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WOULD BANGKOK BE MORE VULNERABLE TO THE ANTICIPATED CHANGING CLIMATE?

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The severe flooding in Thailand in 2011was triggered by the tropical storm Nock-ten at end of July along the Mekong-Thajin and Chao Phraya river basins. There are 4 additional storms that caused medium to heavy rainfall from June to October in the north and north-east of Thailand. Due to limited capacity of the Chao Phraya river and also Pasak river, several overbank flows occurred and also dikes along the river were broken causing excessive flow to many communities beside the river and downstream. The consequence was a total of 815 deaths with 13.6 million people affected and over 20,000 km^2 farmland devastated, the inundation remained until mid-January 2012. Total estimated cost of economic lost was about 45.7 billion US$ with respect to manufacturing industry as seven major industrial estate in the northern provinces of Bangkok were submerged 2-3 m during high flood. This caused interruption to supply chain to car parts regionally and world-wide, e.g. electronic components and hard disk drives. Will Bangkok experience more intense rainfall under the changing climate? The Artificial Neural Network (ANN) technique is adopted in this study to shed some lights on this issue. The present study utilizes ANN to statistically downscale global climate models (GCMs) at some meteorology stations in Bangkok. The study illustrates the applications of the feed forward back propagation using large-scale predictor variables derived from the ERA-Interim reanalysis data, meteorological station data, baseline and future GCM data of certain emission scenarios. The findings will certainly be useful to the policy makers in pondering, e.g. whether the current drainage network system is sufficient to meet the changing climate, and a range of flood adaptation and mitigation measures.

INTRODUCTION

The impact of global warming is likely to increase both the frequency and severity of weather events such as heavy rainfall, shifting in rainy season, increasing in number hot days, cold night. And recently, the first draft report to IPCC [1] in Fifth Assessment Report (AR5) has one more time restate: “Climate change, whether driven by natural or human forcing, can lead to changes in the likelihood of the occurrence or strength of extreme weather and climate events or both”. This in turn, put more weight to its confirmation about the severity of climate change.

The new scenario developed in AR5 to replace the Special Report on Emission Scenario (SRES) in AR4 are called Representative Concentration Pathways (RCPs) which tries to stabilize the radiative forcing by 2100 at certain unit ranging from 2.6, 4.5, 6.0 and 8.5 W/m2. In comparison to Couple Model Inter-comparison Project 3 (CMIP3), the scenario of RCP 4.5 under CMIP5 is slightly less severe than A1B scenario in terms of Radiative forcing. In this study, we cover the whole range of different GCMs using SRES A1B scenario with GCM ECHAM 5 under RCP 4.5 to estimate the uncertainty range in statistical downscaling for Bangkok rainfall.

The mismatches of Global Climate Models (GCMs) in term of spatial and temporal scale and station data at point wise are the main drawback in quantifying future climate at regional scale or specific location. The usual resolution of GCMs spans from 150-400km whilst the local impact is only occurred at much smaller scale. Thus downscaling technique has been developed to give some “added value” to the large scale information to a regional or local scale [2]. There are two fundamental approaches that exist for downscaling of large scale information to a regional or a local scale. The first is a statistical method, called ‘Statistical Downscaling’, which establishes empirical relationships between large scale climate variables and local climate and the other is a method where a higher resolution climate model, widely known as a Regional Climate Model is driven by the GCM output. This technique is called as the ‘Dynamical Downscaling’ or commonly, regional climate modeling. In this study, with the advantage of having full record for station data as well as the urge to evaluate the downscaling of the new RCP dataset, we will apply the statistical downscaling method only.

In this study, we apply the non-linearly relationship by using Artificial neural network (ANN) with the inputs from latest reanalysis data ERA-Interim for training/testing and 3 GCMs (CCSM, ECHAM, MIROC) under SRES A1B and ECHAM RCP 4.5, all filtered by Principle Component Analysis (PCA) method to statistically downscale the precipitation over Bangkok area.

STUDY AREA

The study site Bangkok has coordinate of Longitude 100.35E, Latitude 13.45N, is the capital and commercial city of Thailand and is one of the highly developed cities in Southeast Asia. The area has a tropical type of climate with long duration of sunshine, high temperatures and high humidity.

The Thailand climate is mainly influenced by the Northeast and Southwest monsoon. The Northeast monsoon occurs from middle of October to middle of February when the inter-tropical convergence zone (ITCZ) moves southward. This type of wind brings cool and dry air from the Siberian anticyclone down to the country and creates a dry season for Thailand. The southwest monsoon from May to October gathers humid air from the Indian Ocean when ITCZ moves northward. It first creates a heavy downpour along the west coast of Thailand then spreads over the entire country, forming the wet season. There is a limitation in literature about predicting the future rainfall over Thailand. Most of the studies are about weather forecast or present day comparison.

DATA EXTRACTION

Daily precipitation data for the period 1980-2012 is obtained from Thailand Meteorological Department (TMD) for Bangkok station, it is located in the central of Bangkok, with latitude 13.73 N and longitude 100.56 E.

The predictors dataset which are large scale variables, are obtained from reanalysis data for training/testing process and GCMs for future climate prediction. The relationship between predictors and station data are then constructed using ANN to derive current and future climate variables (predictand). The Reanalysis data used was the ERAI (European ReAnalysis Interim dataset) with latest data from 1980-2012 [3]. The data have a horizontal resolution of 1.5^{o} longitude/latitude. The atmospheric variables including surface and higher level at 500 and 850 millibar are included. These datasets after standardization (a process involving subtracting the mean and divided by its standard deviation) to reduce the systematic bias will then be extracted for 1, 9 and 25 grid points surrounding Bangkok which is represented in Figure 1 at a spatial resolution of 1.5^{o}.

Future climate are obtained from Global Climate Models (GCMs). There are several GCMs used in this study to have the broad view of future climate over Bangkok which are ECHAM5 (1.875^{o}x1.875^{o}) from Max Planck Institute Germany, CCSM3 (1.4^{o} x 1.4^{o}) from National Centre for Atmospheric Research (NCAR), USA and MIROC medium resolution (2.8^{o}x2.8^{o}) from Japan, all using Scenario A1B and the latest ECHAM RCP 4.5 (which is considered to be slightly less in term of radiative forcing than scenario A1B). All the future climate dataset are downloaded for the period 2071-2100 in order to evaluate the future climate by the end of 21st century. All these datasets were regrided to ERAI domain and standardized to reduce the systematic bias.

Figure 1. Distribution of ERA Interim grid boxes (dots indicate 1.5^{o}x1.5^{o}) and the location of 1, 9, 25 boxes surrounding Bangkok (red star)

SELECTION OF PREDICTORS

For downscaling predictand, the selection of appropriate predictors is one of the most important steps in a downscaling exercise. The predictors are chosen by spatial correlation with large scale predictors and cross correlation between reanalysis data and GCMs. The first step supports the selection of domain study as well as selecting sensitive predictors to the station data. In this procedure, spatial correlation was calculated in monthly scale for the present day period between monthly data in Bangkok station with all predictors from reanalysis and GCM data. The correlation analysis is computed using long term monthly data for 30 years from 1980-2010 by both ERAI and Bangkok station data. 16 predictors are selected for this exercise. The spatial correlation is shown in contour line across the map for ERAI. The simple rule used to screen the appropriate predictors is the threshold of 0.45 around Bangkok station area. This helps to remain only the highly correlated predictors to the training procedure in the later part. In addition to the spatial scale, according to Wilby et al. [4], the chosen predictors for training in reanalysis variables ought to be selected in order to maintain the relevance to the downscaled predictands with GCMs. Thus scatter plots and correlation value are shaped together in the selection process. The high correlation coefficient of predictors would help to preserve the structure of reanalysis data in GCMs dataset. The threshold of 0.45 is set to select the appropriate predictors.

ARTIFICIAL NEURAL NETWORK AND PRINCIPLE COMPONENT ANALYSIS

Artificial neural network

An artificial neural network (ANN) is an established technique with a flexible mathematical structure that is capable of identifying complex non-linear relationships between input and output data. The ANN model used in this study is feedforward network with 3 layers: an input layer, a hidden layer and an output layer whereas each layer connecting by weights. This three-layered feedforward network is commonly used due to its general applicability to a variety of different problems [5]. The learning procedure tries to find a set of weights which gives a mapping that fits well with the input and output. The following function as an arbitrary non-linear function could be assumed:

$$F\left(x,w\right)=y \tag{1}$$

where *x* is the input vector (predictors) presented to network, *w* is the weight of the network and *y* is the corresponding output (predictand).

In this study, the sigmoid transfer function is applied in the hidden layer and linear transfer functions in the output layers. The number of node in the hidden layer is calculated in Eq. (2)

$$l=\frac{1}{2}(i+o)+\sqrt{N} \tag{2}$$

where: *l* is number of node in the hidden layer, *i* is the number of input node, o is the number of output node, and *N* is the number of records in training set.

Principle Component Analysis

PCA, also known as the Karhunen Loeve transform, is one of the most popular techniques for dimensionality reduction [6]. PCA is applied to transform the set of correlated N-dimensional predictors into another set of N-dimensional uncorrelated vectors called principal components (PCs) by linear combination, such that most of the information content of the original data set is stored in the first few dimensions of the new set.

In this study, PCA was performed to reduce the dimensionality of the predictors from 1, 9 and 25 grid boxes. The PCs of the PCA method explained about 90% of the information content of the original predictors. These new data sets are provided as input to the ANN downscaling model.

RESULTS

Training and testing using Reanalysis dataset

The performance of statistical downscaling using ANN is first evaluated in terms of the climatology annual cycle of precipitation at study site. The training period for ANN is fix for 15 years from 1986 – 2000 and the testing set is 1980 – 1995. Figure 2 shows the rainfall annual cycle between station data (black line) and downscaled using ERAI (red line) as the driving force. The cycle show quite well match between observation and reanalysis downscaled with 2 peaks captured in May and September and slight over estimation in Jan, Jun and Dec.

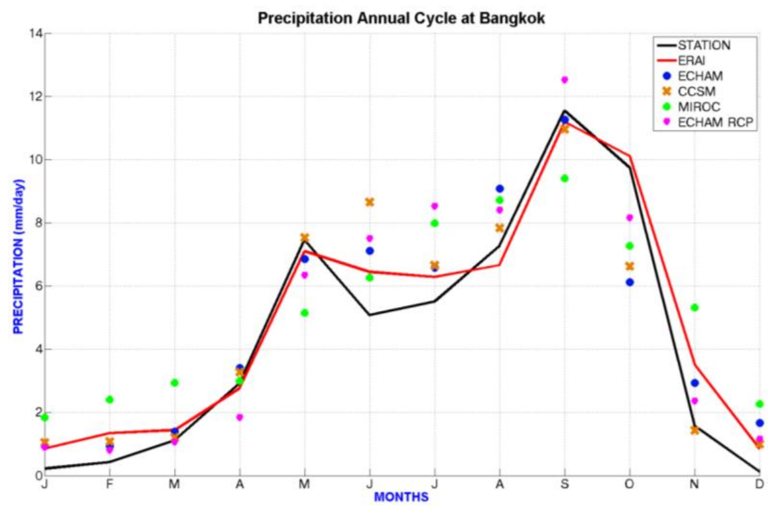

Figure 2. Annual cycle of downscaled precipitation for different datasets, present day climates

Downscaling present day climate from GCMs (1980-2000)

Figure 3 shows the magnitude in annual average precipitation between station and downscaled data. The downscaled GCMs show quite good match with station data compared with ERAI, especially the ECHAM RCP dataset. MIROC displays the highest bias among all.

The annual cycle in Figure 2 also depict the ability to capture the trend of these dataset when downscaling GCMs to present day climate with an exception of MIROC failed to capture the second peak in September.

For present day climate, all GCMs are able to capture the magnitude and distribution of precipitation. The lowest ranking goes to MIROC dataset.

Future rainfall over Bangkok

The future rainfall over Bangkok has been applied for period 2071-2100. This ensemble dataset will give the prediction of precipitation at Bangkok the wider range of uncertainty when dealing with future climate. The delta change factor approach has been applied to indicate the different between future and current day climate using Eq. (3)

$$\Delta(\%) = \frac{(F - P)}{P} * 100 \qquad (3)$$

where F: future rainfall, P: Present day rainfall.

The delta change is compiled for Annual and seasonal scale in Figure 4. In overall, there is an agreement in increasing rainfall over annual and all seasons except a slight decrease of ECHAM A1B in the transition month from March to May. In annual, the scale of increase rainfall is from 10 to 60% for all dataset. The increasing rate is different for all dataset and all period. Among all 4 datasets, ECHAM A1B has the lowest increasing rate. SON period has the extremely high value of CCSM A1B (up to 100% increase).

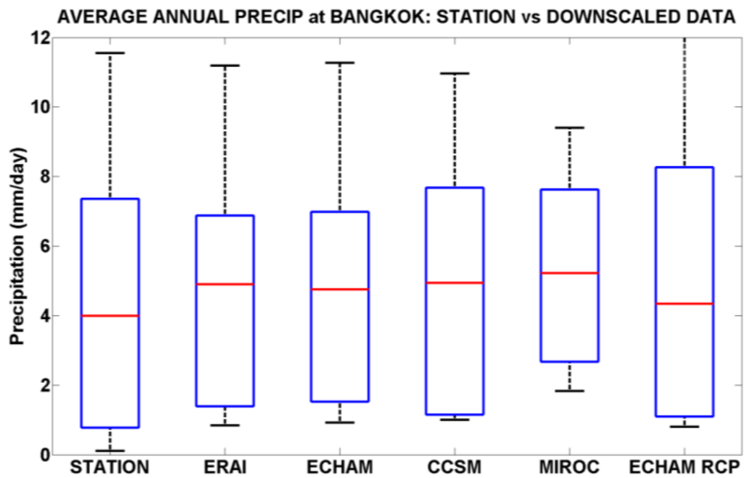

Figure 3. Boxplot for present day climate annual average precipitation between station and downscaled data.

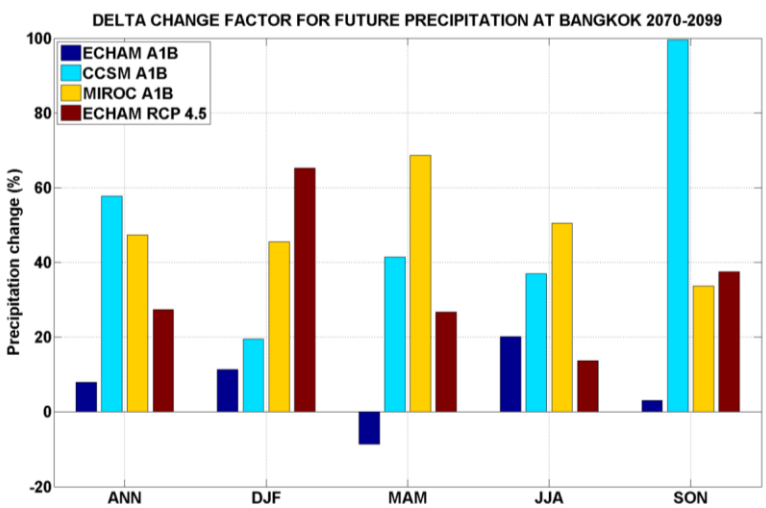

Figure 4. Delta change factor for different downscaled GCMs future precipitation at Bangkok 2070-2099 period (ANN: Annual, DJF: Dec to Feb, MAM: Mar to May, JJA: Jun to Aug, SON: Sep to Nov)

The six precipitation statistical indices were selected to show the mean and extreme value. Its relative change is used to examine the effect of climate change under future emission scenarios.

- PRCPTOT: Total number of wet day (day)
- SDII: Precipitation wet day Intensity (mm/day)
- RX5day: Maximum 5 consecutive rain day (mm)
- R95pTOT: Precipitation 95th percentile (mm)
- CWD: Annual Maximum Wet day frequency or Wet spell (day)
- CDD: Annual Maximum Dry day Frequency or Dry spell (day)

Wet day is defined as daily rainfall more than or equal to 1mm and dry day is less than 1mm. The relative change estimated from future with response to baseline period (1980-2000) will be assessed for 6 different precipitation indices as displayed in Figure 11.The distributions are calculated for the fitted gamma probability distribution functions (PDFs) of these indices for baseline period (plotted as dashed line) and future period (continuous line).

The overall trend for the future wet indices (SDII, PRCPTOT, RX5day, R95pTOT, CWD) are shifting to the right of the present day climate. In contrast, for the future dry indices (CDD), the distribution of the future PDF curve is shifted to the left of the baseline period. It implies that future climate tend to be wetter during wet season and drier during dry season.

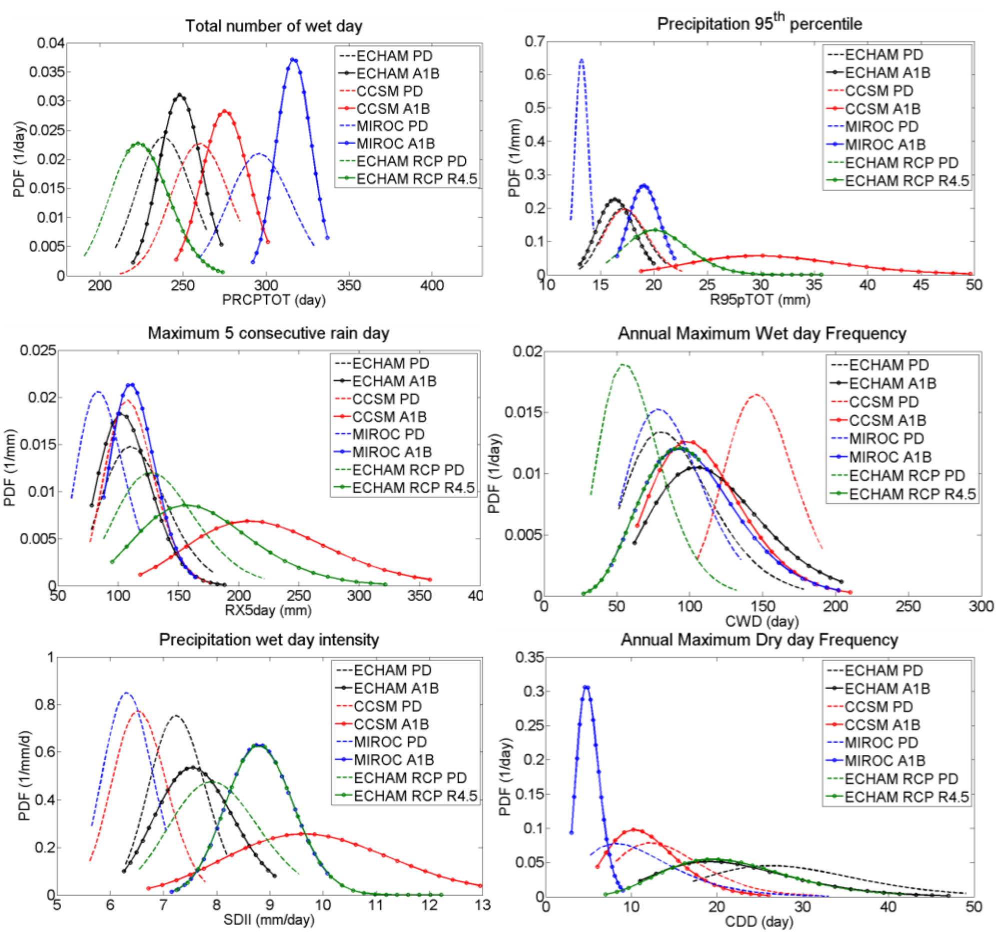

Figure 5. Precipitation indices for downscaled precipitatiob in present day and future GCMs

CONCLUSION

Base on this study, latest reanalysis dataset ERA Interim has been filtered by PCA and statistically downscaled by ANN for the rainfall over Bangkok region. The trained model were then applied to investigate the possible changes in future rainfall using 3 different GCMs (CCSM, ECHAM and MIROC), including both CMIP3 A1B scenario and recent CMIP5 ECHAM RCP 4.5 dataset. The training and testing using ERAI predictors are 10 years each, showing the capability of statistical downscale of PCA and ANN model. Domain sensitivity has been encountered in the study.

Future climate has been applied from the 3 CMIP3 and 1 CMIP5 dataset to find the range of uncertainty of different models and emission scenario. In overall, the future climate indicates an increase in annual rainfall for all datasets. The statistical indices also show an increase toward the future for the wet indices and decrease for dry indices. According to the suggestion of IPCC 2007 to choose more GCMs and more scenarios as possible, this study combine both CMIP3 and CMIP5 scenario to cover the uncertainty range. The CMIP5 dataset show agreement with CMIP3 dataset when being downscaled.

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REFERENCES

[1] IPCC., Working Group I contribution to the IPCC 5th Assessment Report (Final Draft), In: Climate Change 2013: The Physical Science Basis, (2013).

[2] IPCC., Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change In: Climate Change 2001: The Scientific Basis, Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, K. M, C.A. J (eds.), (2001).

[3] Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balmaseda MA, Balsamo G, Bauer P, Bechtold P, Beljaars ACM, van de Berg L, Bidlot J, Bormann N, Delsol C, Dragani R, Fuentes M, Geer AJ, Haimberger L, Healy SB, Hersbach H, Hólm EV, Isaksen L, Kållberg P, Köhler M, Matricardi M, McNally AP, Monge-Sanz BM, Morcrette JJ, Park BK, Peubey C, de Rosnay P, Tavolato C, Thépaut JN, Vitart F, The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society, Vol. 137, (2011), pp. 553-597.

[4] Wilby RL, Tomlinson OJ, Dawson CW. 2003. Multi-site simulation of precipitation by conditional resampling. *Climate Research*, Vol. 23, (2003), pp. 183-194.,

[5] Hsu K-l, Gupta HV, Sorooshian S, Artificial Neural Network Modeling of the Rainfall-Runoff Process. Water Resources Research, Vol. 31, (1995), pp. 2517-2530.

[6] Jolliffe IT, Principal component analysis, Springer, (1986).