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Validation of ELPIS 1980–2010 baseline scenarios using the observed European Climate Assessment data set

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ABSTRACT: Local-scale daily climate scenarios are required for assessment of climate change impacts. ELPIS is a repository of local-scale climate scenarios for Europe, which are based on the LARS-WG weather generator and future projections from 2 multi-model ensembles, CMIP3 and EU-ENSEMBLES. In ELPIS, the site parameters for the 1980–2010 baseline scenarios were estimated by LARS-WG using daily weather from the European Crop Growth Monitoring System (CGMS) used in many European agricultural assessment studies. The objective of this paper was to compare ELPIS baseline scenarios with observed daily weather obtained independently from the European Climate Assessment (ECA) data set. Several statistical tests were used to compare distributions of climatic variables derived from ECA-observed daily weather and ELPIS-generated baseline scenarios. About 30% of selected sites have a difference in altitude of >50 m compared with the CGMS grid-cell altitude that was selected to represent agricultural land within a grid-cell. Differences in altitude can explain significant Kolmogorov-Smirnov test (KS-test) results for distribution of daily temperature and in *t*-tests for temperature monthly means, because of the well-known negative correlation between temperature and elevation. For daily precipitation, the KS-test showed little difference between generated and observed data; however, the more sensitive *t*-test showed significant results for the sites where altitude differences were large. Approximately 11% of sites showed small positive or negative bias in monthly solar radiation, although 86% sites showed >3 significant *t*-test results for monthly means. These results can be explained by differences in conversion of sunshine hours to solar radiation used in CGMS and LARS-WG. We conclude that, considering the limitations above, ELPIS baseline scenarios are suitable for agricultural impact assessments in Europe.

KEY WORDS: Climate change · Impact assessment · Downscaling · LARS-WG

1. INTRODUCTION

Global climate models (GCMs) are state-of-the-art tools used to predict the evolution of the Earth's climate system (Meehl et al. 2007). However, the direct use of climate projections from GCMs for local assessments of climate change impacts is problematic because of the coarse spatial resolution, which results in significant errors, biases and large uncertainty in their output at a local scale, particularly for precipitation (Knutti 2008, Annan & Hargreaves 2010, Iizumi et al. 2010, Eden et al. 2012). Various downscaling techniques have been developed to support local-scale impact assessments, including statistical downscaling (Wilby et al. 1998, Fowler et al. 2007, Maraun et al. 2010) and weather generators (WGs) (Wilks 1992, Barrow & Semenov 1995, Street et al. 2009). These techniques allow for the genera-

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tion of daily local-scale climate scenarios suitable for non-linear process-based impact models, e.g. crop simulation models, which are used in impact assessments (White et al. 2011). Stochastic WGs are the most commonly used tool to generate local-scale daily climate change scenarios. Among various WGs, LARS-WG was intensively tested over diverse climate zones (Semenov et al. 1998, Qian et al. 2004, Qian et al. 2008, Semenov 2008, Street et al. 2009, Haris et al. 2010, Lazzarotto et al. 2010, Semenov et al. 2010, Luo & Yu 2012). Overall performance of LARS-WG in representing the statistical characteristics of observed climatic variables, including extreme events, was generally good (Qian et al. 2008, Semenov 2008, Iizumi et al. 2012a). LARS-WG is available from www.rothamsted.ac.uk/mas-models/larswg.php.

LARS-WG was used recently to develop ELPIS, a repository of local-scale climate scenarios for Europe (Semenov et al. 2010, Semenov & Stratonovitch 2010, Calanca & Semenov in press). ELPIS consists of LARS-WG site parameters for the baseline (1980–2010) climate derived from the European Crop Growth Monitoring System (CGMS) data set (van der Goot 1997), and climate projections from the CMIP3 multi-model ensemble of 15 GCMs (Meehl et al. 2007) and the EU-ENSEMBLES ensemble of 9 regional climate models (van der Linden & Mitchell 2009). LARS-WG generates future climate scenarios by altering the baseline site parameters using change factors derived from climate projections (Semenov & Stratonovitch 2010, Iizumi et al. 2012a).

In ELPIS, site parameters for the baseline climate were derived from the CGMS gridded daily meteorological data set. CGMS was developed by the EC Joint Research Centre for agricultural assessments and yield predictions for major agricultural crops in Europe (Semenov et al. 2010). It is the core of the MARS Crop Yield Forecast System used in forecasting activities in Europe in support of the Common Agricultural Policy. Gridded daily weather in CGMS was constructed by interpolating observed daily weather from a large number of sites to a 25 km grid over Europe (van der Goot 1997). The number of sites used for interpolation varied between climatic variables, with over 2500 sites for precipitation and temperature and under 400 sites for sunshine hours.

The main objective of this study was to compare ELPIS-generated 1980–2010 baseline scenarios with observed daily weather for the same period 1980–2010 at the selected sites obtained from the European Climate Assessment (ECA) data set, which represents one of the best sources of publically available weather records in Europe (Klein Tank et al. 2002, Klok & Klein Tank 2009). We used the Kolmogorov-Smirnov test (KS-test) to compare distributions of daily values, the *t*-test to compare monthly means, and the paired *t*-test for monthly means to check for a potential bias. This comparison is different from a previous comparison of ELPIS-generated baseline scenarios with the CGMS gridded daily weather, as in that study the ability of LARS-WG to reproduce diverse weather patterns in Europe was tested (Semenov et al. 2010).

2. MATERIALS AND METHODS

2.1. The ELPIS baseline scenarios

ELPIS is a repository of LARS-WG site parameters over Europe combined with climate projections from the CMIP3 and EU-ENSEMBLES multi-model ensembles. The LARS-WG site parameters were derived from the CGMS meteorological data set of observed daily weather for the period 1980–2010. Daily weather series in CGMS were interpolated to a 25 km grid across Europe and include precipitation, minimum and maximum temperature, and solar radiation. Daily solar radiation was estimated from daily sunshine hours using Supit's equation (Supit & Van Kappel 1998). The interpolation procedure was selected to ensure that gridded daily values could be interpreted as typical weather over agricultural land and used in agricultural assessments (van der Goot 1997).

Semenov et al. (2010) showed that LARS-WG was able to generate synthetic weather that was statistically similar to the CGMS daily weather (Semenov et al. 2010). By using change factors derived from climate projections to perturb parameters of site distributions of climatic variables, LARS-WG can generate plausible future climate scenarios at a site with weather statistics similar to those predicted by climate models (Semenov & Stratonovitch 2010). Climate scenarios of arbitrary length can be generated; these can be used in risk assessment and analysis of extreme events. For example, Iizumi et al. (2012b) generated a 2000-yr-long precipitation series using the LARS-WG to analyse the statistical characteristics of daily precipitation indices in Japan (Iizumi et al. 2012b). Also, Kapphan et al. (2012) generated 1000 yr of weather records to examine the weather insurance design for agricultural production (Kapphan et al. 2012).

Table 1. Summary of statistical test results. sgn: significant; KS, Kolmogorov-Smirnov test

	Number of sites (total number is 263)					
	Bias sgn[a]	Bias > TR[b]	KS sgn>0[c]	KS sgn>3[c]	*t*-test sgn>0[c]	*t*-test sgn>3[c]
Precipitation	99	65	11	0	81	41
Wet series	–	–	3	0	–	–
Dry series	–	–	0	0	–	–
Min. temperature	152	77	22	17	201	109
Max. temperature	133	59	23	19	166	74
Solar radiation	78	29	95	4	259	225

[a]Number of sites where the bias test showed significant results; the number of sites with the altitude difference >50 m was 88
[b]Number of sites where bias was significant and its absolute value exceeded a threshold (TR). For precipitation, TR = 10 mm; for temperature, TR = 0.6°C; and for solar radiation, TR = 1 MJ m^{-2} d^{-1}. Threshold values were set for each climate variable as a minimum value that exceeds bias calculated for those sites where bias test results were not significant
[c]Number of sites where the number of significant test results was >0 or >3, respectively

2.2. The ECA data set of daily observations

The ECA data set of daily weather is maintained by the Royal Netherlands Meteorological Institute (KNMI) as a part of the European Climate Assessment & Dataset project (Klein Tank et al. 2002). ECA has been widely used for studies on climate extremes and climate change, and represents the best source of publically available daily weather for Europe (Klok & Klein Tank 2009, Flaounas et al. 2012, van den Besselaar et al. 2012). ECA contains observations from a large number of stations located in Europe and the Mediterranean, including over 2500 sites with daily precipitation and over 1300 sites with minimum and maximum temperatures. For a smaller number of sites additional variables are available, including air pressure, cloud cover, sunshine duration, snow depth and relative humidity.

2.3. Validation set-up

For our study, we selected 263 sites from the ECA data set that have observed data for the period 1980–2010 and include daily precipitation, minimum and maximum temperature, and sunshine hours. Sunshine hours were converted into solar radiation using the equation described in Rietveld (1978). The locations of these sites are presented in Fig. S1 (in the Supplement at www-int-res.com/articles/suppl/c057p001_supp.pdf).

For each selected ECA site, LARS-WG site parameters from a corresponding ELPIS grid-cell were used to generate 30 yr of daily weather. ECA-observed and ELPIS-generated baseline weather were compared using statistical tests. The altitude of an ELPIS grid-cell represents the altitude of typical agricultural land within a grid-cell and is not necessarily equal to the altitude of the corresponding ECA site. As will be demonstrated later, this is an important consideration for explaining systematic differences in temperature and precipitation.

We used 3 statistical tests to compare observed and generated daily data. The KS-test was used to compare distribution of daily variables for each month (12 tests for each variable and for each site). The *t*-test was used to compare monthly means of climatic variables (12 tests). To check for a potential bias, we used the paired *t*-test to compare 12 monthly means of ECA-observed and ELPIS-generated daily data under the null hypothesis of no difference. For the seasonal distribution of the length of dry and wet series, the KS-test was used (4 tests for each series, wet or dry). The significance level was set to $\alpha = 0.01$.

Statistical tests were based on the assumption that the observed and generated daily weather data are both random samples from existing distributions, and they tested the null hypothesis that these 2 distributions were the same. For each test we computed a p-value, which is a measure of how likely the data has occurred by chance, assuming the null hypothesis was true. Hence, a very low p-value means that the generated daily weather is unlikely to be the same as the observed weather. A large p-value indicates that the differences between generated and observed weather are small enough that there is insufficient evidence to reject the null hypothesis. Such tests cannot prove that the distributions are the same and the null hypothesis is true. The required closeness of the generated and observed data depends upon the application in which the generated data are used.

3. RESULTS AND DISCUSSION

Table 1 presents a summary of statistical test results comparing ECA-observed and ELPIS-generated baseline scenarios.

3.1. Analysis of precipitation

The KS-test for seasonal distributions of dry series showed no significant results for all 263 sites. The KS-test for the seasonal distribution of wet series (4 tests per site) showed 1 significant result at 2 sites, and 2 significant results at 1 site in Spain (SID03939, Spain). The KS-test for the distribution of daily precipitation (12 tests per site) showed 1 significant result at 3 sites, and 2 significant results at 8 sites. Note, though, that even when samples come from the same distribution, the KS-test allows for a small proportion of significant test results. For instance, when the significance level is set to 0.01, in principle, 1 out of 100 test results could be significant. For precipitation tests, the number of significant results was in line with expectation, if we assume that precipitations are spatially and temporally independent.

Although application of the KS-test to the distribution of daily precipitation amounts (12 tests per sites) showed a relatively small number of significant results, the bias test (1 test per site) was more sensitive and showed significant results at 99 sites (Fig. 1A), compared with 164 sites for which the test indicated no significant bias results (Fig. 1B). For the former sites, bias values varied from 100 to −33.2 mm (Fig. 1C), whereas for the latter, differences were typically of the order of a few millimeters, with only a few sites displaying absolute differences in excess of

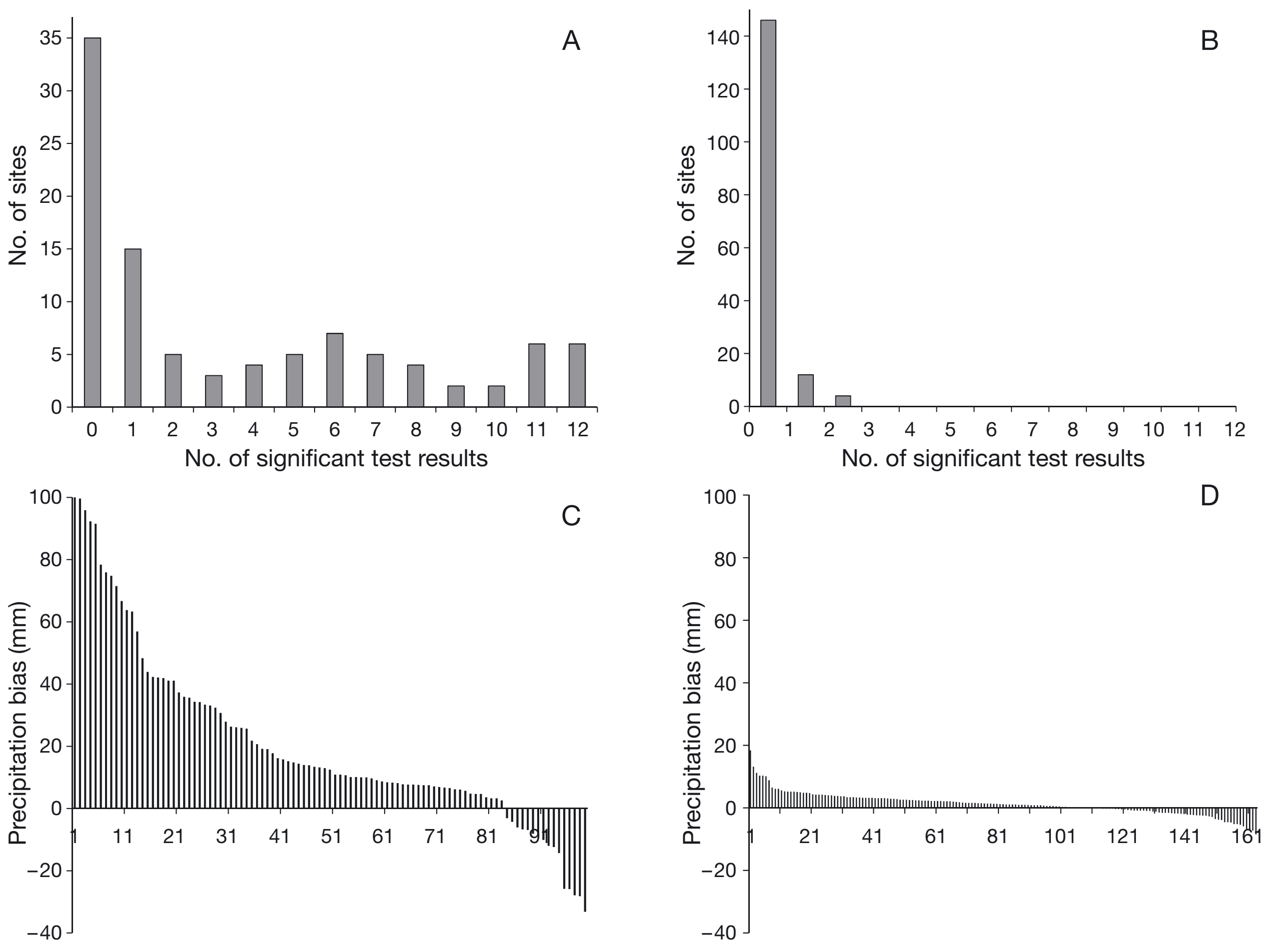

Fig. 1. (A,B) Number of sites with the exact number of significant results for *t*-tests comparing monthly mean precipitation for ECA and ELPIS: (A) sites where the test for precipitation bias showed significant results; (B) sites where test results for precipitation biases were not significant. (C,D) Precipitation bias between ECA and ELPIS calculated as the average difference in mean monthly precipitation: (C) sites ordered from highest to lowest bias, where the test for precipitation bias showed significant results; (D) sites where test results for precipitation bias were not significant

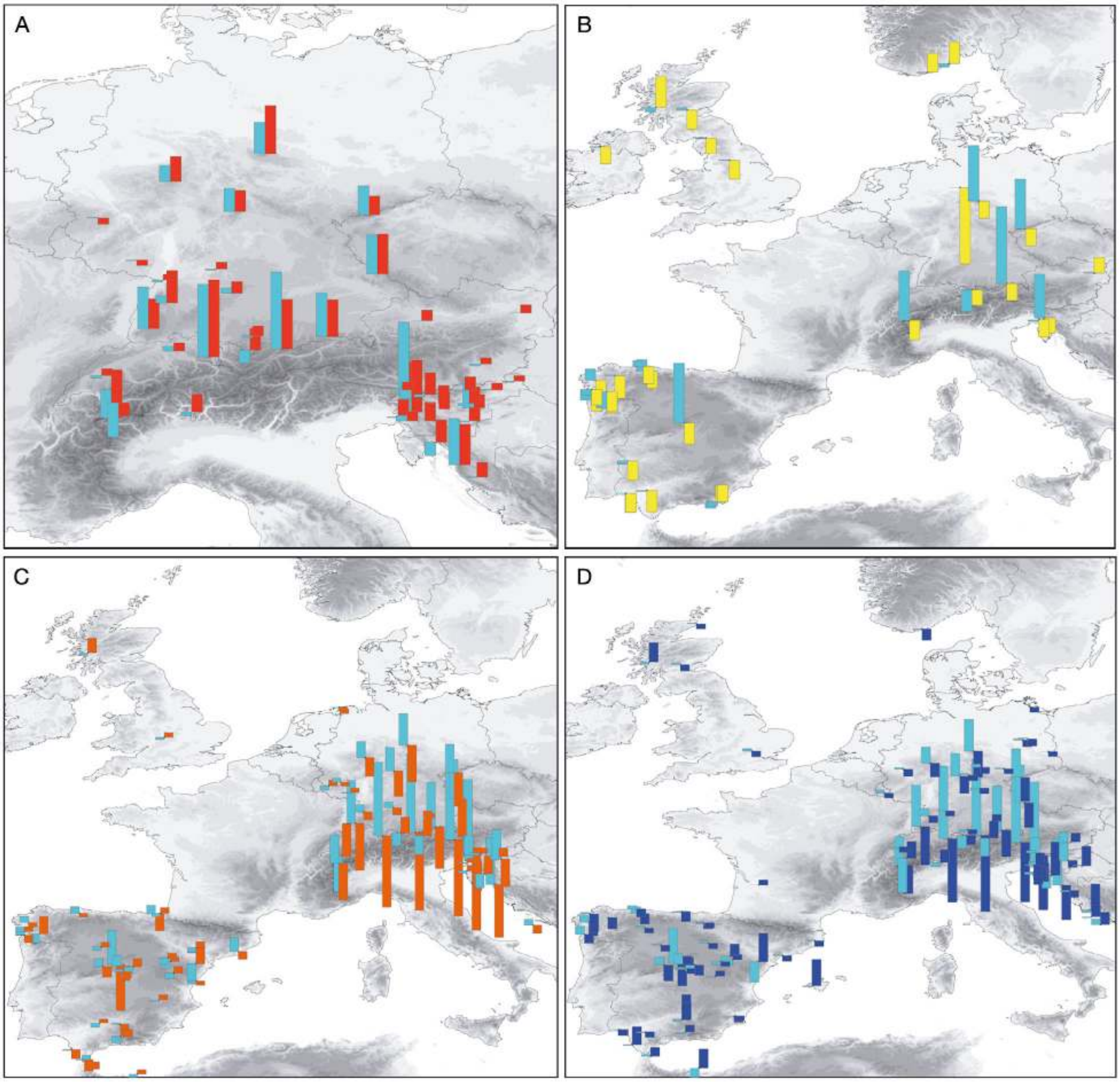

Fig. 2. Differences in altitudes (light blue bars, maximum bar height corresponds to 1900 m) and biases for the sites where the bias test showed significant results and bias exceeded a threshold for (A) precipitation (red bars) (10 mm threshold, maximum bar height corresponds to 150 mm); (B) solar radiation (yellow bars) (1 MJ m^{-2} d^{-1} threshold, maximum bar height corresponds to 5 MJ m^{-2} d^{-1}); and (C) minimum (orange bars) and (D) maximum (dark blue bars) temperatures (0.6°C threshold, maximum bar heights corresponds to 10 and 12°C, respectively)

10 mm (Fig. 1D). This latter value was therefore used as a threshold for further tests as reported in Table 1.

Fig. 2A shows precipitation bias and the altitude difference between an ECA site and a corresponding ELPIS grid-cell for locations where bias was significant and its absolute value exceeded 10 mm. Bias was calculated as an average value between monthly means of observed and ELPIS-generated precipitation. Large precipitation biases are observed at the sites with large altitude differences. This can be explained by the CGMS interpolation method used for precipitation. Daily precipitation for each 25 km grid-cell in CGMS data set was copied from the site that has the lowest site score SR_{site} (km), calculated as (van der Goot 1997):

$$SR_{site} = D + W_{alt}\Delta_{alt} + \Delta_{coast} + \Delta_{barrier} \quad (1)$$

where D is the distance between the weather station and the grid-cell centre (km); Δ_{alt} is the absolute difference (m) between the site and grid-cell altitude; w_{alt} = 0.5 is a weighting factor (km m^{-1}); Δ_{coast} is the absolute difference in corrected distance to coast (km); and $\Delta_{barrier}$ is the climate barrier increment (km). If a test ECA site is situated in a grid-cell with a complex terrain, we can potentially expect larger differences in statistics between ECA-observed and ELPIS-generated precipitation. To illustrate this, we investigated 4 ECA sites where differences in altitudes and precipitation bias were large: SID02006 in Germany, DU-E in the UK, SID00232 in Spain and SID00243 in Switzerland. Table S1 (in the supplement, www.int-res.com/articles/suppl/c057p001_supp.pdf) shows site characteristics including differences in altitude and precipitation bias. In Fig. 3, the location of the SID02006 site is shown in the background of the digital elevation map overlaid with the ELPIS 25 km grid and the agricultural land mask. As seen in this figure, SID02006 is situated in a grid with relatively complex terrain and very little agricultural land. The SID02006 site is almost at the highest point in the grid-cell with a difference in altitude from the CGMS grid-cell of 765 m, which adds, according to Eq. (1), 382.5 km to its site score SR_{site}. Given the land use characteristics, it is most unlikely that SID02006 could have been selected as representative of precipitation for this grid-cell. It is more likely that precipitation for this grid-cell would be assigned from a site situated within one of the neighbouring grid-cells that are predominantly used as agricultural land (Fig. 3). This could explain a precipitation bias of 91.5 mm between SID02006 and a corresponding ELPIS grid-cell. Similar reasoning could explain precipitation biases for 3 other sites (see Table S1, Fig. S5 in the supplement).

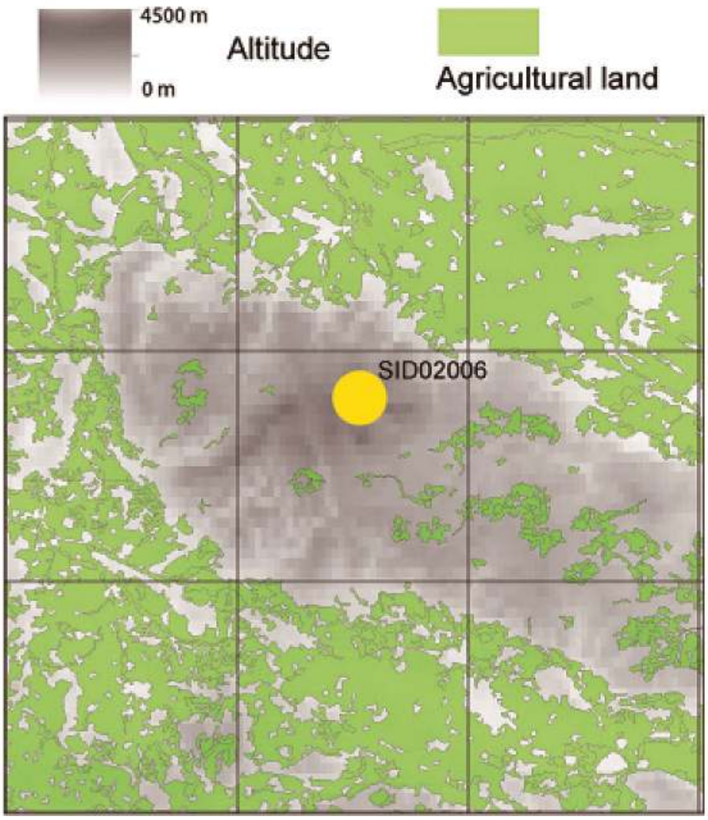

Fig. 3. Location of the SID02006 site (yellow circle) on the digital elevation map (darker grey shades correspond to higher altitudes) overlaid with the ELPIS 25 km grid. Green areas represent agricultural land. The difference in altitude between SID02006 and the corresponding ELPIS grid is 765 m, and precipitation bias is 91.5 mm

3.2. Analysis of temperature

There is a well-known relationship between air temperature and altitude, with an approximate 0.65°C temperature decrease per 100 m increase in altitude up to about 10 km, reflecting the moist adiabatic lapse rate of the standard atmosphere (Wallace & Hobbs 2006). Consequently, we can expect that the difference in altitude between an ECA site and an ELPIS grid-cell could result in a noticeable difference in maximum and minimum temperatures. Fig. 2C,D shows bias for minimum and maximum temperature and altitude differences for those sites where tests for temperature bias were significant. Temperature bias was significant at 51% of sites for maximum temperature and 58% for minimum temperature. As expected, temperature biases were negatively correlated with altitude difference, decreasing by 0.42 and 0.68°C per 100 m for minimum and maximum temperature, respectively (Fig. 4C,D), Maximum temperature bias was better correlated with altitude difference with $R^2 = 0.96$ ($R^2 = 0.69$ for minimum temperature bias). The KS-test showed significant results only for those sites where temperature bias was significant and exceeded 2–3°C (at approximately 8.8% of sites with significant bias results). The *t*-test for monthly mean temperatures was more sensitive: 50% of sites with significant temperature bias for maximum temperature and 61% for minimum temperature showed >3 significant *t*-test results. Nevertheless, for the majority of these sites *t*-test results can be explained by differences in altitude between a site and a grid-cell. The number of sites with the exact number of significant results for *t*-tests and values of temperature biases for maximum and minimum temperature are shown in the supplement (Figs. S2 & S3, respectively).

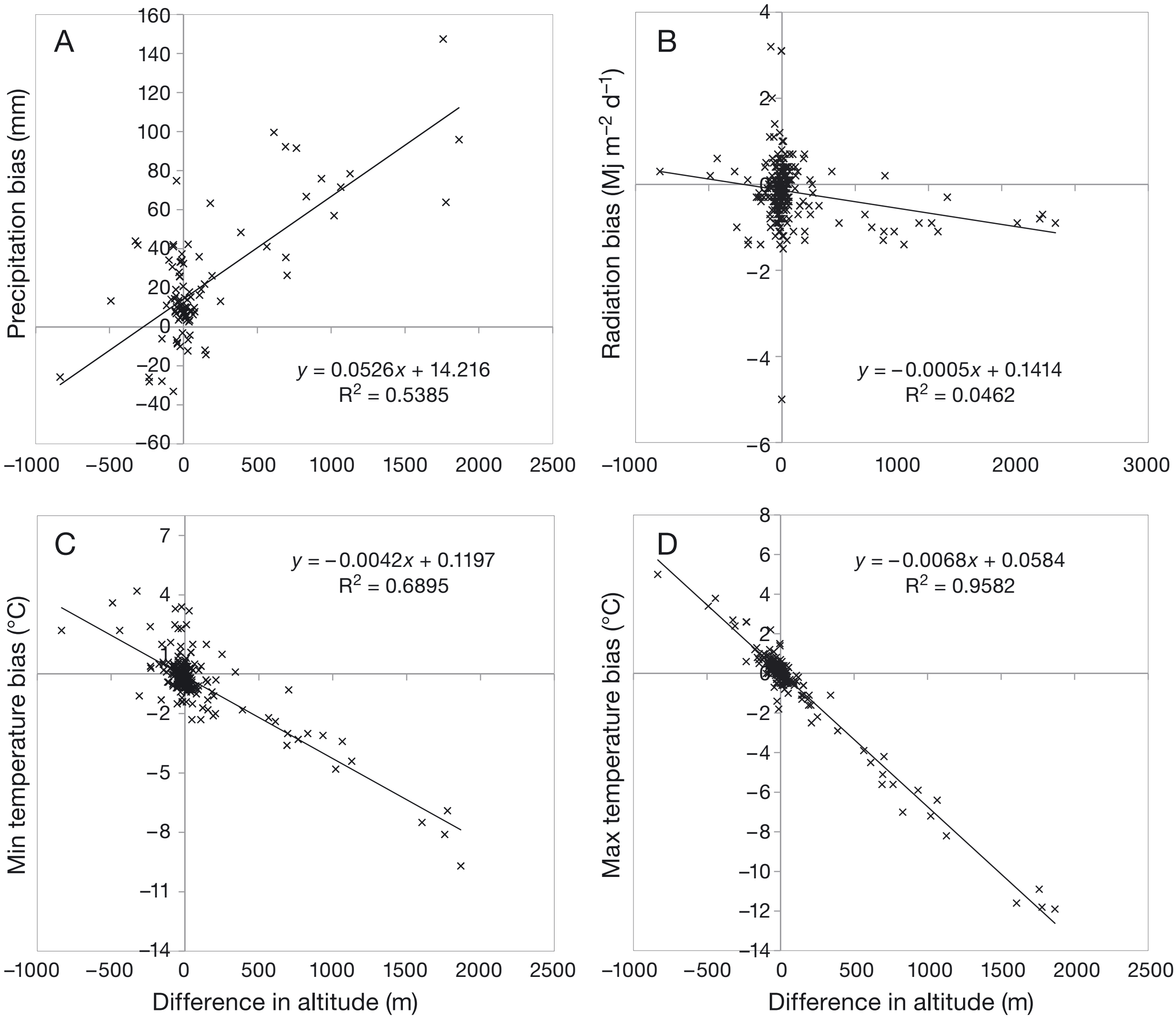

Fig. 4. Regression relationships between differences in altitude and (A) precipitation bias, (B) solar radiation bias, and (C) minimum and (D) maximum temperature biases between an ECA site and a corresponding ELPIS grid-cell. Only sites where tests for biases had significant results are shown

3.3. Analysis of solar radiation

Daily solar radiation was estimated from sunshine hours in CGMS using Supit's equation (Supit & Van Kappel 1998) and for ECA sites using the equation from Rietveld (1978). Because of high variability of solar radiation, only 4 sites showed more than 3 significant results for the KS-test. Solar radiation bias showed little correlation with altitude difference (Fig. 4B), and only at 29 sites was the bias significant and exceeding a threshold of 1 MJ m^{-2} d^{-1} (Table 1, Fig. S4 in the supplement). However, the number of sites where the *t*-test showed >3 significant results was very high: 225 (90%). This could be explained by the different methods used to estimate solar radiation in the CGMS and ECA data sets. A quick comparison of 2 methods to estimate solar radiation at a single site, SID00239 in Switzerland, showed that the Supit & Van Kappel method slightly overestimates observed solar radiation, and the Rietveld method underestimates observed solar radiation (Fig. S6 in the supplement). Different methods in estimation of solar radiation in the CGMS and ECA data sets could explain why 30% of sites have significant results for the solar radiation bias tests. However, the biases were relatively small for the majority of sites and did not exceed 1 MJ m^{-2} d^{-1} (Fig. S4 in the Supplement).

There might be another factor contributing to a large number of significant *t*-test results for solar radiation. The number of sites where observed sunshine hours were available for interpolation in CGMS was substantially less than the number of sites with observed temperature and precipitation. According to the CGMS interpolation procedure, several observed CGMS sites (up to 4) with the lowest score (see Eq. 1) were averaged to estimate solar radiation for a grid-cell. These sites could be far apart, which could result in smoothing the annual cycle for interpolated solar radiation, with slightly decreased summer peaks and increased values of solar radiation during winter compared with the ECA-observed values. Fig. 5 presents 30-yr mean values for daily solar radiation for the ECA site (SID0416) and the corresponding ELPIS grid-cell. The bias test for solar radiation at this site showed no significant result, but the *t*-test for monthly means showed 10 significant results. In ELPIS-generated weather, solar radiation was higher during winter and lower during summer compared with solar radiation estimated for the SID0416 site (Fig. 5). The *t*-test picked up these differences for individual months, but the bias test for radiation showed no significant differences because differences in monthly mean solar radiation during summer have been compensated for by differences during winter.

4. CONCLUSIONS

Table 1 summarises the results of statistical tests comparing ECA-observed and ELPIS-generated baseline weather. Daily 25 km gridded climatic variables in the CGMS dataset were interpolated from observed site records using one (for precipitation) or several (for temperature and solar radiation) sites that have the minimum scores SR_{site} defined by Eq. (1). During interpolation, heavy penalties were added to the site score SR_{site} for the sites with large differences between site and grid-cell altitudes. In CGMS, the grid-cell altitude was selected to represent agricultural land only, even when the proportion of agricultural land in the grid-cell was relatively small. The number of ECA sites where the altitude difference between a CGMS grid-cell and a corresponding ELPIS grid-cell exceeded 50 m was 88 (33%). We were able to explain the majority of significant statistical test results for precipitation and temperatures by these differences in altitude. The number of sites where the KS-test showed >3 significant results for precipitation and wet and dry series was 0; for minimum and maximum temperature it was 17 and 19 sites, respectively, and for solar radiation it was 4 (Table 1). The *t*-test was much more sensitive in detecting significant results in monthly means. Temperature bias was well correlated with altitude difference (Fig. 5), which could explained the large number of sites with significant results for the bias test when bias exceeded the 0.6 C° threshold: 77 sites for minimum and 59 sites for maximum temperature, respectively. Precipitation bias was less correlated with altitude difference (Fig. 4A), and only 65 site test results, where bias exceeded the 10 mm threshold, were significant. The bias for solar radiation, which exceeded the 1 MJ m^{-2} d^{-1}, was significant only at 29 sites, although the number of sites with >3 significant *t*-test results was very high. This can be explained by different equations being used to estimate solar radiation from sunshine hours used in CGMS and for the ECA sites.

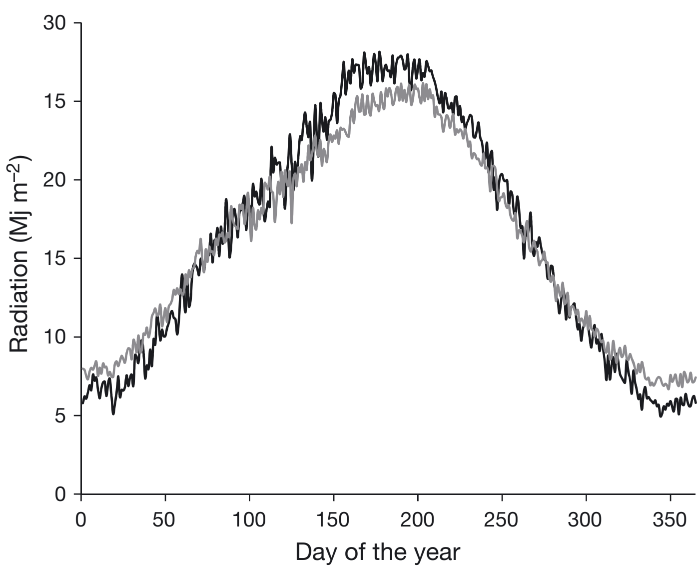

Fig. 5. Mean daily solar radiation for the ECA SID0416 site (black line), and the corresponding ELPIS grid-cell (grey line)

We can conclude that, for agricultural impact assessments in Europe, ELPIS baseline scenarios are suitable, considering the limitations described above. However, we would recommend running additional statistical tests to compare impact indexes computed by impact models using observed and ELPIS-generated daily weather time series to ensure applicability of ELPIS-generated climate scenarios for individual case studies. If ELPIS-based climate scenarios are needed for locations outside of agricultural land, then substantial differences can arise compared with climate scenarios derived using other downscaling techniques.

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