Influence of climate change on extreme values of rainfall

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ABSTRACT

The evaluation of the impact of climate change on extremes is a crucial issue for the resilience of infrastructures and buildings and is a key challenge for adaptation planning policy. In this paper, a suitable procedure for the definition of future trends of precipitation extremes at local scale is presented. Starting from the output of Regional Climate Models, a new weather generator have been implemented to derive factor of changes for daily maximum precipitation considering the different sources of uncertainty affecting climate projections (emission scenarios, global climate model, internal variability). An ensemble of six different climate models have been analyzed and the results are presented for the Italian Mediterranean region proving the ability of the method to define factors of change for climate extremes as well as to assess their evolution in time, also allowing a sound estimate of the uncertainty range associated with different models.

Keywords: Climate Change, Precipitation Extremes, Return Levels, Climate Models, Weather Generator.

1. INTRODUCTION

The evidence of climate change is widely accepted in the scientific community, and since the 1950s, many of the observed changes are unprecedented over decades to centuries [1]. Climate change potentially affects all regions of the world by alteration of natural processes, modification of precipitation patterns, melting of glaciers, rise of sea levels, etc. Whatever the warming scenarios and the level of success of mitigation policies, in the coming decades the impact of climate change is generally expected to increase because of the delayed impacts of past and current greenhouse gas emissions. Then, unavoidable climate change effects need to be considered, taking into account its economic, environmental and social consequences [2].
Climate change has potentially significant adverse implications on the hydrological cycle and water resources [3] as well as on the existing infrastructures, which have been designed according past Codes, under the assumption of stationary climate conditions, which could become inadequate as soon as climate change alters the frequency and the intensity of extremes [4].
The outcomes of many recent studies call for an increase in precipitation extremes due to warming climate, resulting from the observational evidence of heavy rainfall intensifications in several regions all around the world [5] [6]. The observational evidence supports the thermodynamic law, often referred to as the Clausius-Clapeyron relationship, which states that warmer air has a higher water vapor holding capacity [7][8]. According this law, a scaling rate of about 6-7% K^{-1} warming can be predicted, considering the increase in atmospheric moisture content only.
Moreover, the rate of increase of precipitation extremes is affected by multiple factors, like changes in the vertical velocity profile and changes in precipitation efficiency [8].
During the last years, an extensive research in this filed has been carried out to define climate models able to simulate the atmosphere-ocean system and then to provide information about the future climate according different scenarios.
In this paper, a procedure for the assessment of climate change impact on precipitation return levels is presented analyzing the available highest resolution climate projections and evaluating the different sources of uncertainty affecting climate models.

2. CLIMATE MODEL PROJECTIONS

Information about future climate and its change for impact studies is usually inferred from General Circulation Models (GCMs) and at a smaller resolution from Regional Climate Models (RCMs), assuming different greenhouse gasses emission scenarios.
GCMs are able to provide a global coverage for precipitation extremes and the RCMs a more detailed coverage on regional scale [8]. Although some limitations in the ability of current models to simulate precipitation extremes have also been recognized, they allow relatively straightforward investigations into the role of dynamics and other factors that contribute to precipitation intensity [9].
However, often information about climate are required at local scale for impact studies and even at highest resolution a gap remains between the scale of RCM predictions and real applications. One of the most challenging problems in the assessment studies of impacts of climate change is then to bridge this gap and recently, a considerable effort has been made on the development of downscaling techniques for GCMs and RCMs. A comprehensive review on this issue can be found in [10].
Regarding climate projections, three different sources of uncertainty can be identified according to [11]:

- Model uncertainty: as different models may simulate somewhat different changes in the climate, in response to the same radiative forcing;
- Scenario uncertainty: as uncertainty in future emissions of greenhouse gases causes uncertainty in future radiative forcing and hence in the climate.

- Internal Variability of the climate system: as natural fluctuations could arise even in the absence of any radiative forcing of the planet, so potentially to reversing trends associated with anthropogenic climate change.

Of course, in the analysis of climate projections for the assessment of future trends in extremes, all these sources of uncertainty should be duly considered.

In this work, a factor of change approach [3] has been followed to bridge the gap between large scale model and local conditions. The three sources of uncertainty have been taken into account thorough the analysis of an ensemble of different regional climate models (RCMs) outcomes, obtained according different scenarios (RCPs) and implementing a suitable weather generator for the assessment of the internal variability of the models.

Daily climate projection of maximum and minimum temperature (T_{Max} ; T_{Min}) and precipitation (p_r) developed within the EURO-CORDEX initiative [12] have been analyzed in order to generate consistent weather series for the control period 1951-2005 (Historical Experiment), where “run” is forced by observed atmospheric composition changes and for the future period 2006-2100 (RCPs Experiment)[13].

In particular, data provided by the Danish Meteorological Institute (DMI), the CLM Community (CLMcom), the Royal Netherlands Meteorological Institute (KNMI), the Max Planck Institute (MPI-CSC) and the Laboratoire des Sciences du Climat et de l’Environnement – Institute Pierre Simon Laplace (IPSL-INERIS), have been investigated considering two different scenarios, the medium emission scenario (RCP4.5 Experiment) and the highest emission scenario (RCP8.5 Experiment). The model specifications of the analyzed climate projections are sumamrized in Table 1.

Table 1. Overview on the analyzed climate projections and their main characteristics.

Institute	RCM	GCM	Experiment	Period
DMI	HIRHAM5	EC-EARTH	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100
CLMcom	CCLM4-8-17	CNRM-CM5-LR	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100
CLMcom	CCLM4-8-17	EC-EARTH	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100
KNMI	RACMO22E	EC-EARTH	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100
MPI-CSC	REMO2009	MPI-ESM-LR	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100
IPSL-INERIS	WRF331F	CM5A-MR	historical	1951-2005
			RCP4.5	2006-2100
			RCP8.5	2006-2100

Different approach to combine climate models dealing with multi-model ensemble are discussed in literature. In particular, two alternative options can be followed:

- each climate model can be considered as independent and plausible realization of the future climate
- weights can be assigned to climate models based on the performance in reproducing past climate.

A detailed review of these methods can be found in [14]. In this work, unweighted models have been used for the evaluation of changes in extreme temperatures. This approach, known as Ensemble Mean [15], has been opportunely modified here to consider, together with the results obtained from the analysis of the generated weather series associated to each model, the factors of change obtained from the analysis of various climate models, in such a way that the internal variability of the model itself can be appreciated too.

3. STUDY AREA

The following analysis have been carried out for the geographical area which comprises the Zones 3-4 of the Mediterranean climatic region defined by the EN1991-1-3 [12]. These zones are illustrated in Figure 1, together with the 272 cells for which climate projections are provided (EUR-11 grid).

Figure 1. Investigated area in the Italian Mediterranean region

4. METHODOLOGY

4.1 Extreme Value Analysis in a Changing Climate

Classical Extreme Value Theory provides a rigorous framework for the analysis of climate extremes and their return level under the assumption of stationary climate [16]. Since changing climate makes this assumption uncertain, concepts and models accounting for non-stationarity are thus becoming of increasing importance [17]. In this context, a procedure for the estimation of trends in extreme value distribution’s parameters and return levels through the analysis of climate projections in moving time windows, have been developed in [18].

Following this approach, climate data series of daily precipitation (p_r) have been analyzed according different time windows for a correct definition of non-stationary extremes suitable for design.

In particular, the maxima data series have been divided in appropriate time windows of forty year-long shifted by ten years (1956-1996, 1966-2006,…,2056-2095) and for each time window an extreme value analysis has been carried out according to the block maxima approach [19] assuming an extreme value Type I distribution with cumulative distribution function

$$F(x < X) = \exp\left\{-\exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\} \quad with\ \mu \in \mathbb{R} \ \ and\ \sigma > 0 \quad (1)$$

where μ and σ are the location and the scale parameters, respectively. According the least square method, the two distribution’s parameters, μ and σ, have been then estimated for each time window, and, by means of the equation

$$p_k = \mu + \sigma \left\{ -\ln \left[-\ln \left(1 - \frac{1}{m} \right) \right] \right\}, \qquad (2)$$

the values characterized by a probability of exceedance of $1/m$ in 1 year has been determined accordingly, in order to assess the trends of the extremes as well as the factors of change. In particular, according with the current hypotheses, a probability of exceedance of m^{-1}=2% on 1 year has been assumed, corresponding to about 50 years return period, in relation to which the change factor *FC* has been referred, as the ratio between the 50 year return level at the considered time window $p_{r,k}(t)$, and the corresponding 50 year return level at the first time window $p_{r,k}(t=1)$

$$FC(p_{r,k}(t)) = \frac{p_{r,k}(t)}{p_{r,k}(t=1)} \qquad (3)$$

4.2 Weather generator approach

Weather generators are currently used as statistical downscaling technique in climate change impact studies as presented in [3] and [10]. They are statistical models based on regression relations between daily climatic variables, which are able to generate time-series of climatic variables with statistical properties similar to the input ones. In climate changes studies, they are usually applied to generate future weather series from the observed climate statistics factored by a factor of change derived from the analysis of climate model output. The basic assumption is that the climate model could represents better the change in the statistical properties of the climate variable from the present to the future climate, rather than the absolute values of the variables.

In the approach presented by the authors in [20], instead of generating weather series from the statistics of the climate variables, climate data series are generated directly by sampling from the climate model outputs according the algorithm presented in Figure 2. In this way, the internal variability of the climate model can be assessed and uncertainty range for the factor of changes derived from the extreme value analysis of the climate variables can be estimated.

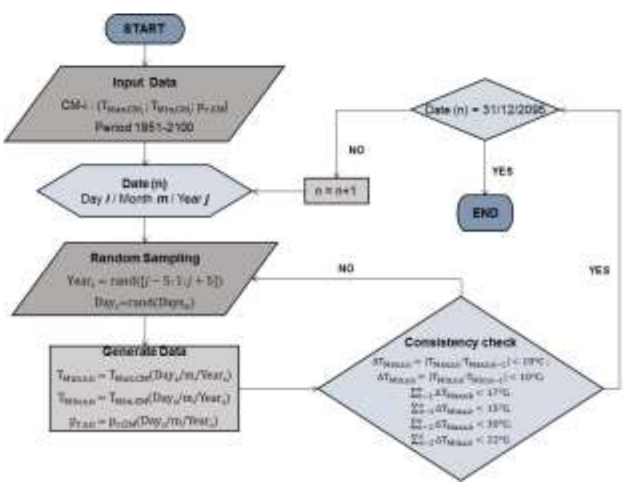

Figure 2. Flow chart of the weather generator algorithm

The input data of the algorithm are the climate data series of daily maximum and minimum air temperatures and precipitation provided by the considered climate model, selected, for example, from those presented in the previous paragraph.

Then, daily data for day *i* of month *m* in year *j* ($T_{\mathrm{Max,s,n}}$; $T_{\mathrm{Min,s,n}}$; $p_{r,s,n}$) are randomly sampled from the daily data of the climate variables at the same month *m* in the period defined by the considered year plus and minus five years [j-5;j+5]. This time window of eleven years for the sampling interval has been considered as appropriate, being long enough to adequately represent the data population as well as short enough to exclude potential effects of climate change in the climate variables.

The random sampling procedure of temperatures and precipitation is implemented with some additional constraints in order to avoid the generation of unrealistic weather data series. In particular, constraints for maximum and minimum temperatures in two, three and five consecutive days have been defined from the analysis of the actual data; so requiring that the following inequalities are fulfilled by the generated data for day *i*:

$$\Delta T_{\mathrm{Max},s,n} = |T_{\mathrm{Max},s,n} - T_{\mathrm{Max},s,n\text{-}1}| < 10°C \qquad (4)$$

$$\Delta T_{\mathrm{Min},s,n} = |T_{\mathrm{Min},s,n} - T_{\mathrm{Min},s,n-1}| < 10°C \qquad (5)$$

$$\sum_{n-1}^{n} \Delta T_{\mathrm{Max},s,k} < 17°C; \sum_{n-1}^{n} \Delta T_{\mathrm{Min},s,k} < 15°C \qquad (6)$$

$$\sum_{n-3}^{n} \Delta T_{\mathrm{Max},s,k} < 30°C; \sum_{n-3}^{n} \Delta T_{\mathrm{Min},s,k} < 22°C \qquad (7)$$

By means of these constraints, consistent climate data series of daily maximum and minimum air temperature ($T_{\mathrm{Max,s}}$; $T_{\mathrm{Min,s}}$) but also precipitation ($p_{r,s}$) have been generated for the period 1956-2095.

Once generated these series, an extreme value analysis can be performed for each series according the procedure presented in the previous paragraph, identifying factor of change for return 50 years return period values of precipitation.

5. FACTOR OF CHANGE MAPS

The results obtained in terms of factors of change for 50 years return period values of precipitation according different climate models have been then combined with equal weights assuming that each individual component of the ensemble is an equally likely representation of future climate.

In this way, different percentiles of the ensemble for a given scenario can be easily evaluated, arriving to estimate changes in extremes together with their uncertainty range. The 25% percentile and 75% percentile have been taken as reference for the prediction interval and have been calculated for each cell in the study region.

Factor of change maps for precipitation can be drawn for each percentile and in order to better represent the results, bivariate color maps have been chosen [21]. The two limit percentiles are then drawn in the same map obtaining in this way a convenient representation of the evolution of extreme precipitation together with their uncertainty interval.

In Figures 3 and 4 factor of change maps for the 50 years return period value of precipitation ($p_{r,k}$) are presented in four time windows (1976-2015, 1996-2035, 2016-2055 and 2035-2075) according the RCP4.5 and RCP8.5 scenario. The resulting mean factor of changes for the region obtained according different percentiles and different time windows are reported in Table 2.

As suggested in [7] and [8], averaging the results over all grid cells allows visualizing changes in heavy rainfall reducing the influence of unforced variability at grid box level where the signal may be obscured by high internal variability. In this way, robust changes in extremes becomes evident, as it is shown in Figure 5.

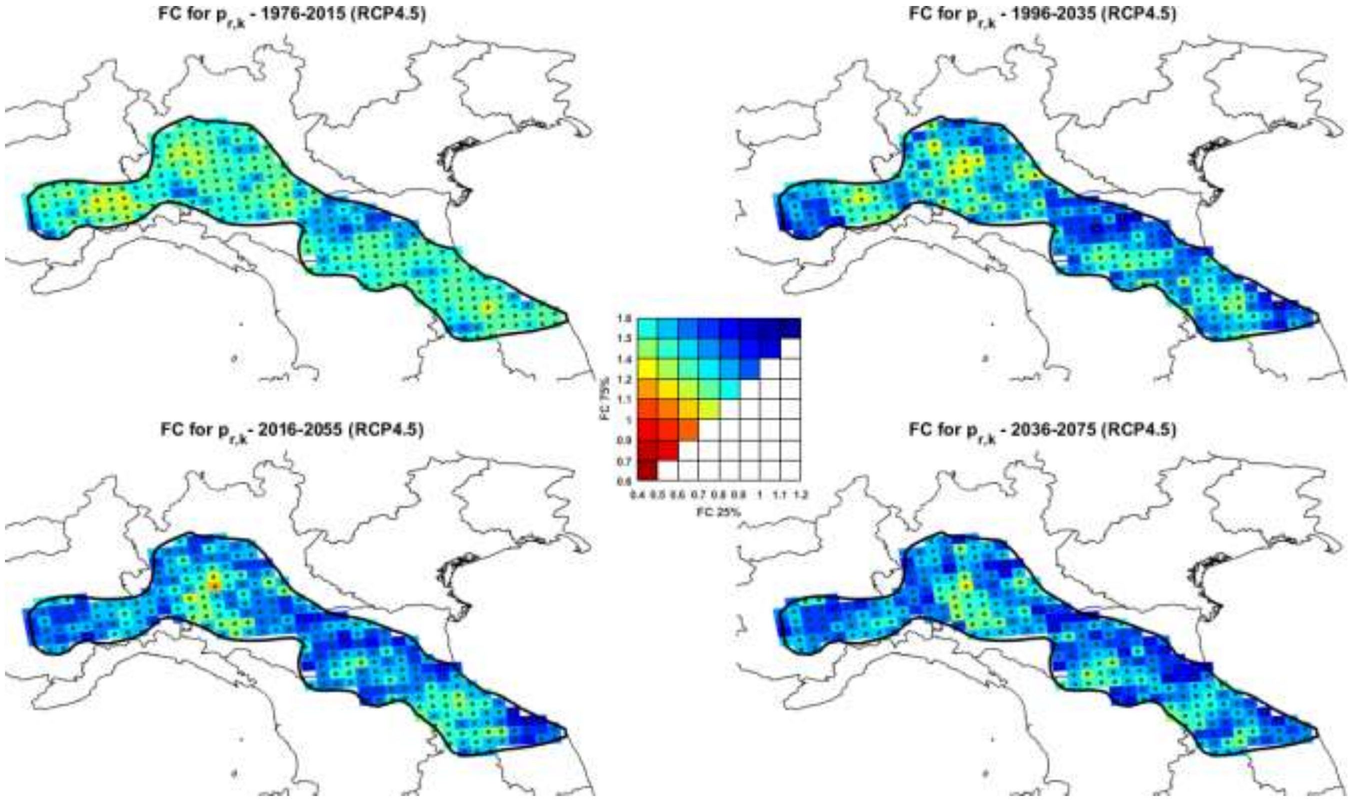

Figure 3. Factor of changes trends in the region of for $p_{r,k}$ Prediction interval [25-75%] Map (Scenario RCP4.5).

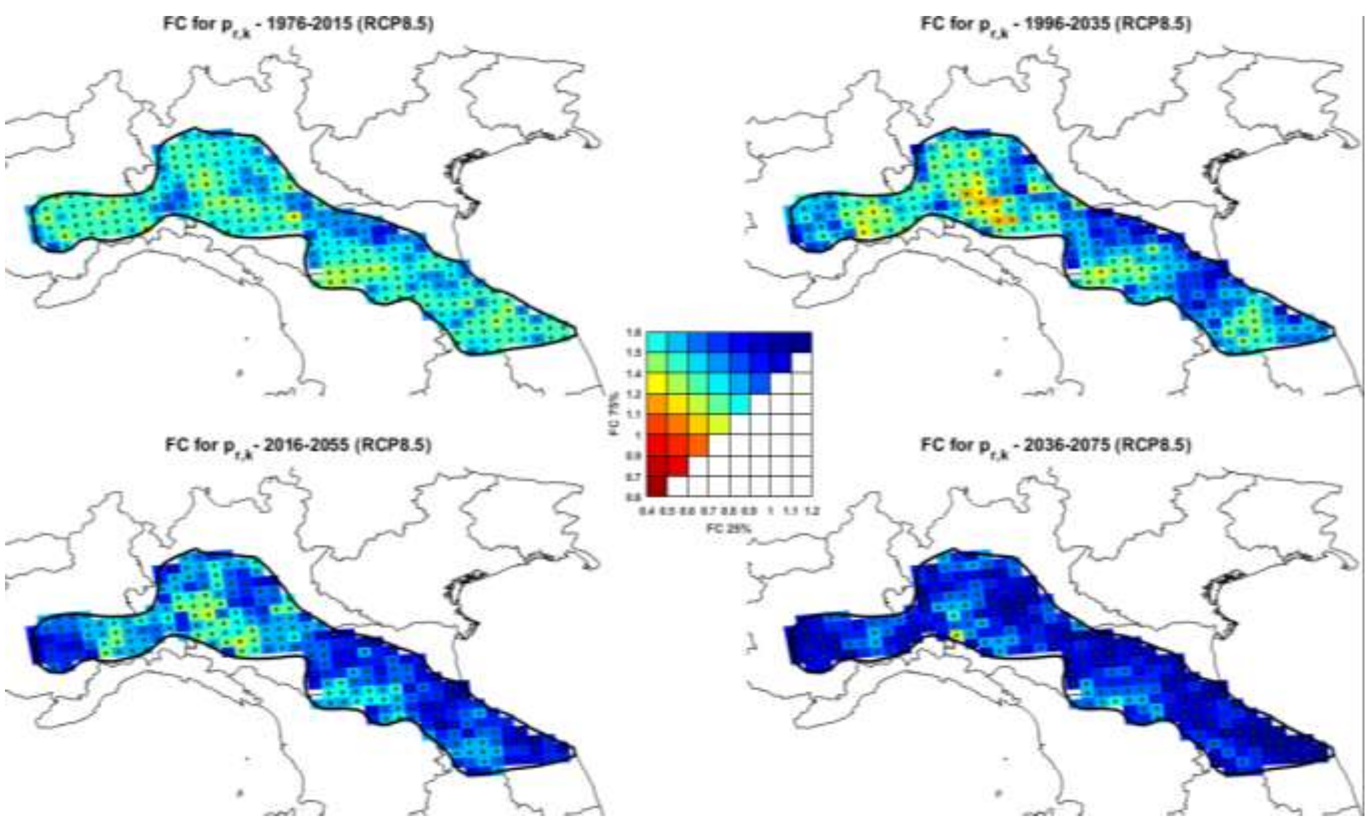

Figure 4. Factor of changes trends in the region of for $p_{r,k}$ Predicition interval [25-75%] Map (Scenario RCP85).

The results confirm that in the 25%-75% prediction intervals an increase in extreme precipitation could be very significant in the near future for the investigated region.
For example, for the time window 2036-2075, assuming a RCP4.5, a factor of change *FC*=1.09 can be envisaged in the region for $p_{r,k}$ a, being *FC*=0.93 and *FC*=1.28 the extremes of the 25%-75% prediction interval, while, assuming a RCP8., it results *FC*=1.20, being *FC*=1.01 and *FC*=1.47.

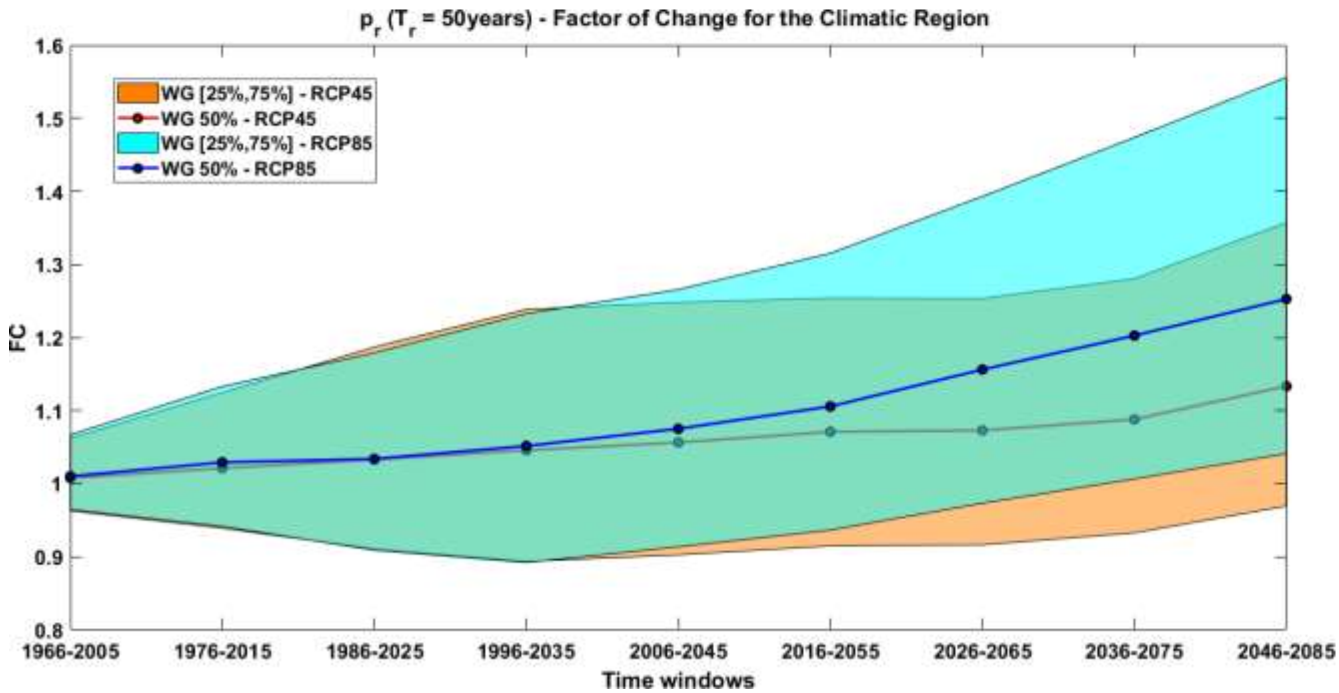

Figure 5. Factor of changes trends in the region of for $p_{r,k}$

Table 2. Mean of Factor of changes percentiles for $p_{r,k}$ in the investigated region .

Time Window	RCP4.5 Factor of Change			RCP8.5 Factor of Change		
	25%	**50%**	75%	25%	**50%**	75%
1966-1995	0,96	**1,01**	1,06	0,96	**1,01**	1,06
1976-2005	0,94	**1,02**	1,12	0,94	**1,02**	1,12
1986-2025	0,91	**1,03**	1,19	0,91	**1,03**	1,18
1996-2035	0,89	**1,05**	1,24	0,89	**1,05**	1,23
2006-2045	0,90	**1,06**	1,25	0,91	**1,08**	1,27
2016-2055	0,91	**1,07**	1,25	0,94	**1,11**	1,32
2026-2065	0,92	**1,07**	1,25	0,97	**1,16**	1,39
2036-2075	0,93	**1,09**	1,28	1,01	**1,20**	1,47
2046-2085	0,97	**1,13**	1,36	1,04	**1,25**	1,56

6. CONCLUSIONS

In order to assess the impact of climate change on extreme rainfall, a suitable procedure for the estimation of future trends starting from the analysis of climate model outputs has been presented.
The proposed method takes into account the three main sources of uncertainty affecting climate projections (emission scenarios, global climate model, internal variability). In particular, an ensemble of six different climate models run according different emission scenarios has been considered in the analysis and a new weather generator developed by the authors has been implemented to assess internal variability.
Each climate data series of the ensemble has been considered as an equally likely representation of future climate and then, an extreme values analysis has been carried out for moving time windows, forty yearlong each, to assess the trend in extreme values of daily precipitation.
In this way, delta factor of changes for 50 year return level precipitation have been derived and their uncertainty range have been evaluated from the ensemble of factor of changes obtained according to the medium emission scenario (RCP4.5) and the highest emission scenario (RCP8.5).
The results, presented in terms of prediction interval maps for the investigated region, show how this technique is very promising and can provide guidance for the assessment of the impacts of climate change on precipitation extremes, allowing also to evaluate the uncertainty in the prediction.
A robust change in precipitation extremes for the study region is detected, confirming the increase of heavy rainfall expected in a warming climate according the well-known Clausius–Clapeyron relationship.
The proposed methodology can be easily extended to different return periods as well as to the evaluation of the future trends in total amount of precipitation in order to obtain a complete description of the effects of climate change on rainfall and of its consequences on the environment.

7. AKNOWLEDGMENT

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