Analysis of Changes in Location-Specific Extreme Precipitation Using an Ensemble of Global Climate Model Output from the Coupled Model Intercomparison Project, Phase 5 (CMIP5)

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Abstract:

Climate models indicate that an increase in global mean temperature will lead to increased frequency and intensity of storms of a variety of types. *Gao et al., 2012* show that Philadelphia, Pennsylvania is expected to experience the greatest increase of precipitation in the United States due to an increase in annual extreme events. We use rain gauge data and high resolution (grid cells smaller than 1.5º) global climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) to analyze discrepancies between historical and modeled data. We then apply this bias to the historical data in order to forecast precipitation into the future. In order to attain the frequency of extreme precipitation, we analyze the data in a Log Pearson Type III distribution.

Introduction

Climate models indicate that an increase in global mean tempeature will lead to increased frequency and intensity of storms of a variety of types. In the United States, the northeast region is expected to experience the most extreme increase in precipitation. *Gao et al., 2012* expect the total annual extreme precipitation in both the northeast and southeast to experience a mean increase of 35% or more in annual extreme precipitation, correlating with a greater risk of flooding. In addition, *Gao et al., 2012* also estimates that due to the increase in heat waves in the northeast, this region is the most susceptible to extreme precipitation and, as a result,, flooding[3]. With rising population and more dense urban areas, safety, health, and damage are of significant importance to urban planners in order to guide the evolution of city infrastructure. This study utilized right tailed statistical distributions to determine increases in precipitation intensity and frequentcy for Philadelphia International Airport rain gauge data for two thirty year periods, 1956-1985 and 1976-2005. We then used Coupled Model Intercomparison Project, Phase 5 global climate models to forecast precipitation for two future thirty year periods, 2001-2030 and 2021-2050. A bias is determined between the global climate models (GCM) and historical data and then applied to the historical data to forecast it for the years 2001-2030 and 2021-2050.

Reasons for an Increase in Extreme Precipitation Events

Precipitation forms when water droplets in clouds grow and combine to become so large that their fall speed exceeds the updraft speed in the cloud, and they then fall out of the cloud. The more water vapor there is below the cloud, and the stronger the updrafts that cause this water vapor to condense into cloud water, the more likely it is that precipitation will form within the clouds. The reason it rains more often in warm climates is because of the increased amount of water vapor in the air due to increased amount of water evaporated[1]. That is, the warmer the atmosphere, the more water vapor it can hold before becoming fully saturated. This suggests that as average temperatures in a given location increase, more water will be retained in the atmosphere at that location before release. This reduces the possibility for lighter precipitation events and increases the possibility for more extreme events. Figure 1 shows the upward trend of high temperatures and saturated water pressure[2].

FIGURE 11. Saturation vapour pressure shown as a function of temperature: e°(T) curve

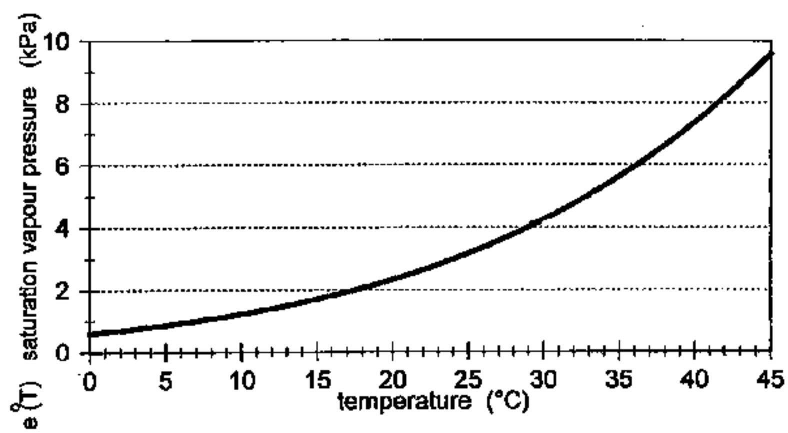


Figure 1 Saturation vapor pressure vs Temperature

Gao et al., 2012 show that Philadephia, PA is also expected to experience an increase in heat wave intensity (ºC), heat wave duration, and heat wave frequency as seen in Table 2.

Table 2. Heat wave intensity, duration and frequency.

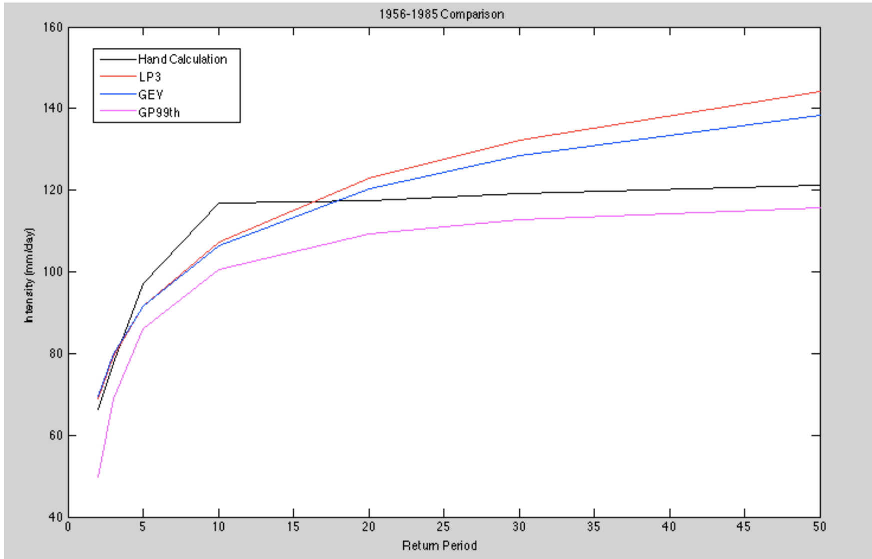
Regions/states	Heat wave intensity (°C)			Heat wave duration (days/event)			Heat wave frequency (events/yr)		
	Present	RCP 8.5	RCP 8.5—Present	Present	RCP 8.5	RCP 8.5—Present	Present	RCP8.5	RCP 8.5—Present
Northeast region	**21.81**	**24.85**	**3.05**	**3.61**	**5.53**	**1.92**	**1.24**	**7.03**	**5.79**
New Hampshire	21.16	24.23	3.07	3.22	5.35	2.13	1.29	7.41	6.12
Vermont	20.84	24.02	3.18	3.37	5.35	1.98	1.15	7.94	6.79
Massachusetts	22.21	25.05	2.84	3.60	5.47	1.87	1.02	7.13	6.11
Connecticut	22.45	25.43	2.98	3.68	5.71	2.03	1.24	6.53	5.29
New York	20.84	24.08	3.24	3.78	5.32	1.54	0.96	7.65	6.69
Pennsylvania	20.97	24.16	3.19	3.85	5.48	1.63	1.33	7.26	5.93

Table 1 Heat wave intensity, duration, and frequency

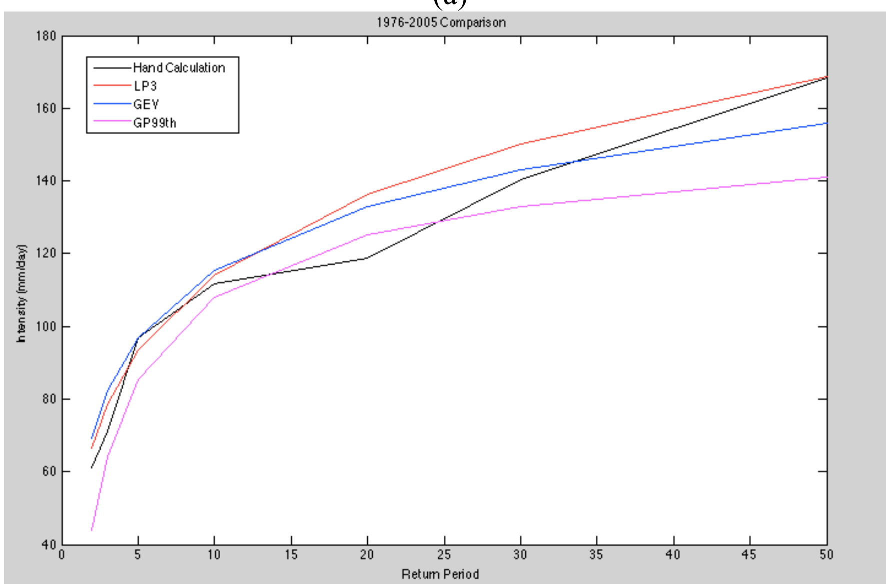
Thus, since Philadelphia is expecting warmer temperatures in the future, it can also expect more precipitation.

Procedure for Choice of Statistical Analysis

Several right tailed statistical distributions were used to analyze precipitation data to determine frequency and intensity of precipitation including Generalized Extreme Value Theory (GEV), Log Pearson Type III (LP3), and Generalized Pareto (GP). GEV and LP3 use the annual maxima of the data and GP uses the 99th percentile of the data. The results of these distributions compared to a manual calculation of the return period are shown in Figure 2 (a-b).



(a)



(b)

Figure 2 Comparison of statistical distributions generated in Matlab for (a) 1956-1985 and (b) 1976-2005. Black line – manual calculation, red line- LP3, blue line- GEV, purple line- GP

These results show that projections using the LP3 distribution overestimate rainfall while those using GP underestimate rainfall. For the purpose of urban planning, overestimation is more useful for application; therefore, LP3 is chosen for this analysis. In addition, a study performed by *Guttman., 1999* analyzing statistical distributions for the Standardized Precipitation Index determined that LP3 produced the fewest number of differences between regional and candidate models, most symmetrical pattern of differences, and exhibited the least spatial and temporal differences. The computation steps of LP3[4] are shown in Figure 3.

$$y = \log x$$

$$w = \left[\ln\left(\frac{1}{p^2}\right)\right]^2 \quad (0 < p \leq 0.5)$$
$$p = 1 - p \quad (p > 0.5)$$

$$z = w - \frac{2.515517 + 0.802853w + 0.010328w^2}{1 + 1.432788w + 0.189269w^2 + 0.001308w^3}$$

$$K_T = z + (z^2 - 1)k + 1/3(z^3 - 6z)k^2 - (z^2 - 1)k^3 + zk^4 + 1/3k^5$$
$$k = \frac{Cs}{6}$$

$$y_T = y_{bar} + K_T s_y$$

$$X_T = 10^{Y_T}$$

Figure 3 Computational steps of LP3

LP3 graphs produce a return period against an associated intensity (mm/day). A return period is an estimate of how long it will be between rainfall events of a given magnitude. For example, Figure 4 shows that a 10 year return period for 1976-2005 is associated with about 110 mm/day of rainfall. This means that Philadelphia is expected to receive a rainfall of 110 mm/day once every 10 years or has a 10% chance of this rainfall in any given year. The results of the LP3 analysis of historical are shown in Figure 4.

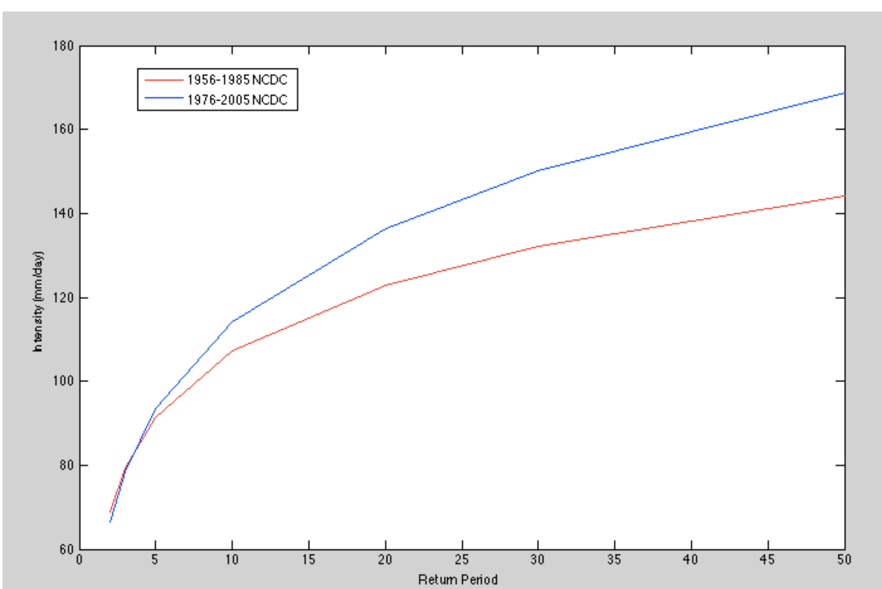


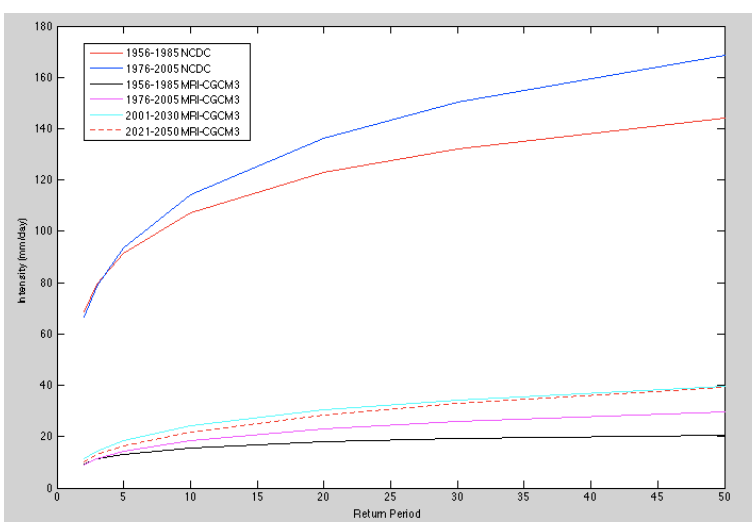
Figure 4 Results of LP3 analysis of historical data produced in Matlab. Blue- 1976-2005, Red- 1956-2005.

This graph shows that for the 1976-2005 period, the frequency of intense rainfall increased as compared to the 1956-2985 period.. This ncrease frequency agrees with previous research findings (*e.g. Frich et al. 2002, Lehtonen et al. 2013, Sun et al. 2007*).

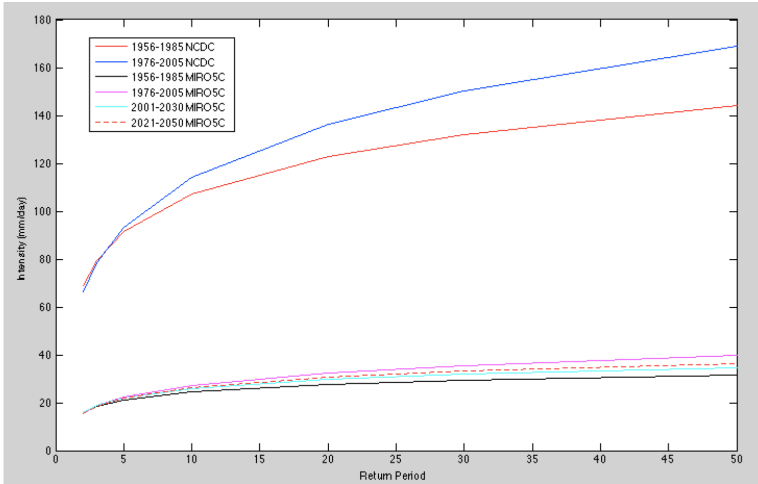
Coupled Model Intercomparison Project, Phase 5

For application purposes, it is necessary to try to predict similar patterns if increases in intensity and frequency will continue into the future. Climate models combine climate physics, topography, historical data, and the speed of computer processing to produce predictions in the form of mathematical solutions based on the input of a large number of variables. For this study, CMIP5 models: MRI-CGCM3, MIROC5, and CCSM4 results were used for analysis. The goal of CMIP5 is to assess the mechanisms responsible for model differences, explore the ability of models to predict climate on decadal time scales, and determine why similarly forced models produce a range of responses[5]. All of the GCMs in this study had produced output with resolution higher than 1.5º. The higher the resolution, the better the results are assumed to be due to incorporation of regional differences including land use and topography, and to variable averages applied across smaller grid cells. The results of the three CMIP5 GCMs are shown in Figure 5 (a-c).

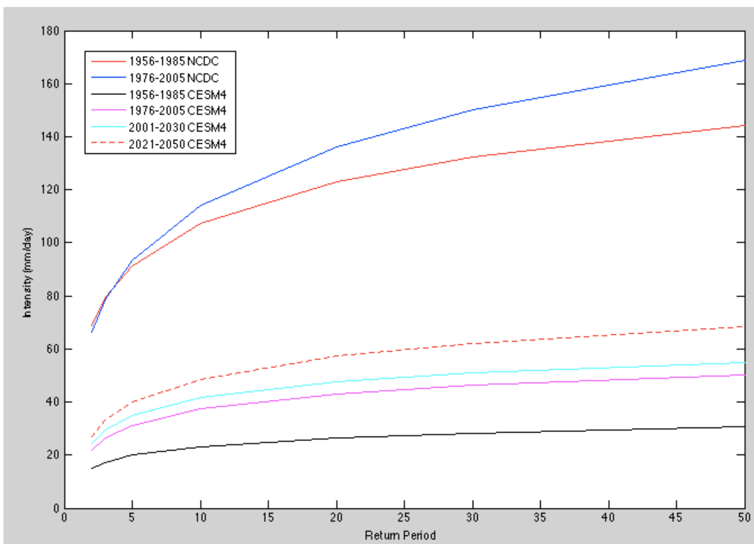
The GCMs severely underestimate precipitation, by as much as 85% in this study. The best performing model in this study was CCSM4 in addition to MIROC5 which produced very similar results of about a 78% difference in historical and modeled results. MRI-CGCM3 produced the worst results. Reasons for this underestimation can be attributed to the GCMs inability to capture regional characteristics and climate phenomena (Lehtonen et al., 2013). In addition, due to the models' low resolution, local extremes are averaged across an entire 1.5x1.5 degree grid cell. Despite its severe underestimation, *Lehtonen et al., 2013* determined that there was no difference between GCMs and higher resolution regional climate models in their tendency towards more extreme precipitation and that despite their inaccuracy, GCMs are still useful in observing trends in future climate.



(a)



(b)



(c)

Figure 5 LP3 analysis of CMIP5 GCMs produced in Matlab. (a) MRI-CGCM3 (b) MIROC5 (c) CCSM4

Extension of Historical Data

Extension of historical data is useful for urban planners so that they can better plan today how to handle the possibility of a more extreme climate in the future. The graphs in Figure 5 (a-c), show a significant difference between historical data and GCM data. Therefore, in order to utilize the trends that the GCMs show, a bias must be determined between the historical data and GCM results. The bias between historical data and output from each model (CCSM4, MIROC5 and MRI-CGCM3) was calculated and tabulated (Table 2). Then, to extend the historical data, an average of the biases from two of the models was used as a multiplier to scale the GCM results into the historical data range.

	Model Bias						Bias Average
Return Year	Bias CCSM 56	Bias MRI 56	Bias MIRO 56	Bias CCSM 76	Bias MRI 76	Bias MIRO 76	CCSM+MIRO
2	4.562669143	7.35231621	4.239085957	3.03114591	7.300051648	4.106851635	3.984938161
3	4.570436045	7.081016432	4.24017787	2.977198216	6.891568696	4.040352032	3.957041041
5	4.589916144	6.923021027	4.275620918	2.982824354	6.539965135	4.010032067	3.964598371
10	4.624419322	6.85597171	4.352360423	3.058843548	6.20305945	4.014697865	4.01258029
20	4.664095742	6.877818886	4.447783344	3.164183816	5.954086446	4.049044768	4.081276917
30	4.688920424	6.916856379	4.509666501	3.24357587	5.834527399	4.07847259	4.130158846
50	4.721516789	6.9865106	4.592751022	3.356207577	5.703850835	4.12320856	4.198420987

Table 2 Calculation of bias between historical and modeled data

MRI-CGCM3 was omited from the average because of its poor results. *Knutti et al., 2010* cites several sources that favor multimodel averages over single model use due to its improved comparison with present day observations in a variety of climate variables. The average bias determined for the two models included is 4.05.

Results

The application of the 4.05 bias to the GCM results for years 2001-2030 and 2021-2050 are shown in Figure 6.

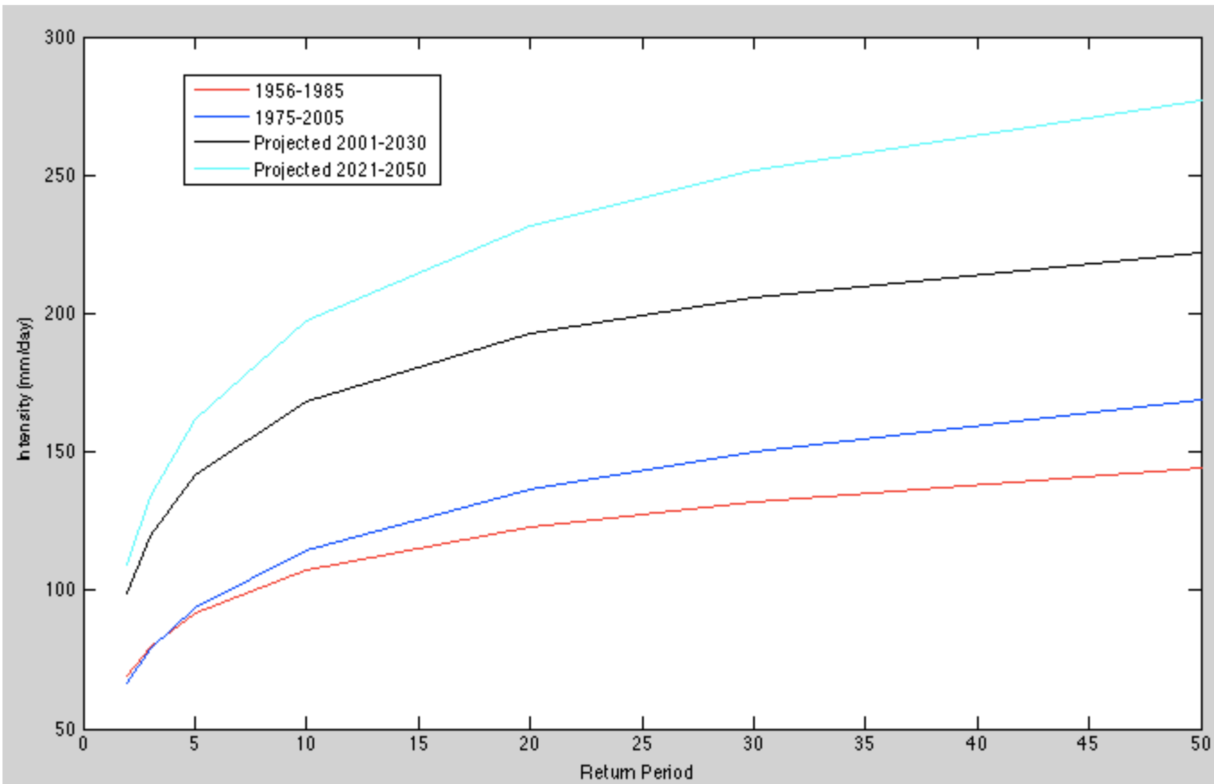


Figure 6 GCM results for 2001-2030 and 2021-2050 using 4.05 bias. Red- 1956-1985, Blue- 1976-2005, Black - 2001-2030, and Light Blue- 2021-2050.

The results follow the increasing trend that was found in Figure 4 and validated by multiple sources cited in *Procedure for Statistical Analysis* section*.* Numerical results developed from GCMs are not reliable enough for use in application, but are instead useful for validating the theory that extreme precipitation is becoming more frequent and intense. However, using these results, as great as a 45% increase in intensity of rainfall is possible.

Conclusions

The significant findings in this study were that frequency of extreme precipitation increased during second thirty year period,1976-2005.Another finding is that the GCMs severely underestimate extreme precipitation due to their low resolution. Of the CMIP5 models, CCSM4 and MIROC5 performed the best compared to historical data and MRI-CGCM3 performed the worst. In order to forecast the historical data into the future a bias was determined as the average of the CCSM4 and MIRO5C models. It was determined that the historical results averaged to be 4.05 times greater than the GCM data. Finally, results from the extended historical data indicate that as great as a 45% increase in intensity of extreme precipitation events

Future Work

With rising population and increasing urban density, it is of pivotal importance for urban planners to plan for increasing extreme precipitation events. Analysis of results from CMIP5 has demonstrated that GCMs severely underestimate precipitation. In order to obtain more reliable results, downscaled analysis of three of the largest cities in America, Philadelphia, Chicago, and New York will be developed in the Weather and Research Forecasting regional climate model (WRF). Because WRF is a higher resolution model including more regional atmospheric and terrain features than a global model (as seen in Figure 7), it can better capture specific location precipitation events. We will compare historical precipitation data and WRF output utilizing a Log Pearson Type III (LP3) distribution for frequency of extreme precipitation events to determine if regional climate models offer improved performance.

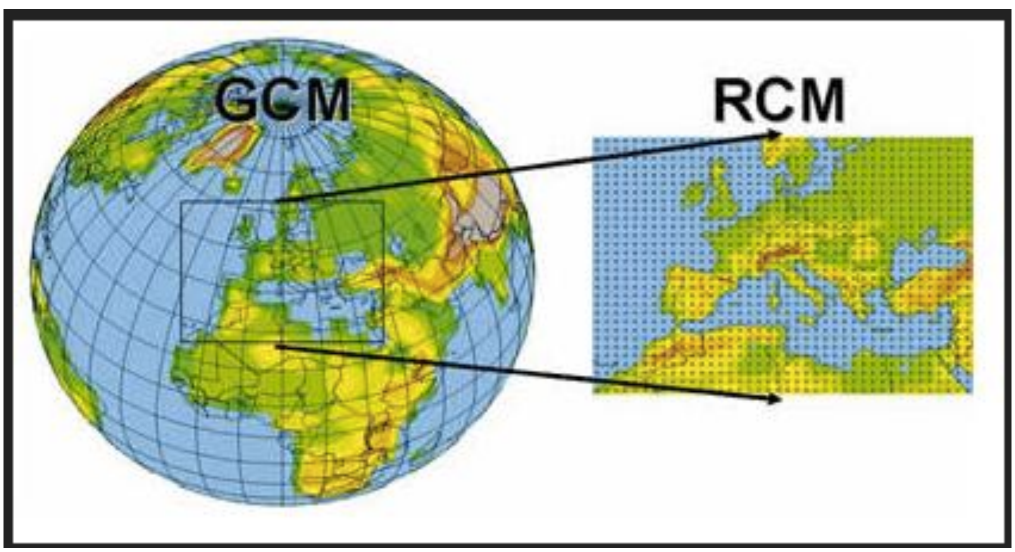


Figure 7 Downscaling from global climate model to regional climate model

References

[1]http://www.weatherquestions.com/What_causes_precipitation.htm

[2]http://www.fao.org/docrep/x0490e/x0490e07.htm

[3]Gao, Y., J. S. Fu, Y. Liu, and J. F. Lamarque. "Projected Changes of Extreme Weather Events in the Eastern United States Based on a High Resolution Climate Modeling System." Environmental Research Letter (2012): n. pag. Print.

[4]Chow, Ven Te, David R. Maidment, and Larry W. Mays. Applied Hydrology. New York: McGraw-Hill, 1988. Print.

[5]http://cmip-pcmdi.llnl.gov/cmip5/index.html?submenuheader=0

[6]Knutti, Reto, Reinhard Furrer, Claudia Tebaldi, Jan Cermak, and Gerald A. Meehl. "Challenges in Combining Projections from Multiple Climate Models." Journal of Climate 23.10 (2010): 2739-758. Print

[7]Frich, P., Lv Alexander, P. Della-Marta, B. Gleason, M. Haylock, Amg Klein Tank, and T. Peterson. "Observed Coherent Changes in Climatic Extremes during the Second Half of the Twentieth Century." *Climate Research* 19 (2002): 193-212. Print.

[8]Guttman, Nathaniel B. "Accepting The Standardized Precipitation Index: A Calculation Algorithm." *JAWRA Journal of the American Water Resources Association* 35.2 (1999): 311-22. Print.

[9]Lehtonen, Ilari, Kimmo Ruosteenoja, and Kirsti Jylhä. "Projected Changes in European Extreme Precipitation Indices on the Basis of Global and Regional Climate Model Ensembles." *INTERNATIONAL JOURNAL OF CLIMATOLOGY* (2013): n. pag. *Wiley Online Library*. Web. 16 July 2013.

[10]Sun, Ying, Susan Solomon, Aiguo Dai, and Robert W. Portmann."How Often Will It Rain?" *Journal of Climate* 20.19 (2007): 4801. Print.

www.googleimages.com