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CLIMATE CHANGE IMPACTS ON EXTREME PRECIPITATION IN GREEK AREAS

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ABSTRACT

In the current paper the effects of climate change on precipitation extremes in Greece are studied. The projections of RegCM3_10 climatic model in particular are evaluated, for a time period of 150 years (1951-2100) in four regions of Greece. The available precipitation data is separated in three parts of equal size (fifty years each), in order to represent the fifty years of the current, the short-term and the long-term future climate. Model precipitation data is found to hold bias, commonly detected in regional climate models, making it necessary to perform various methods of bias correction. Both parametric and non-parametric methods are used for all four regions analysed, selecting the most appropriate for each region. Extreme value theory (EVT) is then implemented for the bias corrected precipitation datasets and both GEV (Generalized Extreme Value Distribution) and GPD (Generalized Pareto Distribution) are fitted. For the GPD, declustering of the excesses over the selected threshold is used to insure independence of exceedences. Return level estimates of each 50 year-period are calculated and compared to assess the changes in the extreme precipitation climate between present and future conditions.

Keywords: climate change, precipitation extremes, bias correction, EVT

1. INTRODUCTION

Extreme precipitation events can give rise to serious flooding and can have severe impacts on the human society, as well as on the environment. The general inception of a changing climate, with extreme meteorological events of higher frequency and intensity increases the exposure of the human society and the environment to severe damages. Therefore, the analysis of extreme meteorological events under present and future climate conditions is of great significance.

Regarding precipitation extremes, increased precipitation intensity in a future climate was one of the earliest model results (Durman et al., 2001; Giorgi et al., 1998; Kothavala, 1997; Hennessy et al., 1997) and remains a consistent result with improved more detailed models. A number of studies conducted by the Intergovernmental Panel on Climate Change (IPCC, 2007) reported tentative evidence for changes in the occurrence of certain meteorological events during the 20th century. The IPCC assessments relied heavily upon the use of General Circulation Models (GCMs), namely large mechanistic models for the global atmosphere. Regional Climate Models (RCMs) simulate regional climate with a more fine resolution, based on a better topography representation. During the previous years, different RCMs have been used to produce high-resolution climate scenario calculations on the European scale (e.g EU-project ENSEMBLES), including the entire Mediterranean basin.

In the past, a large number of climatic studies has been conducted using RCMs for the whole European area (Flocas et al., 2010; Goubanova and Li, 2007; Fowler et al., 2007; Ekström et al., 2005). Jones and Reid (2001) investigate changes in return levels of daily precipitation over Great Britain using a regional climate scenario from the Hadley Centre, in which greenhouse gas concentrations are assumed to increase 1% per year. Booij (2002) determines and compares extreme precipitation from stations, reanalysis projects, GCMs and RCMs in the area of the river Meuse, in Western Europe. Frei et al. (2003) undertake an evaluation of the statistics of daily precipitation as simulated by five RCMs using comprehensive observations in the region of the European Alps. Semmler and Jacob (2004) apply the regional climate model REMO to the European region to investigate the impact of future climate changes on the frequency and intensity of extreme precipitation events. Frei et al. (2006) undertake an analysis of precipitation extremes produced by six RCMs in the European region, to examine the effects of climate change on such events and to detect the model effect on them. Beninston et al. (2007) examine and provide evidence for the dependence of precipitation statistics and extremes on RCM selection. Hanson et al. (2007) provide an overview of the aims, objectives, research activities undertaken, and a selection of results generated in the European Commission funded project entitled “MICE: Modelling the Impact of Climate Extremes”, which focused on changes in temperature, precipitation and wind extremes using RCMs. Nikulin et al. (2011) examine projected future changes in statistics of precipitation extremes in the period 2071-2100 relative to the control climate period and investigate the degree of their dependency on driving GCMs. Tolika et al. (2012) assess the potential regional future changes in seasonal precipitation for the greater area of Greece over the 21st century for different future emission scenarios of IPCC.

Extreme precipitation events are usually analysed and modelled within the framework of Extreme Value Theory (EVT). This theory allows extrapolation of the data to levels more extreme than those observed. Katz et al. (2002) apply EVT to precipitation extremes within a stationary context and by considering trends and dependence on atmospheric-ocean circulation patterns. Fowler and Kilsby (2003) analyse extreme precipitation in the UK using EVT within a regional frequency analysis framework. Feng et al. (2007) model extreme precipitation in China using the Generalized Extreme Value distribution function (GEV). Cooley et al. (2007) produce precipitation return level maps in the area of Colorado by applying hierarchical models for the frequency and the intensity of extreme events. Buishand et al. (2008) use the theory of extremes of continuous processes to estimate the 100-year quantile of the daily area-average rainfall over North Holland by simulating the daily process. Fowler et al. (2010) investigate changes in precipitation extremes in the UK within an extreme value analysis framework. Williems et al. (2012) provide an overview of existing methods for assessing the impacts of climate change on urban rainfall extremes and discuss the future challenges in the field.

In the present work the effects of climate change on precipitation extremes in four areas of the Greek terrain are investigated. In Section 2 the bias correction techniques applied to the climatic data of all four locations are presented and explained. Section 3 includes a general overview of the extreme value models, namely the Generalized Extreme Value (GEV) and the Generalized Pareto (GPD) distributions that will be fitted to the extreme samples. The declustering technique used within the GPD is also presented. Section 4 incorporates the parameter estimation methods used in the present work, namely the Maximum Likelihood Estimation (MLE) and the Generalized Maximum Likelihood Estimation (GMLE). Section 5 presents the different precipitation datasets analysed in the present work, together with their basic statistical characteristics. The main results of the work are presented in Section 6 and its basic conclusions in Section 7.

2. BIAS CORRECTION OF CLIMATIC DATA

Climatic predictions of RCMs are often subject to phenomena of bias, possibly due to the limited process understanding, the incomplete conceptual representation of the atmospheric processes leading to the generation of climate data, the incomplete discretisation, the spatial averaging in each cell of the model grid and other parameters. Bias represents the error component of the model that is independent of time (Haerter et al., 2011) and imposes the processing of the data before using it to estimate the effects of climate change in any domain of study. Particularly, when referring to extreme events, it has been pointed out that if the output of RCMs is not corrected for bias, it leads to unrealistic exceedance probabilities, rendering the analysis of extreme events unreliable (Durman et al., 2001). However, it should be noticed that incorrect representation of the different processes involved in a physical system cannot be rectified by means of bias correction. Within the framework of bias correction methods, the error of the climatic model is considered stationary and the correction techniques and parameterisation for the present climate are also considered valid for the future climate. Therefore, for future projections the bias component is assumed unchangeable (Berg et al., 2012).

Among the bias correction techniques, recent studies mainly using precipitation and temperature data, indicate the quantile mapping methods as the most efficient, even for the most extreme part of the distribution of the studied variables (Themeßl et al., 2011). The above mentioned techniques include the development of transfer functions between the cumulative distribution functions of the data that need to be corrected for bias and the observed dataset. Quantile mapping (also referred to as quantile-quantile transformation) results in a new distribution function for the modelled variable almost equal to the one of the observed variable. The main limitations of the quantile - quantile transformation focus on the preservation of the temporal autocorrelation properties of the data, the independent correction of different variables with biases that might not be independent and the inability to correct the spatial autocorrelation of different variables (Boé et al., 2007).

The methods used in the present work include the development of parametric, as well as non-parametric quantile - quantile transformations. The former transformations include linear, polynomial, exponential and scale functions. The parametric transformations used are presented below (Gudmundsson et al., 2012):

$$\begin{aligned} x_{cor} &= a + bx \\ x_{cor} &= ax^b \\ x_{cor} &= a(x - x_0)^b \\ x_{cor} &= (a + bx)(1 - e^{-x/\tau}) \\ x_{cor} &= (a + bx)(1 - e^{-(x - x_0)/\tau}) \end{aligned} \qquad [1]$$

where x_{cor} is the precipitation quantity of the climatic model after being corrected for bias, x is the precipitation quantity of the model, a, b, τ are the parameters of the bias correction function that are estimated by minimizing the residual sums of squares and x_0 is the dry day correction term (the value of precipitation below which modeled precipitation is set to zero). A higher number of parameters in the models, can provide a better fit to the data. However, this can decrease the reliability of the bias correction method for the future data (Piani et al., 2010). The main disadvantage of the parametric bias correction techniques is the assumption of stationarity that allows using the same transfer function for present and future conditions.

Within the non-parametric framework, the empirical distribution functions of the observed and the modeled data are represented by means of tables of empirical percentiles, while the values between them are assessed by means of a monotonic tricubic spline functions (Gudmundsson et al., 2012). Even if these methods provide better results than their parametric counterparts, they should be implemented with great susceptibility if the model values of the future projections are significantly larger than the training values.

3. EXTREME VALUE MODELS

The univariate Extreme Value Theory (EVT) includes models for block maxima and exceedances over high thresholds (POT models). The first correspond to the family of GEV distributions (Generalized Extreme Value) including the Gumbel (Type I), the Fréchet (Type II) and the Weibull (Type III) distributions. The cumulative distribution function of the GEV for $\xi \neq 0$ is given by the following formula (Coles, 2001):

$$G(x) = \exp[-\{1+\xi\frac{(x-\mu)}{\sigma}\}^{-1/\xi}] \text{ for } 1+\xi\frac{(x-\mu)}{\sigma} > 0 \quad [2]$$

where μ, $\sigma>0$ and ξ are the location, scale and shape parameters of the distribution, respectively. The special case with $\xi=0$ corresponds to the Gumbel distribution function. The above mentioned three limit types resulting from the Extremal Types Theorem, present a completely different tail behavior. For the Weibull function, the upper limit of the distribution is finite, while for the other two types, Fréchet and Gumbel, it tends to infinity. However, the density function of G decays exponentially for the Gumbel distribution function and polynomially for the Fréchet distribution function.

If $X_1, X_2,\ldots, X_n$ is a series of independent random values of a random variable X with common distribution function $F(x)$ and $Y_1, Y_2,\ldots, Y_k$ ($Y_i=X_i-u$) are the excesses over a high enough threshold u, in some asymptotic sense, the conditional distribution of excesses follows the Generalised Pareto Distribution (GPD):

$$H(y) = P(X-u \le x \mid X>u) = 1-(1+\xi\frac{y}{\sigma^*})^{-1/\xi} \text{ with } y>0 \text{ and } 1+\xi\frac{y}{\sigma^*}>0 \quad [3]$$

where $\sigma^*>0$ and ξ denote the scale and shape parameters of the distribution, respectively. For $\xi=0$, the GPD results in an exponential distribution with parameter $1/\sigma^*$. An appropriate threshold u should be selected, which defines the level upon which an extreme event is defined. Two different methodologies are used here for the threshold selection: (a) the mean residual life plot of the excesses of different threshold values and (b) the plots of σ^* and ξ for a variety of possible threshold values. The mean residual life plot consists of the points:

$$\left\{(u, \frac{1}{n_u}\sum_{i=1}^{n_u}(x_i-u) : u < x_{\max}\right\} \quad [4]$$

where $x_1,\ldots x_{nu}$ consist of the n_u observations that exceed u and $x_{\max}$ is the largest of the X_i. An appropriate threshold value is the value of u above which the mean residual life plot is approximately linear and estimates of σ^* and ξ are constant with u. Due to sampling variability, estimates of these parameters will not be exactly constant, but they should be stable after allowance for their sampling errors. The GPD presents a completely different tail behavior based on the value of the shape parameter, ξ. For $\xi<0$ the distribution of excesses has an upper bound, while for $\xi>0$ it has no upper limit.

Modelling the data over a high threshold using the GPD assumes independence of successive observations. In practice, there is considerable short-range dependence in precipitation data. When several threshold exceedances occur close in time they are considered to form a cluster. The presence of short range dependence affects the limiting behaviour of extreme events primary through the value of the extremal index, θ (Ledford and Tawn, 2003). The extremal index is defined as the reciprocal of the mean cluster size and can be calculated as $\theta = n_c/n_u$, where n_c is the number of clusters and n_u the number of exceedances of the threshold. When $\theta = 1$, the extreme value series can be considered approximately independent. A simple way to define a cluster of events, is to set an appropriate threshold and to consider all consecutive events that overpass it to belong to the same cluster. The cluster should be terminated when r consecutive observations fall below the threshold and the next exceedance defines a new one.

The return period of an extreme event describes its expected frequency of appearance. It determines the frequency of average equalization or exceedance of a certain variable. It is usually expressed in years and it is defined as the reciprocal of the annual exceedance frequency. A basic goal of extreme value analysis is the determination of the T-years return level. This is defined as the limit for which the average number of exceedances within a time interval of duration T, is equal to unity. Therefore, the return level determines the (1-1/T) quantile of the distribution function F, corresponding to a return period of T years. For the GEV distribution function and for $\xi \neq 0$, the estimates of the extreme value quantiles are assessed by means of the following (Coles, 2001):

$$z_p = \mu - \frac{\sigma}{\xi}[1-\{-\log(1-p)\}^{-\xi}] \quad [5]$$

where $G(z_p)=1-p$. The variable z_p is the return level corresponding to the $1/p$ years return period, expected to be exceeded on average once every $1/p$ years. For the GPD distribution function the z_p return level is estimated considering the declustering procedure implemented. The short-range dependence between precipitation values is incorporated in the return level estimation through the extremal index, θ. Estimates of extreme quantiles are assessed for $\xi \neq 0$ using the following formula (Coles, 2001):

$$z_p = u + \frac{\sigma}{\xi}[(p \cdot n_y \cdot \zeta_u \cdot \theta)^{\xi} - 1] \qquad [6]$$

where n_y is the number of observations per year and ζ_u the exceedance rate of the threshold, u. For a stationary phenomenon, the return level plot determines the variation of the variable z_p of Eq. [5] or Eq. [6] with the variable y_p =-log(1-p) represented in a logarithmic scale. The variability of the return level estimates is assessed using the delta method:

$$Var(z_p) \approx \nabla z_p{}^{\mathrm{T}} V \nabla z_p \qquad [7]$$

where V is the variance-covariance matrix of the estimates of the parameters of each distribution. The delta function is also calculated for these estimates.

The goodness of fit of both extreme value distributions is judged using diagnostic plots. These diagnostic plots consist of probability plots and quantile plots that compare the empirical and fitted distribution functions of the samples in a probabilistic or data scale, respectively, return level plots and density plots. The return level plots consist of the points {(logy_p, z_p): 0<p<1}, where z_p is calculated using Eq. [5] or [6]. Confidence intervals, calculated using Eq. [7], and empirical estimates of the return level function are also added to the plot, to enable a goodness of fit diagnostic. The density plot includes a comparison of the probability density function of the fitted model with a histogram of the data.

4. PARAMETER ESTIMATION METHODS

The maximum likelihood estimation procedure (MLE) can be utilized to estimate the parameters of the fitted distribution functions. The likelihood function of n independent random variables can be defined as their joint probability density function and can be assessed as a function of the parameter vector **θ** of their distributions. The ML estimator is asymptotically unbiased, consistent and efficient, when the distribution function of the studied variable can be considered known. Also, the MLE procedure can be utilized to assess the standard deviation of the parameters of the fitted model. If $X_1,\ldots, X_n$ are independent random variables following the GEV distribution function, the maximum likelihood function for $\xi \neq 0$ is (Coles, 2001):

$$l(\mu,\sigma,\xi) = -n\log\sigma - (1+1/\xi)\sum_{i=1}^{n}\log[1+\xi(\frac{x_i-\mu}{\sigma})] - \sum_{i=1}^{n}[1+\xi(\frac{x_i-\mu}{\sigma})]^{-1/\xi} \qquad [8]$$

For the GPD the maximum likelihood function for $\xi \neq 0$ is (Coles, 2001):

$$l(\sigma^*,\xi) = -n_u \log\sigma^* - (1+1/\xi)\sum_{i=1}^{n_u}\log(1+\xi\frac{y_i}{\sigma^*}) \qquad [9]$$

where $y_i=x_i-u$ and u is the threshold selected using the procedures described in Section 3.

The MLEs of the parameters μ, σ and ξ of the GEV family of distributions and σ^* and ξ of the GPD family of distributions, result from the maximization of Eq. [8] and [9], respectively. However, this method is not applicable in cases where the MLEs do not exist, or they are not unique or present bias (Koch, 1991). It has been observed that the ML estimator can lead to inadmissible results. However, it has been proven that when the sample size is large enough, the ML estimator is a good choice (van Gelder, 1999).

The MLE procedure has been proven to be fully efficient for large sample sizes, while for small sample sizes the maximum likelihood estimates can be unstable. Also, it is known from the literature that the MLE should be used for parameter estimation of the extreme value distribution functions, when the shape parameter of the distribution is calculated within the interval [-0.5, 0.5]. To remedy the abovementioned problems, the Generalized Maximum Likelihood Estimation (GMLE) procedure is introduced to force the shape parameter to take more realistic values. Based on different studies, the GMLE has been proven to better represent the shape parameter, assuring also a narrower confidence interval of the parameter, especially for precipitation data (Madsen and Rosbjerg, 1997).

Martins and Stedinger (2000) developed the GML estimator, in which the shape parameter is limited to the interval [-0.5, 0.5]. A Beta prior distribution function is constructed for the shape parameter with parameters equal to q=9 and p=6, with a mode at 0.1 and 90% of its probability mass concentrated over values of -0.1 and 0.3. More specifically, according to Martins and Stedinger (2000):

$$\pi(\xi) = \frac{(0.5-\xi)^{p-1}(0.5+\xi)^{q-1}}{B(p,q)} \quad \text{where} \quad B(p,q) = \frac{\Gamma(p)\Gamma(q)}{\Gamma(p+q)} \qquad [10]$$

Therefore, the Generalized Maximum Likelihood (GML) function is:

$$GL(\boldsymbol{\theta}|x) = L(\boldsymbol{\theta}|x)\pi(\xi) \qquad [11]$$

where **θ** is the parameter vector of each distribution function.

5. PRECIPITATION DATASETS

The precipitation datasets of the present work comprise of both climatic predictions of the RegCM3_10 model and observations obtained from the Hellenic National Meteorological Service of Greece for four selected study areas. The four areas studied are presented in Figure 1 and include Thessaloniki (area 1), Lesvos (area 2), Heraklio (area 3) and Corfu (area 4). The selection of the four areas mainly intends in examining Greek locations that can be considered representative in a climatological framework. The study of the extreme present and future precipitation climate in these areas can provide useful information for the entire Greek area.

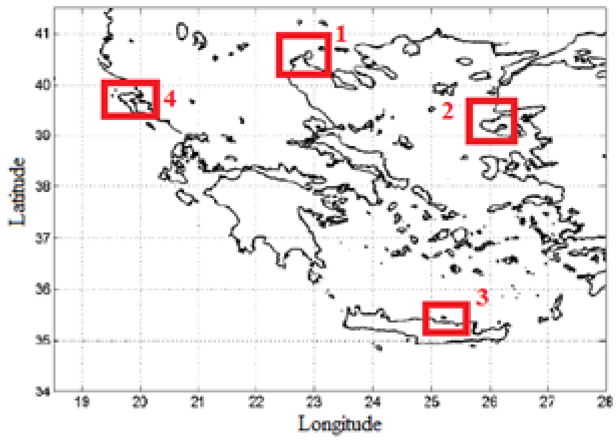

Figure 1. Locations of the four study areas

The datasets provided from the National Meteorological Service (HNMS) correspond to a time period of 43 years (1958-2000) and have a daily time resolution. The locations of the measurements correspond to [22.57°, 40.31°] for area 1, [26.35°, 39.03°] for area 2, [25.09°, 35.19°] for area 3 and [19.55°, 39.37°] for area 4. There are no missing values in the datasets provided.

Climatic data of the present work result from the RegCM3_10 Regional Climate Model (RCM) with 10x10 km spatial resolution for the Greek region. RegCM3_10 is an enhanced version of the regional model RegCM3_25 with a spatial resolution 25x25 km. RegCM3 was built upon the NCAR-Pennsylvania State (PSU) University Mesoscale Model version 4 (MM4) (Dickinson et al., 1989). The model uses the A1B SRES emissions scenario (Jacob, 2007) for its future projections. For the Greek area, the model predicts a small decrease of precipitation and an increase of temperature for the last thirty years of the 21st century (Velikou et al., 2014). However, this decrease is detected only in extreme precipitation in the summer period, while for the winter months there are strong seasonal variations on a local scale. The grid point of the model database closest to the meteorological gauge is selected for the extremal analysis. It should be noted that the topographical characteristics for the locations of the meteorological gauge and the climatic data are taken into consideration, in order to select the grid point that corresponds to a location with similar characteristics with the one where observations are available. Thus, for areas 1 (Thessaloniki) and 4 (Corfu) the grid point closest to the gauging location is selected for further analysis. For area 3 (Heraklio), the gauging location is almost in the middle of the four grid points. In this case, an average of the four time series is utilized. For area 2 (Lesvos), although there is a grid point close to the gauging location, there are significant differences in the topography of the two locations. Therefore, the second closest point to the gauging location is selected.

Bias correction techniques described in Section 2 are then implemented to the model data. The selection of the most appropriate method for such a correction is performed using quantile plots to compare the transfer functions of the candidate models. Both parametric and non-parametric techniques are utilized. Bias correction techniques are implemented to the present climate data (1958-2000) in order to correct the pdf of the simulated values to match the pdf of the observations. To distinguish between parametric and non-parametric methods, it should be noted that even if the non-parametric methods outperform the parametric ones, they may generate inadmissible results outside the range of the correction function. Therefore, when future simulations are significantly higher than the current climate simulations, parametric methods are more usually utilized. After selecting the appropriate transfer function, the correction is also implemented to the future climate simulations. For areas 1 (Thessaloniki) and 3 (Heraklio), the parametric exponential function is selected as the most appropriate bias correction technique. For areas 2 (Lesvos) and 4 (Corfu) the non-parametric approach is utilized, where the empirical distribution functions of the observed and the model data are represented by means of tables of empirical percentiles. The values between them are assessed by means of a monotonic tricubic spline function in the former case and by means of linear interpolation in the latter.

Some basic descriptive statistics for the wet days of all datasets (observations, model data, bias corrected data) and for all four areas are provided in Tables 1-4. The tables include minimum and maximum values, estimates of mean and median, as well as estimates of standard deviation, skewness and kurtosis of the data (wet days only). The number of dry days in each period is also shown.

For the area of Thessaloniki (area 1), it should be noted that the model data of 1951-2000 present different statistical characteristics from the observed data sample (1958-2000). The mean value and the standard deviation of precipitation in the modeled sample are lower than the ones for the observed sample. However, the opposite is true for the statistical measures of skewness and kurtosis. The skewness of the climatic precipitation data is almost 53% higher than the respective measure for the observations, while for kurtosis this proportion raises to almost 94%. These differences become milder after correcting the data for bias. The respective proportions for the corrected datasets are estimated at 20.5% and 24.5%, for skewness and kurtosis, respectively. The mean and maximum values of the bias corrected data (1951-2000) are close to the values estimated for the observations, while the standard deviation is assessed almost 11% higher for the corrected dataset. Comparing the different statistics of the model data for all three periods, a quite stable mean value can be observed, while the higher order statistics present a progressive increase. Therefore, the first future period (2001-2050) presents increased values of 5.3%, 15.4% and 39.5% in standard deviation, skewness and kurtosis, respectively, compared to the present climate period (1951-2000). These proportions are 3.3%, 35% and almost 134%, when comparing the two future periods (2051-2100 and 2001-2050). These differences are quite preserved for the bias corrected samples. Thus, after correcting the data for bias, the first future period presents 7.4%, 17% and almost 42% increase in standard deviation, skewness and kurtosis, respectively, compared to the present climate. When comparing the abovementioned statistical measures of the second future period with the ones of the first future period, the increases reach 8%, 37.5% and almost 144% for standard deviation, skewness and kurtosis, respectively.

Table 1. Descriptive statistics for the wet days of all datasets of area 1 (Thessaloniki)

Statistical measures	Observations	Climatic/ Model data			Bias corrected data		
	1958-2000	1951-2000	2001-2050	2051-2100	1951-2000	2001-2050	2051-2100
Min (mm)	0.1	0.01	0.01	0.01	0.4	0.4	0.4
Max (mm)	98.0	84.8	116.3	185.7	97.8	135.3	218.6
Median (mm)	2.1	0.5	0.5	0.4	1.9	1.9	1.8
Mean (mm)	4.9	2.4	2.5	2.4	5.0	5.0	5.0
Standard deviation (mm)	7.3	5.7	6.0	6.2	8.1	8.7	9.4
Skewness	3.4	5.2	6.0	8.1	4.1	4.8	6.6
Kurtosis	21.7	42.1	58.7	137.2	27	38.3	93.4
Number of dry days	11774	9682	9760	10750	13986	13831	14517

For the area of Lesvos, the mean value and the standard deviation of precipitation in the modeled sample are lower than the ones for the observed sample, while the statistical measures of skewness and kurtosis are assessed higher. The skewness of the climatic precipitation data is 57% higher than the respective estimate for the observations. The kurtosis of the model data is also significantly higher than the one for the observations. These differences are almost negligible after correcting the data for bias. This can be attributed to the non-parametric bias correction method applied. Comparing the different statistics of the model data for all three periods, a quite stable mean value can be observed, while the higher order statistics present an increase in the intermediate period and a subsequent decrease (or stability for the standard deviation) in the last period. Therefore, for the standard deviation, the skewness and the kurtosis, the first future period (2001-2050) presents increased values compared to present climate period, up to 15.7%, 25.5% and 50.6%, respectively. For the period 2051-2100 the statistical measures of skewness and kurtosis decrease by almost 10% and 25%, respectively. After correcting the data for bias, the first future period presents an increase of 15.5%, 27.5% and 45%, in standard deviation, skewness and kurtosis, respectively, compared to the interval 1951-2000. During the second future period, the decreases in the higher moments are lighter and are estimated at almost 5.5% for skewness and 7% for kurtosis.

Table 2. Descriptive statistics for the wet days of all datasets of area 2 (Lesvos)

Statistical measures	Observations	Climatic/ Model data			Bias corrected data		
	1958-2000	1950-2000	2001-2050	2051-2100	1950-2000	2001-2050	2051-2100
Min (mm)	0.1	0.01	0.01	0.01	0.1	0.1	0.1
Max (mm)	127.9	134.5	152.2	128.5	127.9	145.7	127.3
Median (mm)	4.0	1.2	1.1	1.1	4.0	4.0	4.1
Mean (mm)	9.1	3.8	3.9	4.0	9.0	9.6	9.7
Standard deviation (mm)	12.9	7.0	8.1	8.1	12.9	14.9	14.9
Skewness	3.0	4.7	5.9	5.3	2.9	3.7	3.5
Kurtosis	16.5	41.5	62.5	46.9	15.6	22.6	21.0
Number of dry days	12641	11408	11355	12298	14992	14832	15280

For the area of Heraklio (area 3), almost all statistical measures of precipitation in the climatic sample of the present climate are assessed lower than the ones for the observed sample. The differences observed in the basic statistical measures of the two datasets are reduced after correcting the data for bias. Comparing the different statistics of the model data for all three periods, a quite stable mean value and a standard deviation that does not have large variations can be observed, while the higher order statistics present a decrease in the intermediate period and an increase in the last period. Therefore, for skewness and kurtosis, the first future period (2001-2050) presents 17% and 37.8% reduced values, compared to the present climate period. The respective increases for the period 2051-2100 are assessed at 53% and 175%. After correcting the data for bias, the first future period presents a decrease of 27% in skewness and 52.7% in kurtosis, compared to the period 1951-2000. When comparing the statistical measures of standard deviation and skewness of the second future period with the ones of the first future period, the increases reach 21.4% and 80%, respectively. The kurtosis of the wet days of the second future period is almost three times the one estimated for the first future period.

Table 3. Descriptive statistics for the wet days of all datasets of area 3 (Heraklio)

Statistical measures	Observations	Climatic/ Model data			Bias corrected data		
	1958-2000	1950-2000	2001-2050	2051-2100	1950-2000	2001-2050	2051-2100
Min (mm)	0.1	0.01	0.01	0.01	1.0	1.0	1.0
Max (mm)	222.2	102.5	70.8	139.3	222.3	141.5	323.3
Median (mm)	3.0	0.5	0.5	0.4	3.8	4.0	4.1
Mean (mm)	6.7	2.3	2.4	2.3	7.6	7.9	8.1
Standard deviation (mm)	10.6	4.9	4.9	5.3	11.9	11.7	14.2
Skewness	5.5	5.9	4.9	7.5	6.3	4.6	8.3
Kurtosis	72.1	63.5	39.5	108.8	70.4	33.3	123.4
Number of dry days	12612	8827	18862	9812	15086	14867	15375

For the area of Corfu (area 4), the mean value and the standard deviation of precipitation in the climatic sample are lower than the ones for the observed sample, while the statistical measures of skewness and kurtosis are assessed higher. The skewness and the kurtosis of the model precipitation data are about 38% higher than the respective measures for the observations. These differences are almost negligible after correcting the data for bias. This can be attributed to the non-parametric bias correction method applied. Comparing the different statistics of the model data for all three periods, a quite stable mean value can be observed, while the higher order statistics present a decrease in the intermediate period and an increase in the last period. Therefore, for the standard deviation, the skewness and the kurtosis, the first future period (2001-2050) presents decreased values compared to the present climate period (1951-2000), with proportions of 7.4%, 10% and 17.3%, respectively. The respective increases for the period 2051-2100 are assessed at 12.6%, 20% and 46.8%. After correcting the data for bias, the first future period presents a decrease of 6%, 14.3% and 27.5% in standard deviation, skewness and kurtosis, respectively, compared to the period 1951-2000. When comparing the abovementioned statistical measures of the second future period with the ones of the first future period, the increases reach 14.4%, 56.7% and almost 165% for standard deviation, skewness and kurtosis, respectively.

Table 4. Descriptive statistics for the wet days of all datasets of area 4 (Corfu)

Statistical measures	Observations	Climatic/ Model data			Bias corrected data		
	1958-2000	1951-2000	2001-2050	2051-2100	1951-2000	2001-2050	2051-2100
Min (mm)	0.1	0.01	0.01	0.01	0.1	0.1	0.1
Max (mm)	239.3	141.0	133.6	154.0	239.3	211.3	285.4
Median (mm)	4.6	1.1	1.1	1.1	4.6	4.8	5.0
Mean (mm)	10.4	4.4	4.3	4.5	10.3	10.1	10.7
Standard deviation (mm)	14.9	9.4	8.7	9.8	14.8	13.9	15.9
Skewness	3.6	5.0	4.5	5.4	3.5	3.0	4.7
Kurtosis	28.6	39.3	32.5	47.7	26.6	19.3	51.2
Number of dry days	11200	10603	10628	11428	13256	13155	13716

6. ANALYSIS OF EXTREME PRECIPITATION

The analysis of extreme precipitation events includes the fitting of the extreme value distributions GEV and GPD to all datasets (bias corrected present climate, bias corrected future climate, observations) of all the studied locations. The GEV is fitted to annual maxima of precipitation for each study period, while the GPD is fitted to the excesses of appropriately defined thresholds for each location and time period considered. The MLE is used for parameter estimation with both distribution functions. The ML estimator is replaced by the GML estimator, when the former provides inadmissible results in the shape parameter space, accounting for the shape parameter 95% confidence intervals.

For Thessaloniki (area 1) the GEV-MLE fits the annual maxima of the bias corrected sample quite well for the present climate and the first period of the future climate. However, the distribution function of precipitation extremes appears to be upper bounded for the period 1951-2000, while the uncertainty in the return level estimates appears quite increased for the period 2001-2050. For the future period 2051-2100, the GEV-MLE fails to represent the most extreme values of precipitation, even if it presents quite a good fitting to the upper part of the data sample. For implementing the GPD, a time interval of r = 3 days is selected between cluster peaks for all time periods considered, to insure mutual independence between extreme precipitation events. For the present climate period (1951-2000) and the two periods of the future climate (2000-2050 and 2051-2100), the selected thresholds are set at 20mm, 22mm and 17mm, respectively. The respective estimates of the extremal indices are 0.879, 0.895 and 0.847. It should be noted that for all three periods, the standard errors of the parameters are significantly reduced, compared to using the GEV distribution function, therefore limiting uncertainty in return level estimates for both the present and the future climate conditions (this reduction reaches 40.8% (113mm) for the interval 2001-2050 and for a return period of 500 years). The ML estimate of the shape parameter is positive for all three periods considered, identifying a heavy-tailed extreme value distribution, quite common for precipitation extremes. For the third interval considered (2051-2100), the fitted GPD does not again represent the most extreme value of the data sample well, however this value lies closer to the upper 95% confidence interval for a return period of 50 years, compared to the fitted GEV distribution function. Therefore, for the area of Thessaloniki the GPD with its parameters estimated by means of the MLE is selected as the most appropriate model for the present and the future climate conditions.

For Lesvos (area 2), the fitting of the GEV distribution function to the samples of all three periods considered is judged to be good. However, the uncertainty associated with these return level estimates is high enough even for low return periods. Fitting the GPD to all three time periods considered improves the results extracted. For the present climate period (1951-2000) and the two periods of the future climate (2001-2050 and 2051-2100), the selected thresholds are set at 31mm, 34mm and 33mm, respectively. The respective estimates of the extremal indices are 0.822, 0.839 and 0.814. The diagnostic plots for the GPD, not presented here for the sake of brevity, are improved compared to the ones of the GEV for all time intervals, while the uncertainty associated with return level estimates is reduced, compared to fitting the GEV distribution function. It should be noted that for the interval 1951-2000 and for a high return period of 500 years, the uncertainty in precipitation extremes is limited by almost 64% (178mm) when using the GPD, compared to the annual maximum model. The GPD function with its parameters estimated utilizing the MLE procedure is again selected as the best fitted model. Figure 2 presents the return level plot for all three time periods considered (1951-2000, 2001-2050 and 2051-2100) for the areas of Thessaloniki and Lesvos. The plot includes the maximum likelihood estimates and the 95% confidence intervals of precipitation return level for all three periods. Figure 2 also presents the return level plot of the observations (1958-2000) for evaluating the performance of the bias correction method used for each location, together with the data used for all time periods.

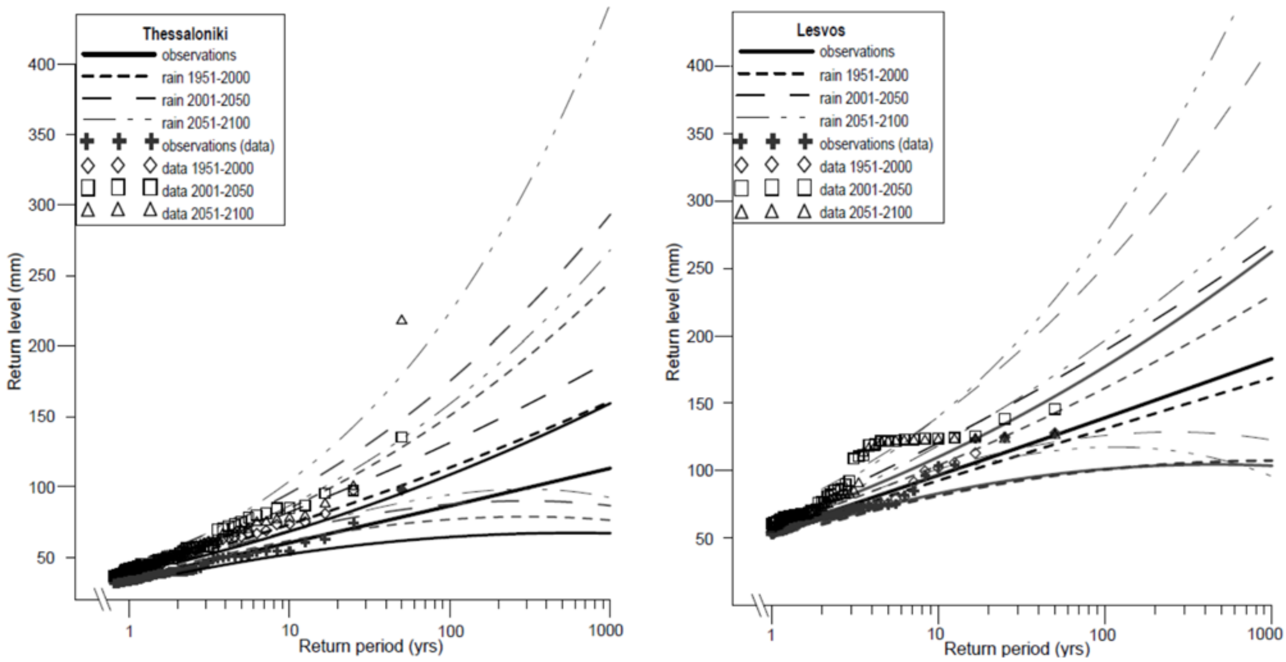

Figure 2. Precipitation return level plots for present and future climate conditions for Thessaloniki and Lesvos

The study of the return level estimates for the area of Thessaloniki indicates an increase in the intensity of extreme precipitation events during the whole future time period. Comparing the precipitation return level estimates of the present climate period (1951-2000) with the ones of the first future period (2001-2050), an increase of 14.6% (14.7 mm) and 15.5% (17.6 mm) can be estimated for the latter one, for return periods of 50 and 100 years, respectively. Confidence interval bounds of the first future period appear also increased compared to the associate bounds of the present climate. During the future time period 2051-2100 precipitation return level estimates also appear increased by 32.8% (33.1 mm) and 39.8% (45.3 mm), compared to the present climate period, for return periods of 50 and 100 years, respectively. Confidence interval bounds and confidence interval ranges also appear increased. Precipitation extremes in Thessaloniki present an upward trend during the three periods considered. From Figure 2 a large difference in return level estimates can be observed between the bias corrected present climate data and the observations (1958-2000). This difference can be attributed to the parametric model utilized for the correction of bias of the climatic data. This model overestimates the extreme percentiles of the data sample, even if it represents the highest observation very well. Another parametric model, which provides a better fit on a quantile-quantile level plot, could provide closer return level estimates between the climatic data and the observations.

In Lesvos, precipitation extremes also appear increased in the future period compared to the present climate conditions. This is valid for both future climate periods. More specifically, for the future period 2001-2050, an increase in extreme precipitation of 39.9% and 44.3%, compared to the present climatic conditions, is assessed for return periods of 50 and 100 years, respectively. These proportions correspond to precipitation of 47.8 mm and 58.1 mm, respectively. During the third time period 2051-2100, the increase is higher and is estimated at 43.1% and 50.1%, respectively. The respective quantities are almost 51.5 mm and 65.6 mm. It should be noted that due to the non-parametric bias correction procedure used, there is a close agreement between precipitation return level estimates of the present climate climatic data and the observations.

For Heraklio (area 3), the GEV-MLE presents inadmissible results in terms of the shape parameter of the model for the two periods of the future climate. The use of the GEV-GMLE model for these two periods leads to better results. However, diagnostic fitting plots, not presented here for the sake of brevity, are significantly improved when fitting the GPD function to all three periods considered. For the present climate period (1951-2000) and the two periods of the future climate (2001-2050 and 2051-2100) the selected thresholds are set at 24mm, 32mm and 34mm, respectively. The respective estimates of the extremal indices are 0.770, 0.840 and 0.850. The GPD-MLE is selected for the first two 50 years periods (1951-2000 and 2001-2050) and the GPD-GMLE is judged to be the most appropriate model for the period 2051-2100. It should be noted that for the period 2001-2050 and for a return period of 500 years, the range of the 95% confidence interval of precipitation becomes narrower by almost 50% when fitting the GPD, compared to the GEV distribution function.

For Corfu (area 4) the GEV-MLE fitted to the bias corrected sample is judged to perform well only for the present climate conditions. For the future period 2001-2050, the GEV distribution does not represent the most extreme value of the dataset, while for the future period 2051-2100 the use of the MLE leads to inadmissible results for the shape parameter of the distribution. Therefore, for this period the GEV distribution is fitted utilizing the GMLE. However, the fitting of the GEV-GMLE to the annual maxima of the period 2051-2100 is judged quite poor, since the most extreme data of the sample are not well represented by the model. For implementing the GPD, a time interval of r = 3 days is selected between cluster peaks for all time periods considered, to insure mutual independence between extreme precipitation events. For the present climate period (1951-2000) and the two periods of the future climate (2001-2050 and 2051-2100) the selected thresholds are set at 34mm, 42mm and 32mm, respectively. The respective estimates of the extremal indices are 0.799, 0.838 and 0.755. The GPD function with parameters estimated using the MLE is also selected in Corfu for modelling precipitation extremes in all three time periods of study. The GPD presents a better fit to the most extreme part of the sample in all time periods, compared to the GEV, while return level confidence intervals are estimated narrower in all three time periods (this difference reaches 77.8% for the period 2051-2100 and for a return period of 500 years). Figure 3 presents the return level plot for all three time periods considered (1951-2000, 2001-2050 and 2051-2100) for the areas of Heraklio and Corfu. The plot includes the maximum likelihood estimates and the 95% confidence intervals of precipitation return level for all three periods. Figure 3 also presents the return level plot of the observations (1958-2000), together with the data used for all time period.

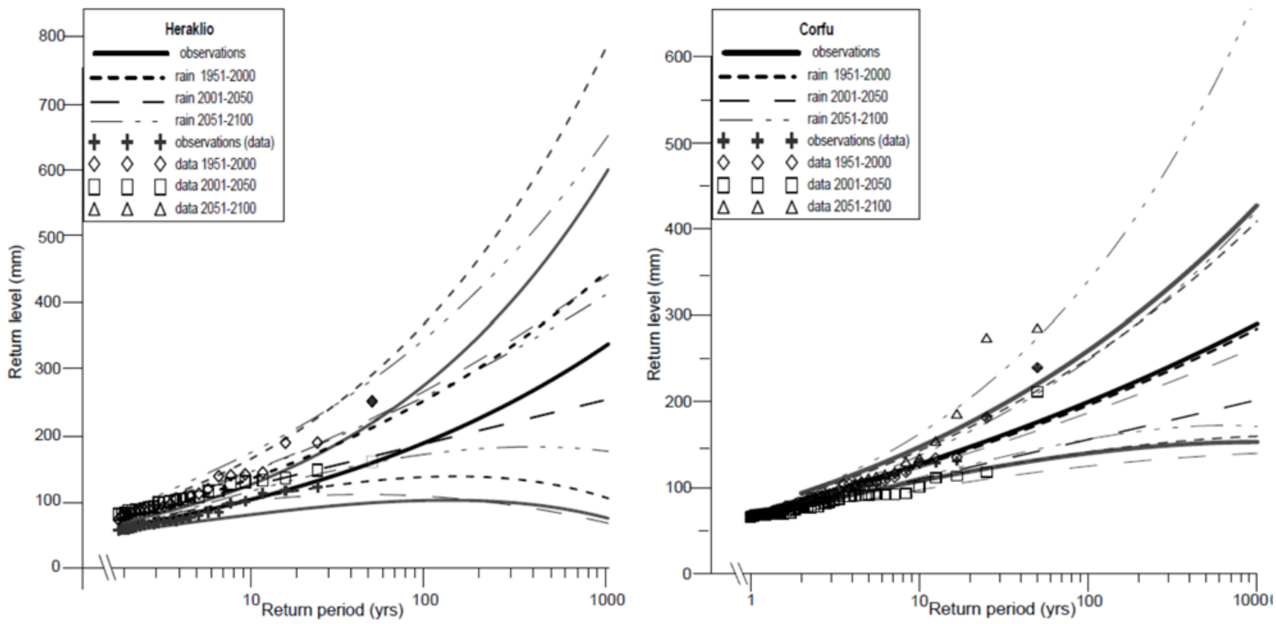

Figure 3. Precipitation return level plots for present and future climate conditions for Heraklio and Corfu

For Heraklio in the intermediate period (2001-2050), a decrease in extreme precipitation, compared to the present climate period, is evident. During the future period 2051-2100, there are no significant changes in extreme precipitation, compared to present climatic conditions. More specifically, for the period 1951-2000, precipitation return level estimates for return periods of 50 and 100 years are assessed at 187.1 mm and 225.3 mm, respectively. For the short-term future period (2001-2050), the respective return level estimates are calculated at 148.6 mm and 166.4 mm. The estimated decrease is 20.5% for a return period of 50 years and 26.1%, for a return period of 100 years. For the long-term future period the precipitation return level estimates for return periods of 50 and 100 years are assessed at 195.6 mm and 229.9 mm, respectively. Therefore, compared to the present climate period, there is an increase in precipitation extremes of almost 4.6% (8.6 mm) for a return period of 50 years and 2.1% (4.7 mm), for a return period of 100 years. From Figure 3, a difference in return level estimates can be observed between the present climate data from the climatic model, after being corrected for bias, and the observations (1958-2000). This difference is attributed to the parametric model utilized for the correction of bias of the climatic data.

In Corfu, during the short-term future period (2001-2050), a decrease in precipitation extremes is presented, compared to present climate conditions, while for the long-term future period an increase is apparent. More specifically, for return periods of 50 and 100 years, the precipitation return level is estimated at 172.5 mm and 195.5 mm, respectively, for the present climate conditions. The respective estimates for the future period 2001-2050 are almost 142.0 mm and 155.8 mm. Therefore, for this future period the decrease in extreme precipitation is assessed at 17.7% and 20.3%, for return periods of 50 and 100 years. On the other hand, for the future period 2051-2100, the 50-years and 100-years precipitation levels are calculated at 209.1 mm and 247.8 mm, respectively. Therefore, for this future period an increase in precipitation return level estimates is assessed, compared to the present climate period. This increase reaches 21.2% and 26.8%, for return periods of 50 and 100 years, respectively. It should be noted that for this area, there is a close agreement between precipitation return level estimates of the present climate mofel data and the observations (1958-2000). This agreement is attributed to the selected non-parametric bias correction method utilized.

7. CONCLUSIONS

In the present work the effects of climate change on precipitation extremes in four selected Greek areas are studied. More specifically, the projections of RegCM3_10 climatic model covering a time period of 150 years (1951-2100) are separated in three parts of equal size, in order to represent the fifty years of the current, the short-term and the long-term future climate. Model precipitation data is found to hold bias, commonly detected in regional climate models, making it necessary to perform various methods of bias correction. Both parametric and non-parametric methods are used for the four regions studied, selecting the most appropriate for each one. Extreme value theory is then implemented for the bias corrected precipitation datasets and both GEV (Generalized Extreme Value Distribution) and GPD (Generalized Pareto Distribution) including the extremal index, θ, for declustering extremes, are fitted. Return level estimates of each 50 year-period are estimated and compared to assess the changes in the extreme precipitation climate between present and future conditions.

In all four areas considered the GPD, which considers more than a single event per year, represents the extreme precipitation climate more concisely than the GEV and with significantly reduced uncertainty associated with return level estimates. More specifically, for a high return period of 500 years this reduction reaches almost 41% in Thessaloniki for 2001-2050, 64% in Lesvos for the period 1951-2000, 50% in Heraklio for 2001-2050 and almost 78% in Corfu for the period 2051-2100. For implementing the GPD, a time interval of r = 3 days is selected between cluster peaks for all time periods considered, to insure mutual independence between extreme precipitation events

For the study area of Thessaloniki an increase in the intensity of extreme precipitation events during the whole future time period is obvious. Comparing the precipitation return level estimates of the present climate period (1951-2000) with the ones of the short-term future period (2001-2050), an increase of 15.5% (17.6 mm) can be estimated for the latter one, for a return period of 100 years. For such a return period during the long-term future time period, precipitation return level estimates also appear increased by almost 40% (45.3 mm), compared to the present climate conditions.

For the area of Lesvos, precipitation extremes appear increased in the future period compared to the present climate conditions. For the future period 2001-2050, an increase in extreme precipitation of about 44.5%, compared to the present climatic conditions, is assessed for a return period of 100 years. During the third time period considered, the increase is greater and is estimated at about 50% for a return period of 100 years.

For the area of Heraklio, extreme precipitation levels are reduced for the short-term future period, while for the long-term future climate precipitation extremes do not change significantly, compared to present climatic conditions. More specifically, during the short-term future period (2001-2050), the 100-years return level estimate of precipitation is decreased to a proportion of 26%, compared to present climate conditions. For the long-term future period, there is a small increase in precipitation extremes of about 2% (4.7 mm), for a return period of 100 years, compared to the period 1951-2000.

Finally, for the area of Corfu, a decrease in precipitation extremes is presented for the short-term future climate, while for the long-term future period precipitation extremes increase again. More specifically, for a return period of 100 years, the decrease in extreme precipitation during the interval 2001-2050 is assessed at about 20.5%, while for the long-term future period (2051-2100) there is an increase of almost 27%, compared to present climate (1951-2000) conditions.

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