 Uncertainty reduction, high resolution, yield bias, bias correction techniques, weather generator

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44 **1. Introduction**

45 Assessment of agricultural impacts of climate change at regional or local level requires
46 accurate and high resolution climate projections (Mearns et al., 2003), as even small biases in
47 the climate variables can have significant consequences when physical and/or biological
48 thresholds are critical for crop growth and development. For instance, some climate models
49 overestimate the occurrence of freezing temperatures in southern Europe (Kjellström et al.,
50 2010; Domínguez et al., 2013), which can lead to unrealistic estimates of freezing damage to
51 crops. Also, overestimation in maximum temperatures (in particular the number of days above
52 35°C, Ruiz-Ramos et al., 2011) can lead to overestimation of yield loss due to heat stress during
53 flowering and grain filling for summer crops in the Iberian Peninsula (IP). Besides, crop models
54 simulate crop development by accumulating daily mean temperature above a base temperature.
55 For these reasons, when using the results of climate models as an input for impact assessment,
56 the biases should be carefully evaluated and where necessary reduced (Wood et al., 2004;
57 Baigorria et al., 2007; and Teutschbein and Seibert, 2010).

58 Global Climate Models (GCMs) generate the variables needed for impact assessment at a
59 spatial resolution generally considered too coarse for most impact studies. One of the
60 downscaling approaches consists of a Regional Climate Model (RCM) forced by boundary and
61 initial conditions generated by a GCM (Giorgi, 1990; Wang et al., 2004). RCMs improve the
62 representation of spatial variability in comparison to GCMs and the simulation of extreme
63 events (Sánchez et al., 2004, 2011; Domínguez et al., 2013). RCMs are generally considered to
64 improve the applicability of simulated climate for impact assessment, especially in regions of
65 complex orography such as the IP (Mínguez et al. 2007 for IP).

66 However, climate output from RCMs still presents biases, i.e. systematic deviations of
67 simulated values from the observed values (Christensen et al., 2008), or just a slight
68 improvement on fine-scale geographic features, unable to compensate the GCM biases (Glötter
69 et al., 2014). Some of these biases are inherited from the driving GCM, while others are
70 intrinsic to the RCM (Kjellström et al., 2010; Nikulin et al., 2011). Comparisons with
71 observations may also be hampered by uncertainties in the observations themselves. The
72 variables presenting large biases vary regionally; for instance, for the RCM ensemble produced
73 in the framework of the ENSEMBLES EU Framework Program Project (van der Linden and
74 Mitchell, 2009): A warm bias was reported for the IP, where summer bias can be related to a
75 combination of incomplete representation of cloud cover and soil moisture (Maraun, 2012),
76 while an underestimation of precipitation was reported for some RCMs (Christensen et al.,
77 2008; Domínguez et al., 2013). Bias reduction has consequences also for climate projections
78 (e.g. Dosio et al., 2012; Bosshard et al., 2013). For instance, when a warm bias in summer in the
79 Mediterranean was reduced, projections of future were found to decrease by up to one degree in
80 the ensemble mean (i.e., by up to 10-20% of the unadjusted projected change) (Boberg and
81 Christensen, 2012).

82 Biases can be reduced by several techniques, e.g. the delta change method, which imposes
83 the climate change signal from GCMs or RCMs on observations without changing the higher
84 moments of the distribution. By using a transfer function (TF), Piani et al., (2010a,b) corrected
85 precipitation and temperature biases from a RCM and a GCM showing good performance not
86 only for means but also for time dependent statistical properties. Their method was adapted by
87 Dosio and Paruolo (2011) and Dosio et al. (2012) to reduce the bias in the ENSEMBLES RCM
88 ensemble, using the observational dataset E-OBS (Haylock et al., 2008) as the reference. This
89 bias correction approach has also been applied for improving crop yield prediction (Ines and
90 Hansen 2006; Oettli et al., 2011), although a debate on the consequences and convenience of

91 bias correcting or not currently exists (e.g. Liu et al., 2014). Bias can also be reduced by using a
92 weather generator (Jones et al., 2011). The above-mentioned studies apply a single post-
93 processing technique; few studies have inter-compared the effect of different bias reduction
94 options on impact projections (see the review by Teutschbein and Seibert, 2012, and Ruffault et
95 al., 2014, for hydrological impacts).

96 In this study we have compared several post-processing methods to correct the biases of
97 ENSEMBLES RCM simulation for IP. The bias corrected results were first evaluated over the
98 present climate 1971-2000. The corrected datasets were also evaluated in terms of their
99 applicability in crop impact studies for the near (2021-2050) and far future (2071-2100).

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101

102 **2. Data and Methods**

103

104 **2.1. Crop Modelling**

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106 CERES-maize (Jones and Kiniry, 1986) is a crop model that includes ecophysiological
107 relationships driving crop growth and development, and simulates the effects of temperature and
108 CO₂ changes on crop photosynthesis and transpiration rates. CERES uses a daily time step and
109 daily data of maximum and minimum temperature (Tmax, Tmin), precipitation and radiation.
110 Crop development is computed using the sum of mean daily temperature (growing degree days,
111 GDD) above a base temperature. This model has been extensively applied to climate impact
112 assessment (Mínguez et al., 2007 for the IP; Bassu et al., 2014).

113 Maize was chosen because it provides a reference for summer crops in the IP, as it
114 comprises 11% of the Spanish irrigated cropping area (which in turn is the 22% of the cropping
115 land in Spain) and more than a third of the irrigated cereal area (MAGRAMA, 2014). Two
116 locations were selected, Aranjuez and Albacete (location map in supplemental material Fig.S-1),
117 because of their availability of referenced field data and their different temperature regimes and
118 orographic conditions. Calibration and validation was done based on previous field experiments
119 using cultivars, management, and specific soil information for each location (see supplemental
120 material, text and Table S-1).

121

122 **2.2. Observed and simulated climate datasets**

123

124 Observed data from the Spanish Meteorological Agency (AEMET) stations span 1961-
125 2010 in Aranjuez and 1971-2010 in Albacete. From both stations, daily Tmax, Tmin,
126 precipitation and radiation were used to evaluate the performance of the simulated datasets
127 described below under present climate.

128 In this study, the original set of 17 high resolution climate change projections generated
129 in the framework of the EU FP6 project ENSEMBLES, was used (hereafter referred to as ENS,
130 see the specific RCMs runs in supplemental material Table S-2) (van der Linden and Mitchell,
131 2009). Simulations forced with the SRES A1B climate change scenario (Nakicenovic and
132 Swart, 2000) spanned the period 1961-2050 (or 1960-2100 in some cases), at a resolution of
133 around 25 km.

134 The second dataset, hereafter referred to as ENS-EOBS, was produced by bias
135 correcting a subset of the ENS dataset (12 RCMs) using the E-OBS version 3.0 observational
136 dataset as a reference (Haylock et al., 2008; see description in supplemental material) for the
137 1961-1990 climate (Dosio and Paruolo, 2011; Dosio et al., 2012), adapting the Piani et al.
138 (2010a, b) technique.

139 Spain02 (Herrera et al., 2012) is an observational dataset for Spain with higher density
140 of underlying stations than E-OBS. This means that using Spain02 rather than E-OBS as
141 reference could improve bias reduction in Spain. Thus here, we also adapt the bias correction
142 technique used by Dosio and Paruolo (2011) to correct the ENS with respect to the Spain02
143 reference, generating the hereafter so called ENS-SPAIN02 dataset.

144 The third dataset was generated by perturbing the CRU weather generator (WG) (Kilsby
145 et al., 2007) with monthly change factors calculated from present and future projections of every
146 RCM of the ENS dataset, generating the hereafter-named ENS-WG dataset. This method was
147 also applied to the ENS-EOBS and ENS-SPAIN02 datasets, obtaining two additional datasets
148 that combine bias correction with use of the WG, ENS-EOBS-WG and ENS-SPAIN02-WG
149 respectively.

150 The last dataset consists of scenarios generated by the simple delta change method, one
151 of the most commonly used techniques (e.g. Rötter et al., 2013). This is referred to hereafter as
152 the DELTA dataset and was obtained by applying monthly change factors projected by
153 individual ENS RCMs to AEMET data.

154 Correspondence between gridded datasets and AEMET stations was done by the nearest
155 neighbour method. Crop simulations were replicated with all datasets (see summary of RCM-
156 based datasets in supplemental material Table S-3) for the period 1971-2000 and for the near
157 (2021-2050) and far future (2071-2100).

158

159 **2.3. Techniques of bias correction and reduction**

160

161 The bias correction technique used in this study has been extensively described in Piani
162 et al. (2010a, b; Dosio and Paruolo 2011; Dosio et al., 2012). Briefly, it is based on the
163 calculation of a parametric transfer function (TF) which, when applied to model output, delivers
164 corrected output with a marginal cumulative distribution function (CDF) which matches that of
165 the observed measurement. The TF depends on the variable to be corrected. For temperature,
166 the TF proposed by Piani et al. (2010b) was a linear equation, with two parameters. For
167 precipitation, the TF was a set of three equations (linear, logarithmical and exponential) with
168 four parameters (adaptation of this method to our case is described in the supplemental
169 material).

170 Also, bias can be reduced by the use of a weather generator (WG); in our case the CRU
171 WG (Kilsby et al., 2007). The WG is calibrated on observed station data and projection output
172 is produced by perturbing the WG parameters with monthly change factors calculated from
173 RCM present and future runs. The system produces series at a daily time resolution, using two
174 stochastic models in series, RainSim and CRU WG (Kilsby et al., 2007), generating the other
175 variables dependent on rainfall (and for humidity and so on, dependent on rainfall and
176 temperature; details are in the supplemental material). For projection of future climate, the
177 procedure includes applying the change factors.

178 A delta change-based ensemble of future projections was generated by applying mean
179 monthly change factors from individual RCM present and future projections to observed station

180 data (AEMET). This method only reflects changes in mean conditions and does not change the
181 future variability. The WG used in this study can be considered as a more sophisticated delta
182 change approach as higher-order statistics are adjusted using RCM-derived change factors.

183 Comparing the three methods, bias correction has the advantage of correcting not only
184 means but also distribution tails. WG method assures consistency among the variables, while
185 delta method is very simple and easy to implement.

186 The Nash–Sutcliffe coefficient of model efficiency (E, described in supplemental
187 material, Nash and Sutcliffe, 1970) was calculated for comparing: 1) AEMET vs. every dataset;
188 and 2) AEMET-derived crop simulation vs. every dataset-derived crop simulation.

189

190 **3. Results**

191

192 **3.1. Bias analysis of climate variables for the period 1971-2000**

193

194 3.1.1. Uncorrected biases: ENS

195

196 The monthly Tmax from the ENS ensemble mean presented biases with respect to
197 observations (AEMET) that ranged from 0.5 to 2°C in Aranjuez, being higher in winter. The
198 bias was close to 0°C in summer (Figure 1a). For Albacete, the biases in mean monthly Tmax
199 were small all the year (Figure 1d). For both locations, the amplitude of the annual cycle of
200 variance was smaller than observed (Figure 1g, j), leading to an underestimation of the variance
201 in autumn and to an overestimation in summer.

202 Biases of monthly Tmin were close to 0°C in Aranjuez (Figure 2a), and the variance
203 was well simulated except in summer, when it was overestimated (Figure 2g). In Albacete
204 (Figure 2d), monthly Tmin was overestimated in winter and summer, while its variance (Figure
205 2j), was underestimated throughout the year.

206 Monthly precipitation in Aranjuez (Figure 3a) showed an overestimation in winter (up
207 to ca. 20 mm per month), and an underestimation in May, with the same pattern for variance
208 (Figure 3g). A similar pattern was found in Albacete (Figure 3d, j).

209

210 3.1.2. Datasets of RCM projections with reduced bias

211

212 Temperatures from the corrected ensemble means presented biases with respect to
213 observations (AEMET) close to 0°C in both locations (Figures 1, 2). The only exception was
214 winter and summer Tmin from ENS-OBS for which biases of ca. 1°C remained, especially in
215 Albacete (Figure 2a, d).

216 However, the bias reduction did not improve the simulation of Tmax variance although
217 ENS-SPAIN02 was the dataset that better matched the observed variance (Figure 1h, k). This
218 maybe explained because SPAIN02 matches better AEMET variance than E-OBS, especially in
219 Albacete. In the case of ENS-WG, the WG shows an annual cycle of variance parallel to that of
220 the observations (AEMET), but with lower values. All datasets underestimated spring and
221 autumn Tmax variance for both locations (Figure 1, lower two rows). The simulation of Tmin
222 variance improved for some seasons and worsened for others (Figure 2, lower two rows).

223 Biases in monthly precipitation were reduced by both ENS-EOBS and ENS-SPAIN02
224 in Aranjuez throughout the year, and for late autumn and winter also by ENS-WG (Figure 3,
225 first row). The variance simulation was similar to that of ENS (Figure 3, third row). In Albacete,
226 the three adjusted datasets simulated better the annual cycle for both mean and variances, but
227 precipitation was slightly underestimated throughout the year, except for ENS-WG which
228 overestimated both mean and variance in summer (Figure 3, third row for mean and last row for
229 variance).

230 The inter-model variability for each dataset showed similar results for both locations
231 (Figures 1 to 3): EOBS and ENS-SPAIN02 showed a smaller spread (ca. half) than ENS for
232 Tmax, Tmin and precipitation. The spread of the mean was smaller than that of the variance for
233 both Tmax and Tmin and all datasets. The spreads were higher for late winter and spring
234 corrected temperatures than for other seasons. Corrected precipitation showed higher spread
235 than temperatures, especially in autumn and spring. Some peaks of spread appeared for some
236 months, corrected variables and locations; some of which were due to a single model, as for
237 instance the high precipitation variance at Albacete in October (Figure 3k).

238 In summary, biases of mean Tmax and Tmin were close to 0°C for the bias reduced
239 datasets and precipitation bias was decreased. Temperature variances were not improved and
240 precipitation variance was only improved for one location. The inter-model spreads of the bias
241 reduced datasets were smaller than that of the uncorrected one. ENS-SPAIN02 showed a
242 slightly better performance with respect to AEMET than the other datasets.

243 Two additional analyses, the calculation of the efficiency coefficient E and the
244 comparison of probability distribution functions (PDFs) for the variables and seasons that are
245 more limiting to crop production in the IP, confirmed these results (see supplementary material
246 text and Table S-4, Figs. S-2, S-3).

247

248 **3.2. Comparison of datasets' performance for crop impact assessment**

249

250 The differences between the crop simulation outputs obtained with the datasets
251 described in section 2.2 compared with maize simulations run with AEMET for the period
252 1971-2000 are referred to hereafter as biases in crop phenology and in yield (Table 1).

253 The projected dates for the relevant crop phenological stages (Table 1) may help to
254 highlight the differences between the climate datasets' results, as well as to understand the
255 consequences of their biases. This is because these dates are computed by the crop model using
256 the sum of projected temperatures over a base temperature (8°C for maize). All post-processing
257 methods improved the simulation of anthesis, maturity dates and grain filling duration (which is
258 relevant for yield formation) in present-day climate, in both locations (Table 1) (these
259 improvements can be partially quantified by comparing the E coefficients, see supplemental
260 material Table S-4).

261 Bias correction resulted in a different yield response for both locations: yield simulation
262 improved in Albacete but biases increased in Aranjuez. This result may be related to the
263 remaining biases in temperatures at Aranjuez, small for the mean but large for the variance. In
264 turn, these remaining biases maybe related to deviations from AEMET of the observational
265 datasets that were used as reference to reduce the ENS biases, as for instance for SPAIN02
266 Tmin at Aranjuez in winter (Figure 2). Nevertheless, absolute yield biases from ENS-EOBS
267 were larger than from ENS-SPAIN02 at both locations (Table 1). Yield simulated with any
268 dataset in combination with the WG showed a very small bias as expected, as these data are
269 pretty much constrained to reproduce the observed mean climate values.

270 ENS presented higher inter-annual variability than ENS-EOBS and ENS-SPAIN02 at
271 both locations (measured by the coefficient of variation YCT, Table 1). When considering WG
272 derived datasets, both locations presented contrasting results. ENS presented higher spread (the
273 coefficient of variation YCS, Table 1) than ENS-EOBS and ENS-SPAIN02 for both locations,
274 in agreement with the results found for the climate variables (Figures 1 to 3).

275 **3.3. Future projections of climate change impacts**

276

277 Phenological and yield projections for near (2021-2050) and far (2070-2100) future (NF
278 and FF, respectively, Table 2) periods obtained with the seven datasets described in section 2.2
279 were compared to evaluate the consequences for climate change impact assessment when using
280 different post-processing techniques. All projected changes are considered with respect to 1971-
281 2000.

282 Phenological projections indicated earlier anthesis and maturity dates and shorter grain
283 filling than those of the 1971-2000 period for both locations, as expected (Ruiz-Ramos et al.,
284 2011). The crop simulations driven by ENS presented later phenological dates than those driven
285 by the bias reduced datasets, especially in Aranjuez. The spread of projections across all
286 datasets was reduced when ENS was excluded, so bias reduction implied a convergence of
287 results. The ensemble spread across datasets also diminished in FF compared to NF, especially
288 in Aranjuez.

289 The projections indicated similar yield decrease in both locations, ranging from 9% to
290 17% for NF and from 24 to 33% for FF (Table 2). The delta change method projected maximum
291 changes in yield at Aranjuez in both periods and at Albacete for FF. Projections were similar
292 whatever the applied post-processing technique for both locations, with differences among
293 methods equal to or lower than 8% and 10% in NF and FF (Table 2), respectively. Differences
294 among yield projections obtained with ENS-EOBS, ENS-SPAIN02 and ENS-WG were even
295 smaller. In general, post-processing methods increased the projected yield changes.

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297

298 **4. Discussion**

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300 Our results show that post-processing techniques can help to reduce uncertainty due to a
301 poor representation of present-day local climate in some locations, providing more realistic
302 results in terms of means of simulated crop phenology and yield, in agreement with Oettli et al.
303 (2011) and Michelangeli et al. (2009). However, the spread found among observational datasets
304 reveals an uncertainty not attributable to RCMs, and highlights the sensitivity to the
305 observational dataset chosen as reference for bias reduction.

306 The comparison of the different post-processing techniques revealed that an
307 overestimation of grain filling duration resulted in an overestimation of crop yield. The
308 differences among simulated yields were temperature-driven because maize was irrigated. The
309 bias reduction of the grain filling length simulation, through correction of temperatures, was
310 enough to improve ENS yield bias in Albacete where the initial bias was small. However, this
311 was not enough to reduce yield bias in Aranjuez, where the ENS bias in grain filling duration
312 was still ca. two weeks, and the remaining biases in temperatures of the bias-reduced datasets
313 were larger than in Albacete. Besides, other factors also affect yield such as the diurnal
314 temperature range (Tmax-Tmin) in specific periods. For this reason, similar phenological dates
315 may result in different crop biomass and yield. This may help to explain the different response

316 in Aranjuez in spite of the improvement in the simulation of phenology.

317 These contrasting effects on phenological and yield biases and ensemble spread for both
318 locations suggest that not only an initial evaluation of the local climate data is needed, but also
319 an evaluation of the effects of these techniques on the impact results. This way, the impact
320 model becomes a tool for evaluating climate models (Stéfanon, et al., 2015). Our results
321 indicated that about 10% of variation in yield projections was due to the latter effects. In case of
322 rainfed crops, this value is expected to increase since much higher uncertainty has been reported
323 for precipitation related variables (e.g. Ruffault et al. (2014) reports 45 % uncertainty in drought
324 intensity anomalies linked to bias correction). This variation should be added to the estimated
325 uncertainty of the modelling chain, i.e. the climate modelling-post-processing-impact modelling
326 chain, along which uncertainty is accumulated. These findings are in agreement with Liu et al.
327 (2014) who reported different effect of bias correction depending on the location and impact
328 variable.

329 We conclude that there would not be a “best” post-processing technique, in agreement
330 with Räisänen and Rätty (2013) and Rätty et al. (2014). When a decision has to be made about
331 choosing a technique, if an initial climate-impact evaluation can be done as we recommend
332 here, bias correction offers opportunity for improvement for those locations with small initial
333 biases. For locations where remaining biases after correction are still large, the use of a weather
334 generator, alone or in combination with bias correction, may be particularly useful, probably
335 because WGs, in contrast to the bias-correction techniques used here, do not correct temperature
336 independently of precipitation, and other variables such as radiation are also adjusted in a
337 consistent way. Such a combined approach may be particularly useful for rainfed simulations in
338 sites where the monthly precipitation bias is still large after bias reduction. Another possible
339 approach for these cases would be to consider several post-processing methods in parallel (in
340 agreement with Rätty et al., 2014). The main limitation is the large number of possible
341 simulations to be run. However, there are sampling methods that can be used to reduce the
342 number of simulations needed (Asseng et al., 2013). Also, bias correction could be applied to
343 the GCM, driving a RCM with a bias-corrected GCM output (Glotter et al., 2014). And an
344 alternative approach to bias reduction would be the selection of the RCM the most consistent
345 with an impact model (Stéfanon et al., 2015), or a reduced ensemble of climate and crop model
346 combinations meeting this criterion.

347 The simulation of interannual variability remains challenging. Oettli et al. (2011) and
348 Michelangeli et al. (2009) report that this difficulty is transmitted to the simulation of yield
349 variability. On the other hand, the simulation of some relevant extremes was improved here, as
350 in the case of Tmax in Albacete, which is a hazardous event for maize flowering at that location.
351 In our study, a small improvement in the simulation of the annual cycle of precipitation was
352 accomplished by reducing RCM bias using SPAIN02. Also, biases in the mean can be different
353 to biases for the high quantiles (Maraun, 2012; Christensen et al., 2008); our results show that
354 post-processing methods and especially bias correction with regard to a high resolution
355 observational dataset (SPAIN02) improved the distributions of the simulated climate variables,
356 in terms of both peak and tails.

357 The mentioned limitations stress that bias reduction remains a temporary solution while
358 model improvement is undertaken. In the meanwhile, further steps may include the correction of
359 other variables such as radiation and multivariate correction (Hoffmann and Rath, 2012; and
360 Piani and Haerter, 2012). For this purpose, reliable reference datasets including radiation data
361 would be needed (E-OBS and Spain02 do not include it).

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365 **5. Conclusions**

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367 The objective of this study was to evaluate the potential of post-processing techniques
368 (in particular, bias correction, a WG combined with RCM-derived change factors, and a very
369 simple delta change method) for improving the quality of crop impact projections.

370 The use of the different post-processing techniques resulted in a difference among crop
371 projections of 10% or less. The added value of these techniques becomes evident in 1) the
372 improvement of crop phenology which is valuable for improving crop simulations and also for
373 cultivar and species suitability studies, 2) the improvement of yield projections, and 3) the
374 reduction of uncertainty because the inter-model (ensemble) spread of the climate models used
375 is reduced. For these improvements, the density of observation stations used to create each
376 reference observational dataset affected the correction performance.

377 The improvement was not the same for both locations and all techniques studied, and no
378 single technique proved to be the best one. We recommend undertaking an initial evaluation of
379 the observed and simulated climate data, their post-processing and implications for impact
380 modelling, as an assessment of climate and crop projection biases may help to select the most
381 robust techniques to build a tailored ensemble, locally designed for a specific crop and its
382 management. Rainfed crop simulations in particular could benefit from this approach. Although
383 this kind of procedure complicates the modelling chain, it is desirable when the objective is to
384 go a step further in the reliability of impact projections.

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388

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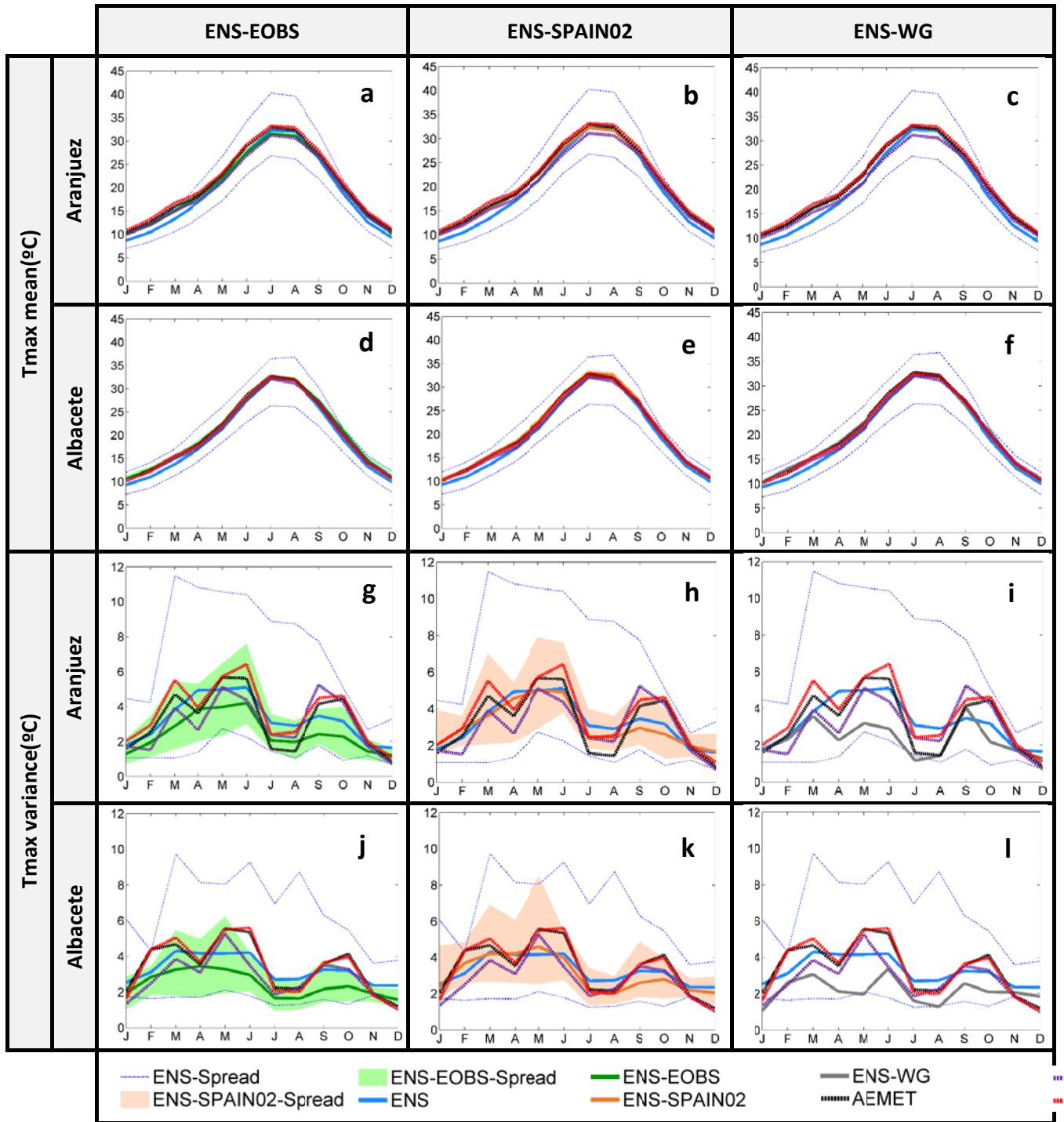
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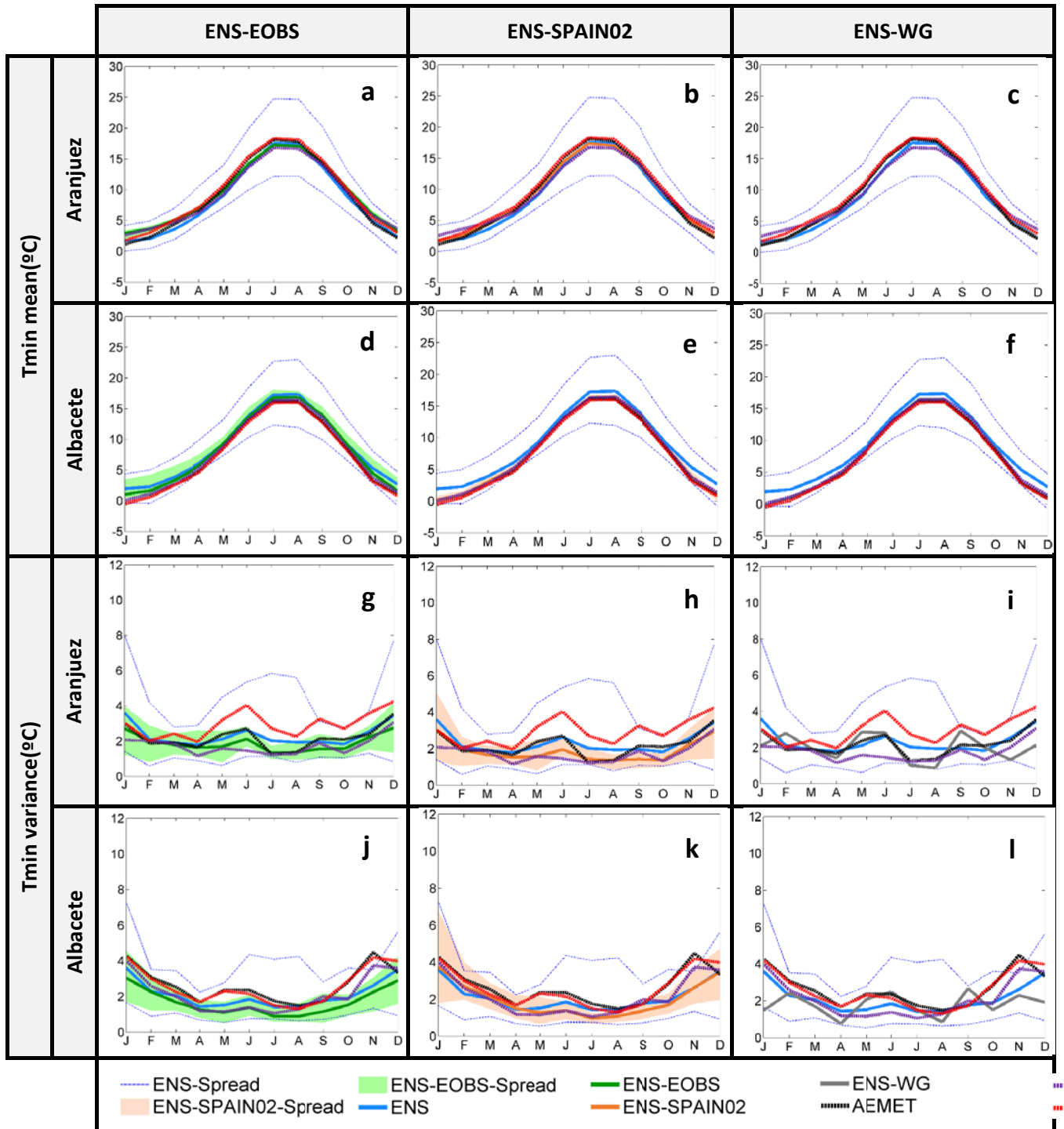
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Figure 1. Comparison of the performance of uncorrected and corrected ensembles in simulating Tmax at Aranjuez and Albacete for the period 1971-2000: Monthly means (top plots) and variance (bottom plots) of Tmax. All plots include data from the observational data sets AEMET, E-OBS and SPAIN02, and from the uncorrected ensemble ENS and ENS's spread, as references. Each column also includes data from one corrected ensemble: Left column: ENS-EOBS, where shaded area shows ENS-EOBS's spread; Central column: ENS-SPAIN02, where shaded area shows ENS-SPAIN02's spread; and Right column: ENS-WG.



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546 **Figure 2.** As Figure 1, but for T_{min}.

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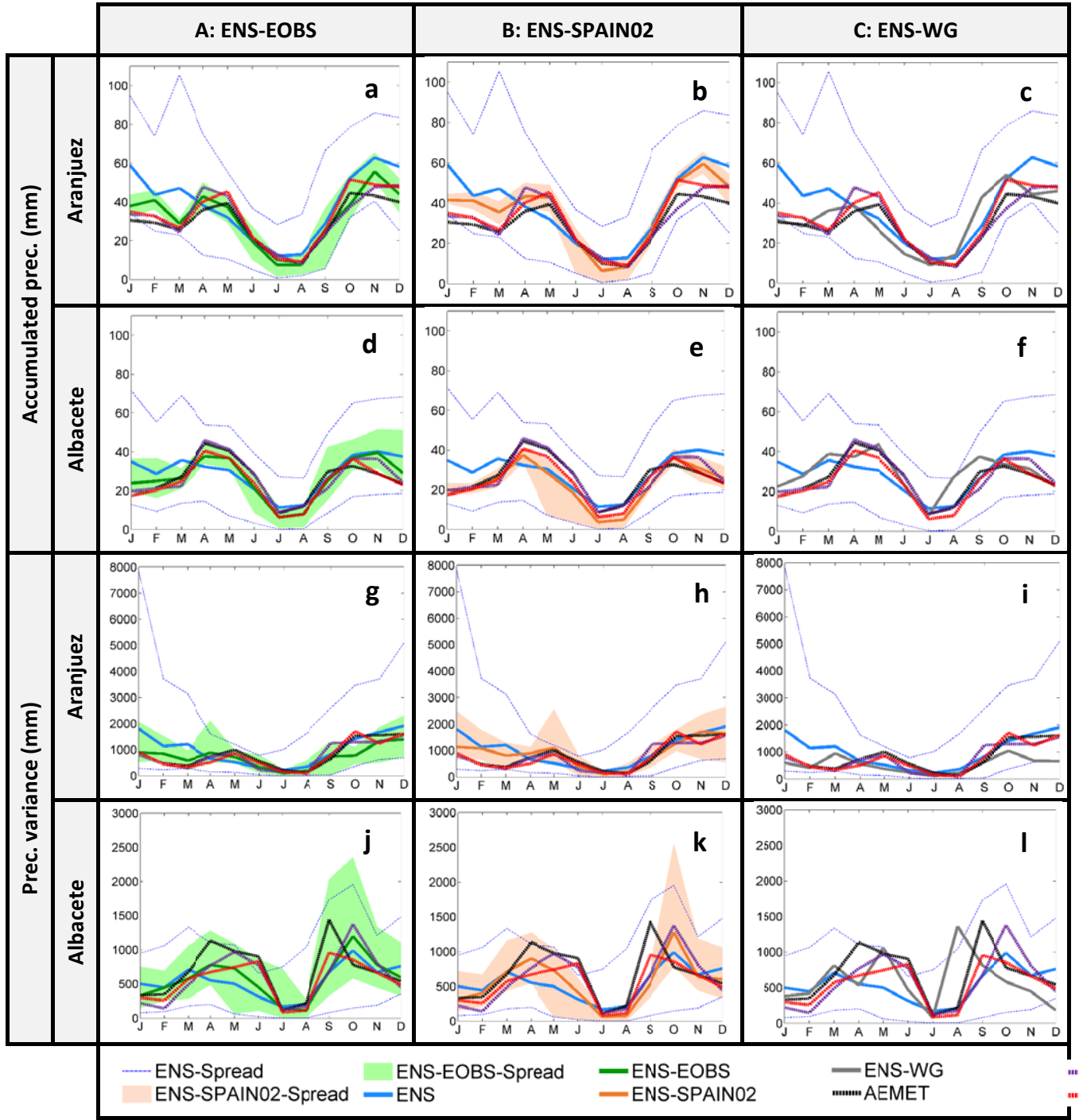
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 557 **Figure 3.** As Figure 1, but for precipitation.
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Table 1. Evaluation of the modelling chain climate-crop for Aranjuez and Albacete in present climate (1971-2000): Comparison of crop phenology. Sowing date (SD), anthesis(AD) and maturity (MD) dates (Julian days, DOY), and grain filling duration (GF, days), yield (YI, kg ha⁻¹) with its interannual variability (coefficient of variation YCT, %) and ensemble spread (coefficient of variation YCS, %), simulated with observed climate (AEMET), with the uncorrected ensemble (ENS) and with the five bias-reduced datasets (ENS-EOBS, ENS-SPAIN02, ENS-WG, ENS-EOBS-WG, ENS-SPAIN02-WG). Yield bias (differences in projected yields regarding simulation conducted with AEMET data, YB). Phenological bias (differences in projected phenological dates regarding simulation conducted with AEMET data): anthesis date bias (ADB, days), maturity date bias (MDB, days), and grain filling duration bias (GFB, days).

Ensemble/ Method	SD	AD	MD	GF	ADB	MDB	GFB	YI	YCT	YCS	YB
Maize 1971-2000											
Aranjuez											
AEMET	105	210	260	49	n/a	n/a	n/a	9437	15,6	0	n/a
ENS	107	218	281	64	7	22	15	10039	32,8	27,6	602
ENS-DELTA	105	210	260	49	0	0	0	9437	15,6	0	0
ENS-EOBS	105	213	266	53	3	7	4	10966	16,2	5,2	1529
ENS-SPAIN02	105	211	263	52	0	3	3	10813	13,6	5,7	1376
ENS-WG	107	207	254	47	-4	-5	-2	9898	13,2	0	461
ENS-EOBS-WG	107	207	254	47	-4	-5	-2	9898	13,2	0	461
ENS-SPAIN02-WG	107	207	254	47	-4	-5	-2	9898	13,2	0	461
Albacete											
AEMET	105	204	256	52	n/a	n/a	n/a	11155	11	0	n/a
ENS	109	206	264	58	2	7	6	10561	33,1	15,7	-593
ENS-DELTA	105	204	256	52	0	0	0	11155	11	0	0
ENS-EOBS	108	202	251	50	-2	-5	-3	10735	17,9	14,3	-420
ENS-SPAIN02	108	201	251	50	-3	-5	-3	10769	17,9	6,7	-385
ENS-WG	106	200	250	50	-3	-6	-3	11238	8	0	84
ENS-EOBS-WG	106	200	250	50	-3	-6	-3	11238	8	0	84
ENS-SPAIN02-WG	106	200	250	50	-3	-6	-3	11238	8	0	84

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Table 2. Crop projections for Aranjuez and Albacete: sowing date (SD, Julian days, DOY), phenology anthesis date (AD) and maturity date (MD) in Julian days (DOY) and grain filling duration (GF), days and maize yield (kg ha⁻¹) with its interannual variability (coefficient of variation YCT, %) and ensemble spread (coefficient of variation YCS, %), simulated with the uncorrected ensemble (ENS) and with the five bias-reduced datasets (ENS-EOBS, ENS-SPAIN02, ENS-WG, ENS-EOBS-WG, ENS-SPAIN02-WG), for the near future (NF, 2021-2050) and for the far future (FF, 2071-2100), under the A1B scenarios. Mean changes of the anthesis date (ADC), maturity date (MDC) grain filling duration (GFC) and yield (YC) are calculated regarding the corresponding 1971-2000 (present climate) projections, as difference (A1B-present, days) for phenology and as percentages for yield ((A1B-present)*100/present).

Ensemble/ Method	SD	AD	ADC	MD	MDC	GF	GFC	YI	YC	YCT	YCS
Maize 2021-2050											
Aranjuez											
AEMET	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
ENS	108	208	-10	257	-24	49	-15	8638	-11	35,1	35,4
ENS-DELTA	106	203	-7	245	-15	41	-8	7870	-17	15,0	6,3
ENS-EOBS	106	205	-8	249	-17	44	-9	9486	-13	16,2	4,2
ENS-SPAIN02	105	203	-8	246	-17	43	-9	9171	-15	13,1	4,3
ENS-WG	105	201	-6	242	-12	41	-7	8148	-14	12,5	6,7
ENS-EOBS-WG	105	202	-5	242	-12	41	-7	8232	-13	11,4	8,1
ENS-SPAIN02-WG	105	202	-5	243	-11	41	-6	8238	-13	14,8	7,4
Albacete											
AEMET	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
ENS	109	197	-9	243	-20	46	-12	8956	-13	37,1	30,8
ENS-DELTA	106	196	-8	241	-16	45	-8	9868	-12	10,1	6,0
ENS-EOBS	108	195	-6	239	-12	44	-6	9679	-10	19,2	9,5
ENS-SPAIN02	108	195	-7	238	-13	44	-6	9411	-12	21,7	3,0
ENS-WG	106	194	-7	237	-13	44	-6	9460	-15	9,4	4,4
ENS-EOBS-WG	107	195	-6	239	-11	44	-5	9714	-13	8,1	6,8
ENS-SPAIN02-WG	106	194	-7	238	-12	44	-6	9427	-15	10,3	6,1
Maize 2071-2100											
Aranjuez											
AEMET	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
ENS	107	196	-22	234	-47	39	-25	6064	-31	46,4	38,4
ENS-DELTA	106	193	-18	229	-31	36	-13	5972	-37	19,5	10,6
ENS-EOBS	107	194	-19	231	-36	36	-17	7369	-33	27,5	12,6
ENS-SPAIN02	105	192	-19	229	-34	37	-15	7167	-34	19,0	9,7
ENS-WG	106	191	-16	227	-27	36	-11	6506	-31	18,5	9,5
ENS-EOBS-WG	105	191	-16	228	-26	37	-11	6656	-29	18,8	10,2
ENS-SPAIN02-WG	106	191	-16	228	-26	37	-11	6716	-29	21,0	11,2
Albacete											
AEMET	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
ENS	108	186	-20	225	-39	39	-19	6913	-30	43,2	31,3
ENS-DELTA	106	186	-18	225	-32	39	-13	7608	-32	24,5	10,5
ENS-EOBS	109	187	-15	225	-26	38	-11	7882	-26	34,1	13,6
ENS-SPAIN02	108	185	-16	224	-27	39	-11	7519	-30	34,1	14,7
ENS-WG	106	185	-16	223	-26	39	-11	7822	-30	18,8	10,0
ENS-EOBS-WG	107	186	-15	226	-24	40	-9	8148	-27	19,1	8,1
ENS-SPAIN02-WG	107	185	-16	224	-25	40	-10	8089	-27	16,5	9,7