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AGROMETEOROLOGY - Article

Using climate change models to assess the probability of weather extremes events: a local scale study based on the generalized extreme value distribution

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ABSTRACT: Regional climate models (e.g. Eta) nested to global climate models (e.g. HadGEM2-ES and MIROC5) have been used to assess potential impacts of climate change at regional scales. This study used the generalized extreme value distribution (GEV) to evaluate the ability of two nested models (Eta-HadGEM2-ES and Eta-MIROC5) to assess the probability of daily extremes of air temperature and precipitation in the location of Campinas, state of São Paulo, Brazil. Within a control run (1961-2005), correction factors based on the GEV parameters have been proposed to approach the distributions generated from the models to those built from the weather station of Campinas. Both models were also used to estimate the probability of daily extremes of air temperature (maximum and minimum) and precipitation for the 2041-2070 period. Two concentration paths of greenhouse gases (RCP 4.5 and 8.5) have been considered. Although both models project changes to warmer conditions, the responses of Eta-Hadgem2-ES to both RCPs are significantly larger than that of Eta-Miroc5. While Eta-Hadgem2-ES suggests the location of Campinas will be free from agronomic frost events, Eta-Miroc5 indicates that air temperature values equal to or lower than 5 and 2 °C are expected to present a cumulative probability of ~0.20 and ~0.05, respectively (RCP 8.5). Moreover, while the Eta-Miroc5 projected a reduction in the extreme-precipitation amounts, the Eta-Hadgem2-ES projected implausible large daily precipitation amounts. The Eta-Miroc5 performed better than the Eta-Hadgem2-ES for assessing the probability of air temperature and precipitation in Campinas. This latter statement holds particularly true for daily-extreme precipitation data.

Key words: climate change, local impacts, Eta model, nested models.

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INTRODUCTION

There are increasing evidences that climate change has affected the spatial and temporal distribution of extreme meteorological events at global and regional scales (Richards 1993; Karl et al. 1999; Manton et al. 2001; Kharin and Zwiers 2005; Wang et al. 2004; Vincent et al. 2005; Haylock et al. 2006; Alexander et al. 2006; Nadarajah and Choi 2007; Pujol et al. 2007; Felici et al. 2007; El Adlouni et al. 2007; Furió and Meneu 2011; Sugahara et al. 2009). This change is of particular concern because such events constitute 80% of the annually US$100 billion damages in global economy, with thousands of deaths each year (IFRC/RCS 2011). Naturally, these major social disruptions trigged by extreme weather conditions justify scientific efforts addressing their geophysical dynamics as well as their changing statistical properties (New et al. 2007).

Global climate models (GCM; also called atmosphere-ocean general circulation models) may be regarded as invaluable tools for assessing Earth's potential response to altered atmospheric conditions (Kharin et al. 2007; 2013; Cooley and Sain 2010; Foley 2010; Chou et al. 2014a). Although the GCM have gained in complexity in recent years (e.g. IPCC 2007; 2013), they typically have a spatial resolution ranging from 100 to 300 km. This feature limits their ability to assess impacts of climate change at a local scale (Cooley and Sain 2010; Chou et al. 2014a). On such background, regional climate models (RCM) have been nested to GCM in order to provide suitable spatial resolution for local impact studies (Cooley and Sain 2010; Chou et al. 2014a). Accordingly, these nested Regional Global models, with grid size of tens of kilometers, provide a unique opportunity to understand potential impacts of climate change at fine scales (Cooley and Sain 2010).

Different from weather forecast models, the above-mentioned models are not intended to accurately represent observational weather data. Instead, their runs over a time span – usually decades – are only intended to simulate plausible climate projections for a particular set of boundary conditions that have been provided by a specific GCM (Cooley and Sain 2010). From a mathematical standpoint, this latter statement implies that datasets generated from RCM runs are expected to present feasible statistical distributions of the meteorological variables. In control runs – where these nested models are used to represent the current/observed climate (e.g. 1961-1990; Cooley and Sain 2010) – the parameters shaping the distribution of generated/simulated data should approach those of their corresponding observational data (Kharin et al. 2007; Kharin et al. 2013).

The generalized extreme value distribution (GEV) has been used to model the distribution of extreme weather events, including air temperature and precipitation (Frei et al. 2006; Kharin et al. 2007; 2013; Cooley and Sain 2010). Therefore, this distribution can be used to quantify how well parameters shaping the distribution of simulated data represent the regional climatology of a particular area. More specifically, this 3-parameter function can be used to assess model's bias affecting the location, the scale and the tail behavior of distributions built from simulated data in regard to those built from observational data. In addition, because it is impossible to collect observations for future climate conditions (Foley et al. 2010), using the GEV in control runs is a preliminary step to verify if a particular climate model can be used to assess potential effects of climate change on future extreme weather events (Kharin et al. 2007; 2013).

Regarding regional climate models, the Eta model – developed by the Brazilian National Institute for Space Research (INPE) – has been used in the elaboration of a National Communication to the United Nations Framework Convention of Climate Change (Chou et al. 2014a). Although the Eta model, nested to GCM such as HadGEM2-ES or MIROC5, has already been used to address climate change over South America under distinct downscaling scenarios (Chou et al. 2014a; 2014b), there is no study assessing the performance of such nested models on the basis of the Extreme Value Theory. This theory, which is based on distributions such as the GEV, was used in this study to evaluate the following hypothesis: both Eta-HadGEM2-ES and Eta-MIROC5 models can be used in studies addressing local impacts of climate change.

In order to provide statistical information supporting this hypothesis, the goal of this study was to evaluate the ability of these two nested models (Eta-HadGEM2-ES and Eta-MIROC5) to assess the probability of daily extremes of air temperature and precipitation in the location of Campinas, state of São Paulo, Brazil. Considering regional climate models are likely to exhibit bias in respect to their corresponding weather stations (Ines and Hansen 2006; Bárdossy and Pegram 2011), this study developed correction factors (CF) in order to approach the parameters shaping the distributions of daily-extremes generated from the nested models to those obtained from the weather station of Campinas (State of São Paulo, Brazil during 1961 to 2005). Finally, as a case study, these two climate models were used to estimate the probability of daily-extremes of air temperature and precipitation for the period of 2041-2070. Two concentration paths of greenhouse gases corresponding to 4.5 W·m^{-2} (RCP 4.5) and 8.5 W·m^{-2} (RCP 8.5; Chou et al. 2014b) have been considered.

DATA AND METHODS

The observational data (Campinas, São Paulo, Brazil; 22°54' S, 47°05' W and 669 m) were obtained from the Agronomic Institute of Campinas (IAC/APTA/SAA). This weather station has been selected because it presents no missing data and its consistency was evaluated in previous studies (Pereira et al. 2018; Blain et al. 2018). There were considered daily extremes of precipitation (Pre), minimum (Tmin) and maximum (Tmax) air temperature data. Campinas is situated in the State of São Paulo, a tropical/subtropical South American Region in which the rainy season occurs in the austral summer while in the winter predominates the high-pressure system of the South Atlantic (Vera et al. 2006). Further information on the climate of this region can be found in several studies (Raia and Cavalcanti 2008; Vera et al. 2006; Gan et al. 2004; Carvalho et al. 2004; Zhou and Lau 1998).

Climate models

The Hadley Centre Global Environmental Model (HadGEM2-ES) (Collins et al. 2011; Martin et al. 2011) is a grid-point model presenting a resolution equivalent to ~1.275° in latitude and ~1.875° in longitude (Chou et al. 2014b). The HadGEM2-ES can be regarded as an earth system model capable of representing the carbon cycle. The Model for Interdisciplinary Research on Climate (MIROC5) presents a horizontal resolution of ~1.408° in latitude and ~1.406° in longitude. It is coupled to COCO and SPRINTARS models (Chou et al. 2014b) and uses the MATSIRO land surface scheme (Takata et al. 2003) with six soil layers. The Eta model, adopted for downscaling, uses the Betts-Miller scheme (Betts and Miller 1986; Janjić 1994) to parameterize shallow and deep convections. While the NOAH scheme is used to describe land-surface processes, cloud microphysics follow Zhao scheme (Zhao et al. 1997). Further information on these three models can be found in Chou et al. (2014a; 2014b) and references therein.

Statistical analyses

Trend and stationary test

As previously described, datasets generated from any climate model within a control run (1961-2005) are expected to present feasible statistical distributions of the meteorological variables. Therefore, parameters shaping these distributions should be as close as possible to those parameters obtained from their corresponding observational data (Frei et al. 2006, Kharin et al. 2007; 2013; Cooley and Sain 2010; Um et al. 2017). Considering the presence of trends and other non-stationaries components may affect the probabilistic structure of any time series, both Mann-Kendall trend test (Kendall and Stuart 1967) and Kwiatkowski-Phillips-Schmidt-Shin stationary test (KPSS) have been applied to the observational datasets as well as to those datasets generated from the climate models (Um et al. 2017).

The Mann-Kendall test is widely used and its algorithm, which was originally designated for uncorrelated data, has been described in several studies (e.g. Yue et al. 2002). With regard to the datasets used in this study, the time span between two consecutive records is, in general, one year (block maxima approach). Therefore, we assumed the presence of no significant serial correlation. The Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al. 1992) was used to evaluate the hypothesis (H_0) that the datasets are stationaries around a [possible] deterministic trend. The algorithm of this latter test, including its critical values, can be found in Kwiatkowski et al. (1992).

Generalized Extreme Value distribution and goodness-of-fit tests

The GEV is a parametric distribution in which the cumulative probability of a particular event x is given by its three parameters: location (μ), scale (σ) and shape (ξ). These parameters can be estimated from distinct methods, including maximum likelihood, generalized maximum likelihood and L-moments. As pointed out by Wilks (2011), the results of both maximum likelihood and L-moments are frequently similar for large and moderate sample sizes. For small samples, the L-moments usually lead to better estimates than the maximum likelihood does. Since the GEV distribution was applied to a 30-year period (1941-2070), which is usually regarded as the lowest length of record required for climatic characterizations, the L-moments method (Hosking 1990; 1992) has been adopted in this study.

The cumulative density and the quantile functions of the GEV distribution are given by Eqs. 1 and 2, respectively. The 95% confidence interval for each parameter estimates has been calculated by the bootstrap method described in Khaliq et al. (2006).

$$F(x) = \frac{1}{\sigma} exp\left\{-\left[1+\frac{(x-\mu)}{\sigma}\right]^{-1/\xi} \frac{(x-\mu)}{\sigma}\right\} \quad (1)$$

$$f^{-1}(p) = \mu + \frac{\sigma}{\xi}\{[-\ln(p)]^{-\xi} - 1\} \quad (2)$$

Both Lilliefors (Lilliefors 1967) and Anderson-Darling (Anderson and Darling 1954) goodness-of-fit tests were used to verify if the GEV distribution can be used to assess the probability of daily-extremes obtained from the three data sources of this study. These two tests have been widely used in climatological studies and their calculation algorithm can be found in (Wilks 2011; Shin et al. 2011). These two goodness-of-fit tests have been performed at 5% significance level. The outcomes of both Mann-Kendall and Kwiatkowski-Phillips-Schmidt-Shin have been evaluated at 5 and 10% significance level.

As previously described, estimates provided by climate models are likely to exhibit biases in respect to their corresponding observational data. These biases may be corrected by using the Universal Downscaling Method (e.g. Ines and Hansen 2006; Bárdossy and Pegram 2011). Within a control run, this latter method relates the distribution of data generated by a climate model with that of the corresponding observational data (Themeßl et al. 2011; Bárdossy and Pegram 2011). Therefore, the idea behind this statistical correction method is to approach distributions of datasets generated by a climate model to their corresponding distributions obtained from observational datasets. Since this study uses the GEV to assess models' performance, such correction can be performed by a simple numerical comparison between the GEV parameters generated from the nested models (Eta-HadGEM2-ES or Eta-MIROC5) with those GEV parameters obtained from the weather station of Campinas (Eq. 3). This latter statement is based on the fact that the three GEV parameters define the position of the distribution with regards to its origin (μ parameter), its spread (σ parameter) and its tail behavior (ξ parameter; Coles 2001). In other words, the correction factors (CF) calculated from Eq. 3 approach the distribution of the data generated by the climate models to those of the observed data.

$$CF = \theta_{\text{weather station}} - \theta_{\text{climate model}} \quad (3)$$

where: $\theta_{\text{weather station}}$ is a the GEV parameter estimated from the weather station data and $\theta_{\text{climate model}}$ is the corresponding GEV parameter estimated from Eta-HadGEM2-ES or Eta-MIROC5.

The use of Eq. 3 (correction factor) in the climate scenario (2041-2070; RCP 4.5 and RCP 8.5) is described in Fig. 1.

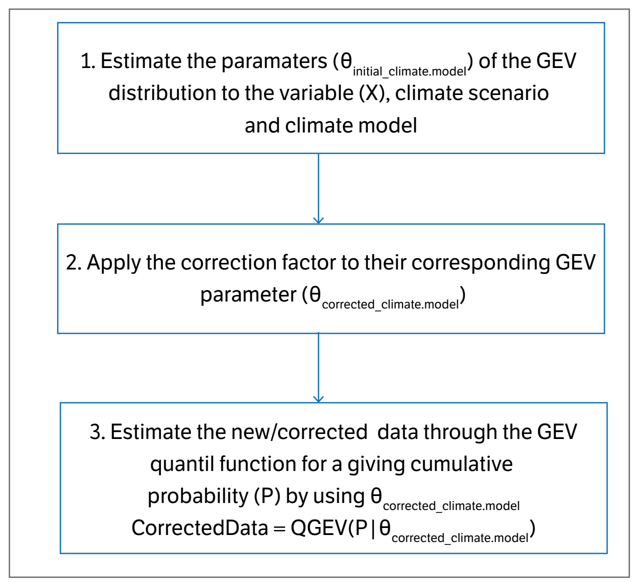

Figure 1. Applying the correction factors proposed in this study to Eta-HadGEM2-ES or Eta-MIROC5 extreme-daily data.

RESULTS AND DISCUSSION

Control Run (1961-2005)

Trend and stationary test

Both precipitation and minimum air temperature data obtained from the weather station of Campinas presented significant increasing trends respectively at 5 and 10% significance level (Mann-Kendall test; Table 1). This result is consistent with previous studies describing signs of climate change in the location of Campinas (Blain 2011; Pereira et al. 2018). For both climate models, such a trend could only be detected in the precipitation series, with data generated by the Eta-MIROC5 reaching the 5% significance level. In other words, none of the models was able to reproduce the trend observed in the Tmin observational data. Finally, no trend has been detected in the three Tmax datasets (observational and simulated). This lack of trend in these latter series is in line with previous studies (e.g. Blain 2013) investigating trends in the Tmax series of Campinas. The Kwiatkowski-Phillips-Schmidt-Shin test indicated that all series are stationaries around a significant/non-significant deterministic trend (Um et al. 2017). Therefore, this latter test supports the assumption that apart from trends there is no other non-random component (e.g. serial correlation) affecting the GEV estimates. This lack of significant auto-correlation holds true for the three data sources used in this study (weather station, Eta-HadGEM2-ES and Eta-MIROC5), supporting the use of a parametric distribution such as the GEV.

Table 1. Mann Kendall (trend) test and Kwiatkowski–Phillips–Schmidt–Shin stationary tests applied to daily extremes of minimum (Tmin), maximum (Tmax) air temperature and precipitation (Pre) data. The data datasets have been obtained from the weather station of Campinas (state of São Paulo, Brazil) and two nested models: Eta-HadGEM2-ES or Eta-MIROC5.

	Mann Kendall (trend) test: p-value		
	Weather station	Eta-Hadgem	Eta-Miroc
Tmin	0.03**	0.24	0.27
Tmax	0.52	0.84	0.14
Pre	0.07*	0.08*	0.00*
	Kwiatkowski–Phillips–Schmidt–Shin		
Tmin	> 0.10	> 0.10	> 0.10
Tmax	> 0.10	> 0.10	> 0.10
Pre	> 0.10	> 0.10	> 0.10

* Significant at 10%; ** significant at 5%.

Generalized Extreme Value distribution and goodness-of-fit tests (control run)

The hypothesis that daily-extremes obtained from the weather of station of Campinas have been drawn from a GEV distribution is supported by both goodness-of-fit tests (Table 2). These tests also indicated that this latter parametric distribution could be used to assess the probability of daily-extreme data generated by both climate models (Eta-HadGEM2-ES and Eta-MIROC5). In other words, the outcomes of the two goodness-of-fit tests indicate that the data derived from the two climate models as well as those obtained from the weather station of Campinas were drawn from populations approaching the GEV distribution. This statement is in line with (i) previous studies using the GEV to assess the probability of Tmin, Tmax and Pre data derived from climate models (Kharin et al. 2007; 2013) as well as with (ii) other studies that applied this latter function to assess the probability of such extreme data in the location of Campinas (Blain 2013). Finally, the results of Table 2 further support the use of the GEV distribution (Eqs. 1 and 2) for evaluating the ability of both nested models to assess the probability of air temperature and precipitation daily extremes in the location of Campinas.

Table 2. Goodness-of-fit tests (Lilliefors and Anderson-Darling; AD performed at 5% significance level) applied to daily extremes of minimum (Tmin), maximum (Tmax) air temperature and precipitation (Pre) data. The data datasets have been obtained from the weather station of Campinas (state of São Paulo, Brazil) and two nested models: Eta-HadGEM2-ES or Eta-MIROC5.

Source	Lilliefors	Lilliefors_{crit}	AD	AD_{crit}
Weather station	0.072	0.098	0.320	0.659
	0.045	0.097	0.253	0.592
	0.086	0.104	0.505	0.537
Eta-HadGEM2-ES	0.067	0.098	0.386	0.703
	0.051	0.098	0.203	0.590
	0.078	0.099	0.320	0.608
Eta-MIROC5	0.050	0.098	0.150	0.624
	0.072	0.098	0.352	0.619
	0.049	0.097	0.113	0.601

Considering the sign correction performed when the GEV was applied to extreme minima (–1*Tmin; Coles 2001; Wilks 2011), the Eta-HadGEM2-ES model tend to systematically underestimate the Tmin leading to a location parameter, which defines the position of the distribution with respect to the origin (Delgado et al. 2010), significantly lower than that obtained from the weather station (~9.5 °C; Fig. 2a). For this model, the other two GEV parameters representing the spread (scale parameter) and the tail behavior of the distribution (shape parameter) presented no significant difference in respect to those derived from the weather station. In other words, the dispersion/spread of the Tmin data generated from the Eta-HadGEM2-ES is statistically equal to that of the observational data. In addition, both distributions converge to the Weibull or Fisher-Tippett Type III form ($\xi > 0$; Delgado et al. 2010;

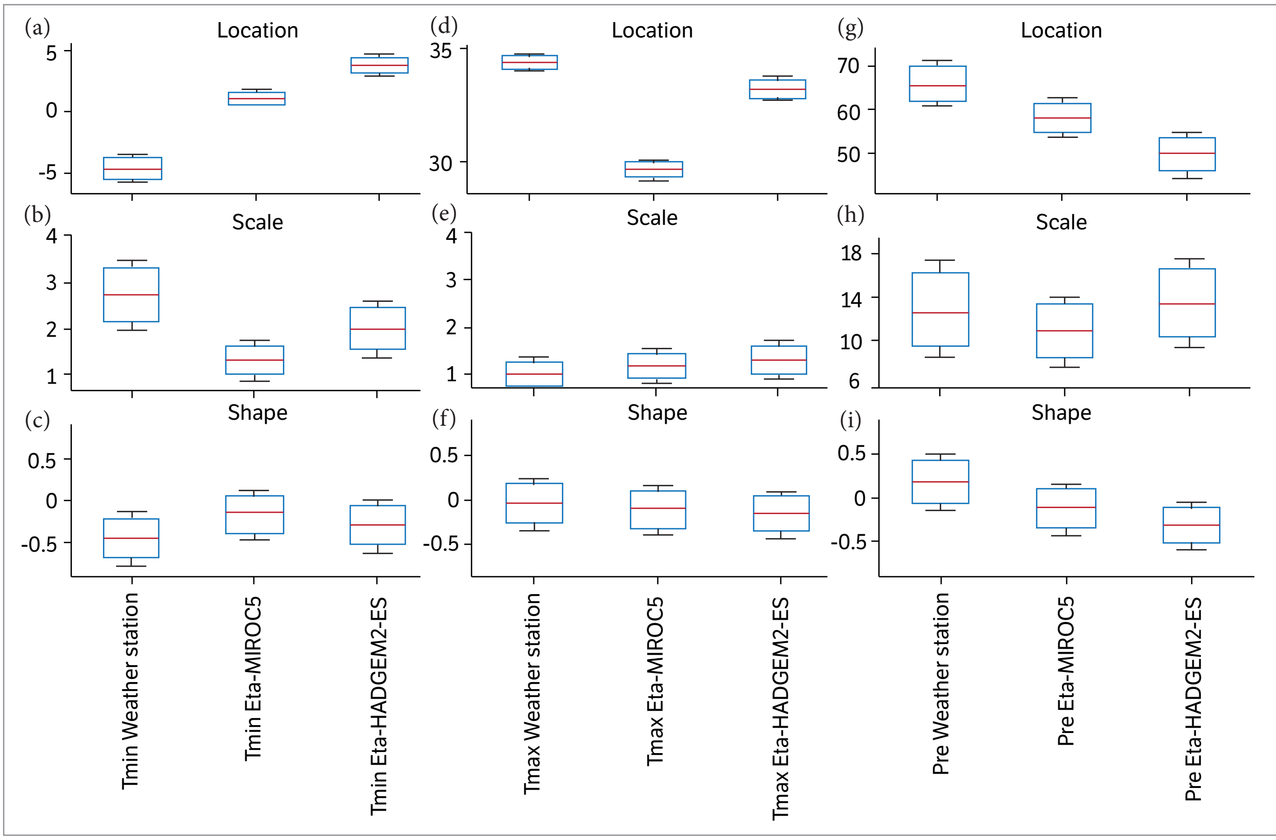

Figure 2. Parameters of the generalized extreme value distribution estimated from daily extremes of minimum air temperature (a, b and c), maximum air temperature (d, e and f) and precipitation (g, h and i). Campinas, state of São Paulo, Brazil (1961-2005).

Wilks 2011). Therefore, the correction factor (Eq. 3) to be used for Eta-Hadgem2-ES Tmin data derived from this latter model for the location of Campinas may only address the numeric difference between location parameters (Fig. 2a; Eta-HadGEM2-ES vs. weather station).

With regard to the Eta-MIROC5, the results of Fig. 2b also indicate that this latter model tends to underestimate the Tmin data in the location of Campinas. Although the location parameter estimated from this latter model is higher than that of the Eta-HadGEM2-ES, it is still significantly lower (~5. °C) than that obtained from the weather station. Thus, the Eta-MIROC5 Tmin values tend to be, on average, 5. °C lower than those observed at the weather station of Campinas. In addition, different from the Eta-HadGEM2-ES, the scale parameter derived from the Eta-MIROC5 is also significantly lower than that obtained from the weather station data (Fig. 2b; the sign correction does not affect the scale and shape parameters of the GEV distribution; Coles 2001; Blain 2011). In other words, the dispersion/spread of the Tmin data generated from the Eta-MIROC5 is also significantly lower than that of the ground data (different scale parameters). Therefore, the correction factor (Eq. 3) to be used for Tmin data derived from the Eta-MIROC5 model should address the numeric difference between the location and scale parameters of these two datasets (Fig. 2b; Eta-MIROC5 and weather station).

Considering the maximum air temperature, both nested models presented location parameters significantly lower than those obtained from the weather station (~1.3 °C for the Eta-HadGEM2-ES and ~5.1 °C for the Eta-MIROC5; Figs. 2c, 2d). For both models, the other two parameters of the GEV distribution (scale and shape) presented no significant difference in respect to those obtained from the weather station. The Tmax data of both models also converge to the Weibull or Fisher-Tippett Type III form (equivalents shape parameters; Delgado et al. 2010; Wilks 2011). Therefore, the correction factor (Eq. 3) to be used for Tmax data may only address the numeric difference between location parameters of the models (Eta-HadGEM2-ES or Eta-MIROC5) and the weather station (Figs. 2c, 2d; climate models vs weather station).

With regard to the precipitation series, the three GEV parameters derived from the data generated by the Eta-MIROC5 are statistically equal to those obtained from the weather station (Fig. 2e), suggesting the use of no correction factor. As observed for the air temperature series (Tmax and Tmin), the precipitation data generated by the Eta-HadGEM2-ES presented location parameter significantly lower than that obtained from the weather station (~16.7 mm; Fig. 2e). The other two parameters of the GEV distribution (scale and shape) presented no significant difference in respect to those derived from the weather station. Therefore, the correction factor to be used for Pre data derived from this latter model in the location of Campinas may only address the numeric difference between the location parameters of these two datasets.

Case study: climate scenarios RCP 4.5 and RCP 8.5 (1941-2070)

Before evaluating changes in the probabilistic structure of Tmin, Tmax and Pre series, it is worth mentioning that there were no significant numerical differences between the shape parameters estimated in the control run (1961-2005; including weather station data – Fig. 3) and those estimated within each RCP scenario (2041-2070). This result is in line with the statement that the GEV-shape parameter is unlikely to change under climate change (Wilson and Toumi 2005).

With regards to minimum air temperature, both Eta-HadGEM2-ES and Eta-MIROC5 project changes to warmer conditions in respect to 1961-2005 data. However, it is interesting to note that these two models show no remarkable difference between both climate scenarios (4.5 and 8.5). In fact, considering cumulative probabilities ranging from ~0.15 and ~0.85, the Eta-MIROC5 simulates for the RCP 8.5 Tmin values numeric lower than those simulated for the RCP 4.5 scenario (Figs. 3a, 3b). The Eta-HadGEM2-ES presented the greatest change to warmer conditions. According to this latter model, Tmin values lower than 12 °C would become unlikely to be observed (cumulative probability lower than 0.02). From the agronomic standpoint, air temperature values lower than 5 °C may cause damages to susceptible crops (e.g. Banana). For crops such as coffee and citrus, this critical low limit is 2 °C (Sentelhas et al. 1995). Therefore,

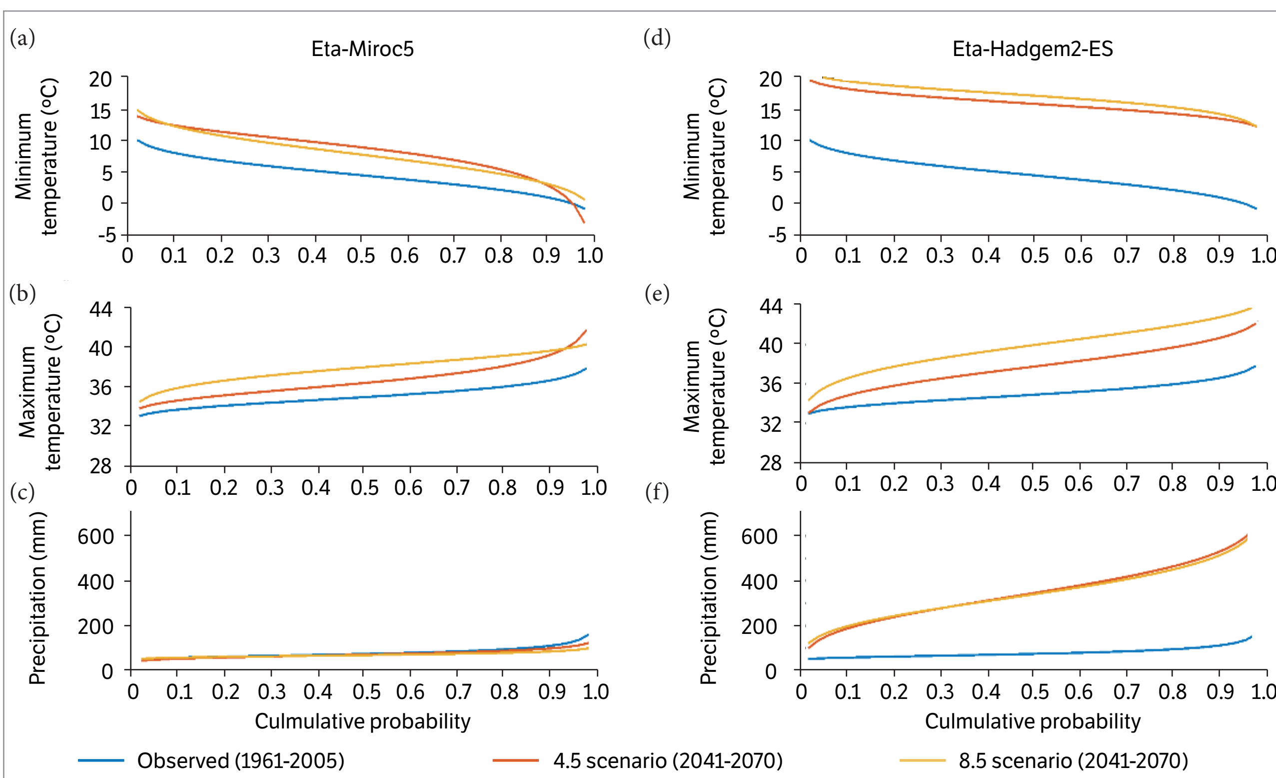

Figure 3. Cumulative probability of daily extremes of minimum and maximum air temperature and precipitation, considering two concentration paths of greenhouse gases: RCP 4.5 (a, b and c) and RCP 8.5 (d, e, f) and two nested climate models (Eta-Miroc5 and Eta-Hadgem2-ES) Campinas, state of São Paulo, Brazil.

the climate scenarios projected by the Eta-Hadgem2-ES differs significantly from that projected by the Eta-Miroc5 (2041-2070). With regard to the Eta-Hadgem2-ES, the results depicted in Fig. 3b suggests that the location of Campinas will be virtually free from agronomic frost events (2041-2070). Nevertheless, the results of the Eta-Miroc5 (2041-2070) indicate that Tmin values equal to or lower than 5 °C and 2 °C will present a cumulative probability of ~0.20 and ~0.05, respectively (8.5 scenario). In other words, the Eta-Miroc5 projections do not support the assumption that the location of Campinas will be free from agronomic frost events during the analyzed period (2041-2070).

The changes projected by both models for the maximum air temperature series were similar to those projected for the Tmin series (Figs. 3c, 3d). In other words, both Eta-Hadgem2-ES and Eta-Miroc5 projected changes to warmer conditions with the Eta-Hadgem2-ES showing the greatest shift in respect to the observed period (1961-2005). However, differently from the Tmin series, there was no significant difference between the two climate scenarios (RCP 4.5 and RCP 8.5) considered in this study. This latter statement is particularly true for the Eta-Hadgem2-ES. As observed for both Tmin and Tmax series, the Eta-Hadgem2-ES model projected the greatest change in the probabilistic structure of extreme precipitation data (Figs. 3e, 3f). In fact, this model seems to overestimate the effect of both RCP scenarios on the extreme precipitation data. For instance, daily amounts as higher as 350 mm presented cumulative probability ~0.50 (median of the series). Even without the use of the correction factor, the Pre value associated with such probability level is ~330 mm. The Eta-Hadgem2-ES also projected no significant difference for the two climate scenarios (RCP 4.5 and RCP 8.5). On the other hand, the Eta-Miroc5 generated a feasible distribution describing a decrease in the extreme precipitation amounts. The greatest decreased is observed for the RCP 8.5 scenario (Fig. 3f). In summary, the response of Eta-Hadgem2-ES to both RCPs scenarios is larger than those of the Eta-Miroc5. This latter statement holds true for all variables analyzed in this study (Tmin, Tmax and Pre) and, as discussed in next section, it is in line with those observed by Chou et al. (2014b) for seasonal mean values of air temperature and precipitation series.

FINAL REMARKS

As previously described, Chou et al. (2014b) have already used both Eta-Hadgem2-ES and Eta-Miroc5 to assess climate change over South America (2011-2100). Based on seasonal mean values, this latter study projected changes to warmer conditions with the Eta-Hadgem2-ES simulating the largest warming (RCP 8.5; with respect to the 1961-1990 period). The results found in this local scale study suggest the changes in daily-extremes of air temperature (Tmax and Tmin) in the location of Campinas, São Paulo will follow the same pattern observed by Chou et al. (2014b) at seasonal scale. The changes to more extreme events observed in the air temperature series of this study are also in line with those observed by Kharin et al. (2007; 2013) for tropical/subtropical regions of the globe. With regard to the precipitation series, Chou et al. (2014b) observed a reduction in the Southeast of Brazil, with the regions between Southeast and South exhibiting the most mixed signs of change. This pattern (or uncertainty) was also observed in this study. While the Eta-Miroc5 projected a reduction in the extreme precipitation amounts, the Eta-Hadgem2-ES projected a large increase in the occurrence of such events. At this point, it has to be mentioned that this latter nested model projected unfeasible statistical distributions for the Pre series with virtually implausible daily-precipitation amounts.

In summary, the above-mentioned results along with those of the control run (1961-2005) indicate the Eta-Miroc5 performs better than the Eta-Hadgem2-ES for assessing the probability of air temperature and precipitation in the location of Campinas, state of São Paulo, Brazil. This latter statement holds particularly true for daily-extreme precipitation data.

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