APN CAPaBLE

- Making a Difference –

Scientific Capacity Building & Enhancement for Sustainable Development in Developing Countries

Training Course on Regional Downscaling for Asia-Pacific Region Using APEC Climate Centre Global Seasonal Climate Prediction

Final Report for APN CAPaBLE Project:

CBA2008-03NSY-Ashok

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Final Report submitted to APN

Overview of project work and outcomes

Non-technical summary

Developing economies in Asia-Pacific, like many other such nations around the globe, are dependent on agriculture. In an overwhelming majority of these countries, the farming activities are rain-dependent, and consequently suffer from the recent extreme droughts/floods due to climate change. Lack of reliable local climate prediction is a serious constraint for efficeint adaptation to such challenge. For example, Vietnam lost ~US$110000000 due to the big drought in 2005, which affected ~8 million farmers. In Philippines, 13 million hectares is typically affected by drought/floods.

Nowadays, the Global Circulation Models (GCM) have become the main tool of climate studies and climate prediction/projection on a wide range of time scales from months to decades and hundreds of year. State-of-the-art models are able to quite successfully reproduce large scale atmospheric processes, particularly response of large scale circulation to changes in external forcings such as concentration of radiatively active gases, large scale surface properties, etc. To provide accurate information for regional applications climate prediction products from General Circulation Models (GCM) have to be "downscaled". Most National Meteorological and Hydrological Services (NMHSs), particularly those of developing countries, do not have the expertise to downscale GCM outputs to local climate conditions. The carried out training course, which combined the lectures, sharing of experience, and computer lab sessions for development of downscaling tools for regional climate prediction, resulted in enhancement of the capacity of climate prediction over the Asia-Pacific region. Participants from NMHSs of the Philippines, Thailand, and Vietnam learned how to make downscaling predictions based on existing the existing APEC Climate Center (APCC) Multi-Model Ensemble (MME) global seasonal forecasts.

For NMHS' use, APCC provides access to its forecasts in digital data format via internet, as well as access to Climate Information Tool Kit (CLIK) developed for climate data processing and analysis, that implies implementation of the received knowledge and skill in the national climate prediction institutions of the participants.

Objectives

-To enhance capacity of regional climate prediction within Asia-Pacific, through training of specialists from NMHSs and transfer of state-of-the-art downscaling prediction technology

-To provide basis for sustainable development of the Asia-Pacific region, especially for developing countries, by ensuring that participants will gain knowledge necessary for continuing research and development of regional climate prediction tools

-To develop reliable tools for regional climate prediction based on global MME products disseminated by APCC for the use of NMHSs of Asia-Pacific countries, and to leverage the end value of existing APCC MME forecasts

- To share knowledge and experience of the participants in climate prediction/projection

- To develop the basis for future collaboration between the institutions represented by the participants

Amount received and number years supported

The Grant awarded to this project was: US$ 40,000 for 2008-09

- Funding utilized is US$ 32000

Work undertaken

In advance of the training course, the specialists of APCC, Hydrometeorological Research Centre of the Russian Federation, and National Institute for Water and Atmosphere (New Zealand) prepared the lecture and seminar materials. APCC prepared hard- and software necessary for the course. The participants were appointed by the NHMSs. The training course "Regional Downscaling for Asia-Pacific Region using APEC Climate Center's operational Global rolling monthly 3-monthl Climate Prediction" was conducted at APEC Climate Center, Busan, Republic of Korea, from September 22 to November 10, 2008. The participants from the Philippines, Thailand, Vietnam, the Russian Federation, Republic of Korea took a course of lectures, seminars and, mainly, computer lab sessions. During these sessions participants developed their applications based on the CLIK (Climate Information Tool Kit) software, developed by the APCC.

Results

The main results of the Training Course can be summarized as:

1. Theoretical knowledge in up-to-data downscaling techniques and in multi-model

combination. The participants acquired the latest downscaling and regional climate prediction technique and become able to apply these techniques in their home institutions.
2. Practical experience in access to and processing of the APCC data – global model outputs along with practical experience in the usage of the APCC CLIK for the purposes of downscaling
3. Ready to use CLIK software with internet-based access and control and customization for downscaling prediction customization for each participant's region of interest, using global APCC MME forecast as input.
4. Theoretical knowledge in downscaling theory provides the participants with capability to continue improvement of downscaling methods for their regional use and development of their particular region-oriented applications using CLIK.
5. Enhancement of existing and development of new cooperation practice in the region.

Relevance to the APN CAPaBLE Programme and its Objectives

The work carried out under the project was consistent with the objectives of APN's CAPaBLE Programme. Specifically:

It enhances the capacity of regional climate prediction of developing countries of the region by training participants form NMHSs and developing improved and more reliable regional climate prediction tools based on downscaling.
It leverages the end value of existing MME seasonal prediction products freely distributed by APCC.
The resulting enhanced capability for climate prediction should also lead to better local and regional planning and preparedness for impacts of climate extremes and climate variability.

This project is also relevant for generating knowledge of changes of the climate system on short-term/seasonal timescales (including climate extremes related to El Nino/La Nina), for translating their impact on the local scale, and for creating a network for transferring and sharing climate prediction information through enhanced regional and international cooperation.

Self evaluation

Results from the project match the posted objectives. Specifically, the specialists from the developing countries got necessary knowledge and experience in operation with outputs from global circulation models and state-of-the-art downscaling tools;

in developing of their particular options of the downscaling software; and as a result, participants become able to further adjust downscaling schemes to their particular conditions, develop new schemes. The very important result from the course is opportunity for cooperative development and implementation of the downscaling tools.

Potential for further work

APCC provides free access to its data and user-friendly CLIK interface via Internet for the specialists from NMHSs of the Asia-Pacific region. Owing to the training course the participants become able to perform downscaling from the APCC forecasts via the Internet interface in the real-time mode (operational forecast) using existing methods. Within the framework of CLIK software, there is a potential for development and implementation of new advanced downscaling methods, which provides the bases for further cooperation between APCC and NMHSs – the users of the APCC data and software.

Publications

1. CD-ROM: Lecture and seminar materials from the Training Course
2. Web-site: Lecture and seminar materials from the Training Course
3. Manual on the CLIK
4. Paper "Downscaling from the multi-model ensemble predictions for East Asia" (under preparation, to be submitted to GRL).

Acknowledgments

The organizers and participants are deeply thankful to APN for providing the funding for the Training Course under the CAPaBLE Programme. Participants are very thankful to APCC for providing the funding and huge in-kind help in the form of forecast data as well as faculty. The PL also thanks the former proponents Drs. C.-K. Park and C.-Y. Tam for their work.

Technical Report

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Introduction

In the past 20 years, climate scientists have made tremendous advances in understanding and modeling the variability and predictability of the climate system since the dynamical predictability recognized (Charney and Shukla 1981; Shukla 1981, 1985; Miyakoda et al 1986) and boundary-forced predictability broadened the possibility of climate prediction (Charney and Shukla 1981; Shukla 1985; Bengtsson et al. 1993). Prediction of seasonal-to-interannual climate variations has become operational since the NCEP and ECMWF started to produce operational ensemble forecast using atmospheric general circulation models (AGCMs) (Tracton and Kalnay 1993; Palmer et al. 1993). A number of meteorological centers worldwide have implemented routine dynamical seasonal predictions using coupled atmosphere-ocean-land climate models, such as ECMWF, NCEP, and Bureau of Meteorology Research Centre (BMRC) (Palmer et al. 2004; Saha et al. 2006; Wang et al. 2002). It has been also recognized that multi-model ensemble (MME) seasonal prediction is superior to any individual models due to effective reduction in inherent model errors (Krishnamurti et al. 1999, 2000; Doblas-Reyes et al., 2000; Shukla et al. 2000; Palmer et al. 2000, 2004; Kharin et al. 2002; Barnston et al. 2003; Yun et al., 2003 and 2005). Now, the MME prediction has become operational at the European Center for Medium range Weather Forecasting (ECMWF) in Europe, APEC Climate Center (APCC) in Asia-Pacific region, and International Research Institute for Climate and Society (IRI) in USA. The APEC Climate Center is a major APEC science activity that was established in November 2005 during the leaders meeting of the Asia-Pacific Economic Forum in Busan, Korea. It produces seasonal and monthly forecasts of climate conditions for all seasons around the globe. Till 2007, APCC was issuing operational seasonal forecasts four times a year. However, since January 2008, APCC has started issuing monthly rolling 3-month forecasts since January.

APCC climate forecasts are based on model simulations from 15 prominent climate forecasting centers (See Figure 1) and institutes in the APEC region. These forecasts are collected and combined using state-of-the-art schemes to produce a statistically 'consensual' forecast. The APCC forecasts are based not just on the magnitude of the seasonal changes that are predicted, but also take into accounts their simulated probability.

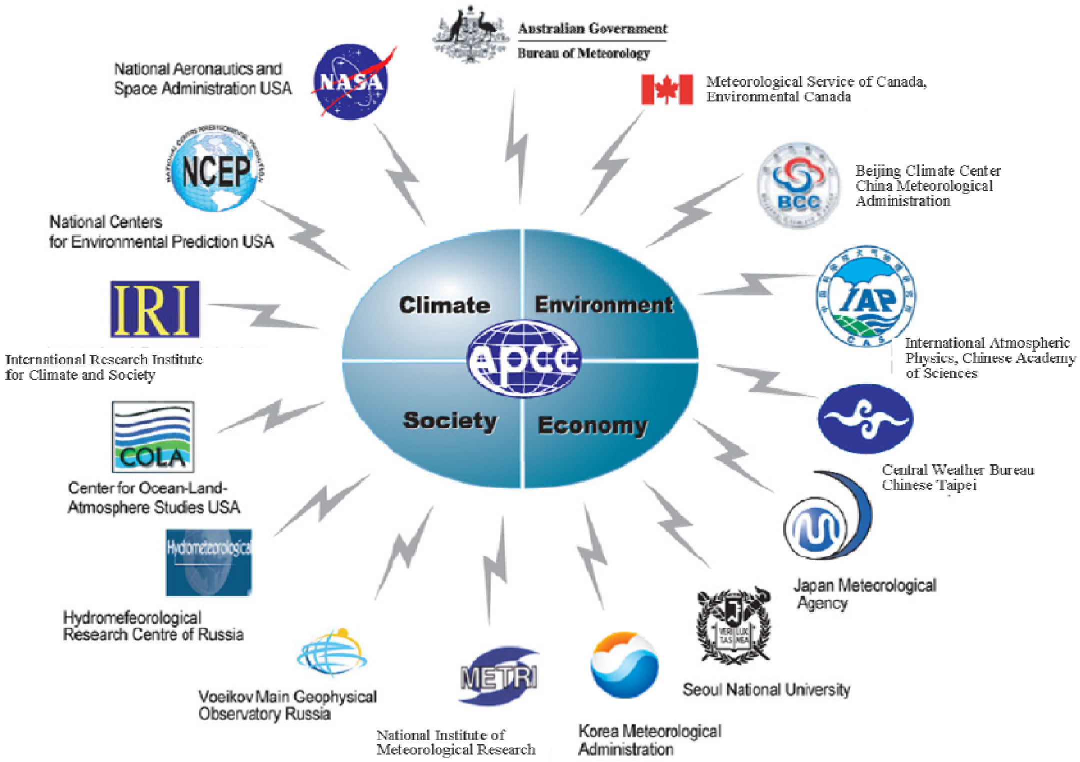

Figure. 1 Multi-Institutional cooperation

Original dynamical model data including forecasts and hindcasts are firstly collected from the model holders in APEC members. Then these data are subject to standardization of format. These data are stored in each file with only one variable, one ensemble member and one month. Next, quality check procedures are performed for the forecast data, and the data, which clear the quality control, are used for further MME procedure of hindcast, in conjunction with observed datasets to develop to calculate the relevant hindcast statistics/relationships, and also to generate the MME forecasts.

APCC produces seasonal forecasts of precipitation, T850, Z500, with relevant hindcasts, applying five methods:

1. Simple composite method (SCM)
2. Probabilistic forecast (GAUS)
3. Step-wise pattern projection (SPP)
4. Multiple regression based blend of model ensemble means (MRG)
5. Synthetic multi-model ensemble (SSE)

The time schedule for APCC operational procedure is generally made as table 2.1. During the first 10 days in the month before the forecasting season, all participating model data are collected. From the middle of the second week, these data are processed into basic data with the same format and then Quality Checks are conducted for these basic data. Then, from the middle of the second week to the middle of the third week, APCC MME forecasts are carried out. After that, two days are needed for APCC outlook. The outlook is published every month after prior consultation and discussions with the working group and SAC of APCC (see Appendix-I for the latest monthly 3-month forecast outlook from APCC).

Nowadays, the Global Circulation Models (GCM) have become the main tool of climate studies and climate prediction/projection on a wide range of time scales from months to decades and hundreds of year. State-of-the-art models are able to quite successfully reproduce large scale atmospheric processes, particularly response of large scale circulation to changes in external forcings such as concentration of radiatively active gases, large scale surface properties, etc. However, small scale climate peculiarities are oftern limited by the global model coarse spatial resolution or the approximations involved in parameterizing the atmospheric/oceanic physical processes. Moreover, local climate conditions are strongly affected by local surface properties, such as relief, ground-water distribution, vegetation, soil, etc. since these local surface properties modulate the impact from the large scale circulation on the local climate.

Therefore, there is a strong need in linking local climate conditions with large scale atmospheric processes simulated by GCMs. In general, the purpose of downscaling is to transfer the model simulated climatic signal from the coarse model grid to target station (city, town, settlement) taking into account the local surface properties. For some variables, poorly reproduced and predicted by the models, such as rainfall, downscaling appears the only way to obtain reliable prediction/projection.

The main goal of the conducted training course on downscaling was

-To enhance capacity of regional climate prediction within Asia-Pacific, through training of specialists from NMHSs and transfer of state-of-the-art downscaling prediction technology

-To provide basis for sustainable development of the Asia-Pacific region, especially for developing countries, by ensuring that participants will gain knowledge necessary for continuing research and development of regional climate prediction tools

-To develop reliable tools for regional climate prediction based on global MME products disseminated by the APEC climate Center (APCC for the use of NMHSs of Asia-Pacific countries, and to leverage the end value of existing APCC multi-model multi-ensemble (MME) forecasts. The basis for using the APEC climate center glonal prediction products to develop regional climate predictions is because it is now known that the multi-model multi-ensemble (MME) prediction technology, involving dynamic climate forecasts from several constituemt numerical model produces results significantly improved as compared to many of the results from the individual models (See Yun et al., 2003, 2005 for details). A number of meteorological centers worldwide have implemented routine dynamical seasonal predictions using coupled atmosphere-ocean-land climate models, such as ECMWF, APCC, IRI etc. APCC operates the world's biggest MME setup to issue its operational monthly 3-month forecasts. It has also developed expertise in statistical downscaling of its predictions for Korea and produces operational downscaling products.

2. Methodology

2.a. Course organization

There were three stages of the course implementation.

On the first, preparatory stage, APCC prepared and equipped with computers and all the necessary communication facilities the working places for the participants.

Specialists from APCC prepared lectures on deterministic downscaling methods and seminars on the use of APCC computing system and a software kit.

HMC prepared the lectures on probabilistic downscaling and multi-model approach to climate prediction.

NIWA provided the lectures on downscaling with application of the linear algebra based methods.

The second stage, was the training course. The training course "Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction" was conducted at APEC Climate Center, Busan, Republic of Korea, from September 22 to November 10, 2008 (The Program of the training course – see Appendix I). Four participants came to Busan from the Asia-Pacific countries (List of participants – see Appendix II). It was opened with the seminars where climate peculiarities of each of the participating countries were analyzed. The following training course combined lectures, seminars and hand-on computer sessions.

Lectures. The lectures cover three main topics: Theory and strategy of downscaling from the GCM outputs; Deterministic and probabilistic downscaling technique; Multimodel approach in downscaling practice.

Seminars. The nuances and peculiarities of various downscaling realizations were discussed and analyzed in the seminars. Special attention was paid to possible sources of the errors and methods allowing the developers to avoid those errors. Another topic also performed in a seminar form was the training in the use of the APCC computing system and software kit (CLIK – Climate Prediction and Information Toolkit (developed at APCC), NCL – NCAR Command Language, GRADS, Fortran).

Computer sessions. The main part of the course consisted of the hand-on computer sessions. On the basis of the knowledge obtained in the lectures and seminars, the participants trained in developing their own downscaling applications using the CLIK, APCC model predictions and the station data from their countries. Obtained results were verified, analyzed, necessary corrections made and new series of experiments performed.

The third stage was the analysis of the obtained results and report writing.

2.b. Technical methodology of dynamical seasonal forecasting and downscaling

2.b. 1 Simple Composite Method (SCM)

The following pages depict the 4 deterministic and 1 probabilistic forecast and hindcast MME methods used in the APCC climate predictions, followed by brief descriptions of the statistical downscaling philosophy and, finally, the online climate information tools. The partyicipant trainees were provided a thorough tringing on all these issues. The training coverrd npot only theoretical aspects, bit also hands-on operational training and also access to the the relevant softwares.

Multi-model ensemble (MME) technology has been considered as one of efficient solution to improve the weather and climate forecasts. The basic idea of MME is to avoid model inherent error by using a number of independent and skilful models in the hope of a better coverage of the whole possible climate phase spaces. SCM is a deterministic forecast scheme as a simple arithmetic mean of predictions based on individual member models. In SCM, there is an assumption that each model is relatively independent and to some extent, it has the capability to forecast the regional climate well, therefore we can expect a well model forecast by simple composite of each model prediction from different models. This scheme keeps the model dynamics due to the simple spatial filtering for each variable at each grid point. In addition, this simple scheme contains the common advantage and limitation of the model predictions, therefore, it could be a good benchmark used to evaluate other MME schemes.

SCM forecast constructed with bias-corrected data is given by

$$S_t = \overline{O} + \frac{1}{N}\sum_{i=1}^{N}(F_{i,t} - \overline{F_i})$$

(2.1)

where, $F_{i,t}$ is the i^{th} model forecast at time t, $\overline{F_i}$ and $\overline{O}$ is the climatology of the i^{th} forecast and observation, respectively, and N is the number of forecast models involved. Therefore, the SCM results are generated by the combination of bias-corrected model forecast anomalies. Skill improvements result from the bias removal and from the reduction of the climate noise by ensemble averaging. In this scheme, the ensemble mean assigns the same weight of *1/N* to each of the *N* member models in anywhere regardless of their relative performance.

2.*b. 2 Stepwise Pattern Projection Method (SPM)*

The new MME method (MME-SPPM) is based on the statistical downscaling method, which is named the stepwise pattern projection model (SPPM). The SPPM technique is an improved version of the current APCC MME method, CPPM. The major differences between the two techniques lie in the procedure for pre-predictor selection and the optimal choice of posterior prediction. It is shown that MME-SPPM offers better skill over the regions in which the average of individual model skill is poor.

The SPPM procedure consists of three steps: pre-predictor selection, pattern projection, and optimal choice of prediction. In the first step, qualified predictors are selected based on cross-validated correlation for the training period. The predictor field is reconstructed by using the selected 100 predictors at different grids which are best correlated with the predictand. In the second step, the covariance pattern is constructed between observed and reconstructed predicted pattern and then prediction is obtained by projecting predicted pattern on the covariance pattern using the following equation:

$$X_P(t) = \sigma_Y \sum_i \frac{COV(i) \bullet X(i,t)}{\sigma_X^2(i)}$$

(2.2)

where is the new predicted predictand at time t, is the observed standard deviation of predictand, is the covariance pattern between observed predictand and reconstructed predictor field, is the predictor at grid i and time t, and is the variance of the predictor at grid i. In the final step, we determine whether or not the selected predictand is predictable at each grid point using double cross-validation with a given threshold correlation skill, say 0.3. The threshold value of correlation skill is subjectively chosen here. Thus, the rigorous test will be needed to determine the value for optimal prediction. If the prediction skill of double cross validation with the selected predictor pattern does fall below the threshold value, we consider the predictand is not predictable and then give up that predictor and prediction at that grid point. To make a final MME prediction, we apply a simple multi-model composite using available prediction after applying SPPM to individual models. We performed sensitivity study in order to determine optimal parameters of SPPM package based on independent forecast experiment. We also developed the method to produce improved multi-model probabilistic forecast after applying SPPM to each model.

2.b.3 Multiple Regression (MRG)

The conventional multi-model superensemble forecast (Krishnamurti et al., 2000b) constructed with bias-corrected data is given by

$$S_t = \overline{O} + \sum_{i=1}^{n} a_i (F_{i,t} - \overline{F}_i) \qquad (2.3.)$$

Where, $F_{i,t}$ is the i^{th} model forecast for time t, $\overline{F}_i$ is the appropriate monthly mean of the i^{th} forecast over the training period, $\overline{O}$ is the observed monthly mean over the training period, a_i are regression coefficients obtained by a minimization procedure during the training period, and n is the number of forecast models involved. The multi-model superensemble forecast in equation (2.3.1) is not directly influenced by the systematic errors of forecast models involved because the anomalies term $(F_{i,t} - \overline{F}_i)$ in the equation accounts for each model's own seasonal climatology.

At each grid point for each model of the multi-model superensemble the respective weights are generated using pointwise multiple regression technique based on the training period.

For obtaining the weights, the covariance matrix is built with the seasonal cycle-removed anomaly ($F^{'}$),

$$C_{i,j} = \sum_{t=0}^{Train} F'_{i,t} F'_{j,t} \,, \qquad (2.4)$$

Where Train denote the training period, and i and j the i th and j th forecast models, respectively.

The goal of regression is to express a set of data as a linear function of input data. For this, we construct a set of linear algebraic equations,

$$C \cdot x = \tilde{o}' \,, \qquad (2.5)$$

Where $\tilde{o}_j' = \sum_{t=0}^{Train} O_t' F_{j,t}'$ is a (n x 1) vector containing the covariances of the observations with the individual models for which we want to find a linear regression formula, and o' is seasonal mean-removed observation anomaly, C is the (n x n) covariance matrix, and x is an (n x 1) vector of regression coefficients (the unknowns). In the convectional superensemble approach, the regression coefficients are obtained using Gauss-Jordan elimination with pivoting. The covariance matrix C and o' are rearranged into a diagonal matrix C′ and o'', and the solution vector is obtained as

$$x^T = \left(\frac{\tilde{o}_1''}{C_{11}'}, \ldots, \frac{\tilde{o}_n''}{C_{nn}'} \right) , \qquad (2.6)$$

where the superscript T denotes the transpose.

The Gauss-Jordan elimination method for obtaining the regression coefficients between different model forecasts is not numerically robust. Problems arise if a zero pivot element is encountered on the diagonal, because the solution procedure involves division by the diagonal elements. Note that if there are fewer equations than unknowns, the regression equation defines an underdetermined system such that there are more regression coefficients than the number of $\{o_j'\}$. In such a situation, there is no unique solution and the covariance matrix is said to be singular. In general, use of the Gauss-Jordan elimination method for solving the regression problem is not recommendable since singularity problem like the above are occasionally encountered. In practice, when a singularity is detected, the superensemble forecast is replaced by an ensemble forecast.

SVD is applied to the computation of the regression coefficients for a set of different model forecasts. The SVD of the covariance matrix C is its decomposition into a product of three different matrices. The covariance matrix C can be rewritten as a sum of outer products of columns of a matrix U and rows of a transposed matrix V^T, represented as

$$C_{i,j} = \left(UWV^T\right)_{i,j} = \sum_{k=1}^{n} w_k U_{ik} V_{jk}$$,

(2.7)

Here U and V are (n x n) matrices that obey the orthogonality relations and W is an (n x n) diagonal matrix, which contains rank k real positive singular values(w_k) arranged in decreasing magnitude. Because the covariance matrix C is a square symmetric matrix, $C^T = VWU^T = UWT^T = C$. This proves that the left and right singular vector U and V are equal. Therefore, the method used can also be called principal component analysis(PCA). The decomposition can be used to obtain the regression coefficients:

$$x = V \cdot \left[diag\left(\frac{1}{w_j}\right)\right] \cdot (U^T \cdot \tilde{Q}')$$

(2.8)

The pointwise regression model using the SVD method removes the singular matrix problem that cannot be entirely solved with the Gauss–Jordan elimination method.

Moreover, solving Eq. (2.8) with zeroing of the small singular values gives better regression coefficients than the SVD solution where the small values w_j are left as nonzero. If the small w_j values are retained as nonzero, it usually makes the residual | C · x 2 $\tilde{o}$ | larger (Press et al. 1992). This means that if we have a situation where most of the w_j singular values of a matrix C are small, then C will be better approximated by only a few large w_j singular values in the sum of Eq. (2.7).

2.b.5 Synthetic Super Ensemble (SSE)

Despite the continuous improvement of both dynamical and empirical models, the predictive skill of extended forecasts remains quite low. Multi-model ensemble predictions rely on statistical relationships established from an analysis of past observations (Chang et al., 2000). This means that the multi-model ensemble prediction depends strongly on the past performance of individual member models.

In the context of seasonal climate forecasts, many studies (Krishnamurti et al., 1999, 2000a,b, 2001, 2003; Doblas-Reyes et al., 2000; Pavan and Doblas-Reyes 2000; Stephenson and Doblas-Reyes 2000; Kharin and Zwiers 2002; Peng et al., 2002; Stefanova and Krishnamurti, 2002; Yun et al., 2003; Palmer et al., 2004) have discussed various multi-model approaches for forecasting of anomalies, such as the ensemble mean, the unbiased ensemble mean and the superensemble forecast. These are defined as follows:

$$E_b = \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{O})$$

$$E_c = \frac{1}{N}\sum_{i=1}^{N}(F_i - \overline{F_i}) \tag{2.9}$$

$$S = \sum_{i=1}^{N} a_i (F_i - \overline{F_i})$$

Here, E_b is the ensemble mean, E_c is the unbiased ensemble mean, S is the superensemble, F_i is the *i*th model forecast out of *N* models, $\overline{F_i}$ is the monthly or seasonal mean of the *i*th forecast over the training period, $\overline{O}$ is the observed monthly or seasonal mean over the training period, and a_i is the regression coefficient of the *i*th model. The difference between these approaches comes from the mean bias and the weights. Both the unbiased ensemble mean and the superensemble contain no mean bias because the seasonal climatologies of the models have been considered. The difference between the unbiased ensemble and the superensemble comes from the differential weighting of the models in the latter case. A major aspect of the superensemble forecast is the training of the forecast data set. The superensemble prediction skill during the forecast phase could be improved when the input multi-model predictions are statistically corrected to reduce the model errors.

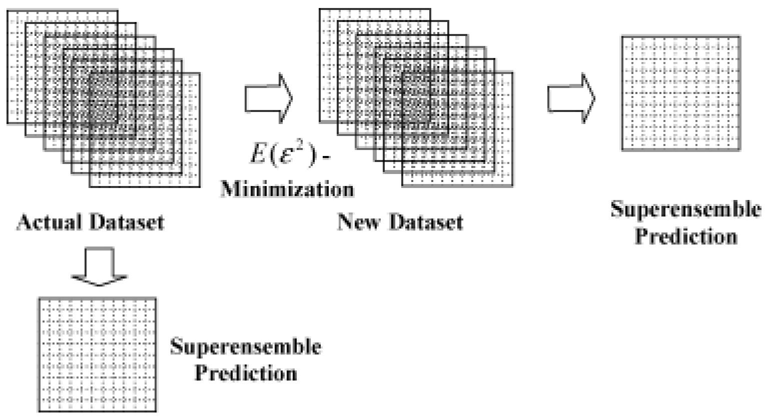

Fig. 2. Schematic chart for the superensemble prediction system. The new data set is generated from the original data set by minimizing the residual

error variance $E(\varepsilon^2)$ for each model

Figure 2. is a schematic chart illustrating the algorithm. The new data set is generated from the original data set by finding a consistent spatial pattern between the observed analysis and each model. This procedure is a linear regression problem in EOF space. The newly generated set of EOF-filtered data is then used as an input multi-model data set for ensemble/superensemble forecast. The computational procedure for generating the new data set is described below.

The observation data (O) and the multi-model forecast data set (F_i) can be written as linear combinations of EOFs, which describe the spatial and temporal variability:

$$O(x,t) = \sum_n \tilde{O}_n(t)\phi_n(x) \qquad (2.10a)$$

$$F_i(x,T) = \sum_n \tilde{F}_{i,n}(T)\varphi_{i,n}(x)$$

(2.10b)

Here, $\tilde{O}_n(t)$, $\tilde{F}_{i,n}(t)$ and $\phi_n(x)$, $\varphi_{i,n}(x)$ are the principal component (PC) time series and the corresponding EOFs of the nth mode for the observation and model forecast, respectively. Index *I* indicates a particular member model. The PCs in eqs. (2.10) represent the time evolution of spatial patterns during the training period (t) and the whole forecast time period (t). We can now estimate a consistent pattern between the observation and the forecast data, which evolves according to the PC time series of the training observations. The regression relationship between the observation PC time series and the number of PC time series of individual model forecast data can be written as

$$\tilde{O}(t) = \sum_n \alpha_{i,n}\tilde{F}_{i,n}(t) + \varepsilon_{i,n}(t)\,. \qquad (2.11)$$

With eq. (2.11) we can express the observation time series as a linear combination of the predictor time series. To obtain the regression coefficients $\alpha_{i,n}$ the regression is performed in the EOF domain. The regression coefficients $\alpha_{i,n}$ are found such that the residual error is minimized. The covariance matrix is constructed with the PC time series of each model. For obtaining the regression coefficients $\alpha_{i,n}$, the covariance matrix is built with the seasonal cycle-removed anomaly. Once the regression coefficients $\alpha_{i,n}$ are found, the PC time series of new data set is written as

$$\tilde{F}_i^{reg}(T) = \sum_n \alpha_{i,n}\tilde{F}_{i,n}(T) \qquad (2.12)$$

The new data set is now generated by reconstruction with corresponding EOFs and PCs:

$$\tilde{F}_i^{syn}(x,T) = \sum_n \tilde{F}_{i,n}^{reg}(T)\phi_n(x) \,. \qquad (2.13)$$

This EOF-filtered data set generated from the DEMETER coupled multi-model is used as an input data set for both multi-model ensemble and superensemble prediction systems that produce deterministic forecasts. What is unique about the new data set is that it minimizes the variance of the residual error between the observations and each of the member models. The residual error variance is minimized using a least-squares error approach.

2.b.5 Probabilistic Multi-Model Ensemble (PMME)

Probabilistic forecast are categorized as below-, near-, and above-normal based on predictions obtained from each member model. Each member model predictions are available with different number of ensemble members. Three equiprobable categories are classified by using normal (Gaussian) fitting method. The three categories for each member model are defined from climatological chance of occurrence for each category is 33.3% for the hindcast period. For each category, the forecast probability is obtained by counting the number of individual members that prediction a seasonal mean in that category, and combining on the basis of full probability formula with the weight according to square root of ensemble size for each model. The more detail methodology is as following.

Gaussian approximation is underlain by the assumption that the variable is theoretically normally distributed, $T \sim N(\mu,\sigma)$ and all deviations from the Normal distribution are occasional due to the small sample size. This approach is not new, it is rather traditional and has been used in numerous studies in the past (Leith, 1973; Madden, 1976; Zwiers, 1996; Kharin and Zwiers, 2001; Kharin and Zwiers, 2003, and many others).

We use hindcast data for estimation of the tercile boundaries (x_b and x_a) and forecast data for estimation of the probabilities associated with each of the tercile. Within this approach, we assume that probability distribution functions of both hindcast and forecast are Gaussian PDFs.

We approximate probability distribution of the hindcast data with the normal one with parameters μ and σ estimated based on the hindcast sample (ensemble). The two boundaries to determine three equiprobable categories are defined as x_b = μ -0.43 σ and x_a = μ +0.43 σ. Forecast data probability distribution is also approximated with normal one with parameters μ and σ estimated based on the forecast sample (ensemble). Probabilities of the terciles are estimated as,

$$P_x(B) = \Pr ob[x \le x_b] = \int_{-\infty}^{x_b} f(x)dx$$

(2.14)

$$P_x(N) = \Pr ob[x_a < x \le x_b] = \int_{-\infty}^{x_a} f(x)dx - P_x(B)$$

(2.15)

$$P_x(A) = \Pr ob[x_a < x] = 1 - P_x(B) - P_x(N)$$

(2.16)

where $f(x)$ is Gaussian probability distribution function:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(x-\mu)^2}{2\sigma^2})$$

(2.17)

and μ and σ are the mean and standard deviation of the forecast data (ensemble).

Figure 3 illustrates the probabilities of observing X in one of the three equiprobable categories condition. The lower and upper threshold are defined by 33.3% and 66.7% cumulative quantiles, respectively, of a probability density function (PDF) fitting to climatological PDF.

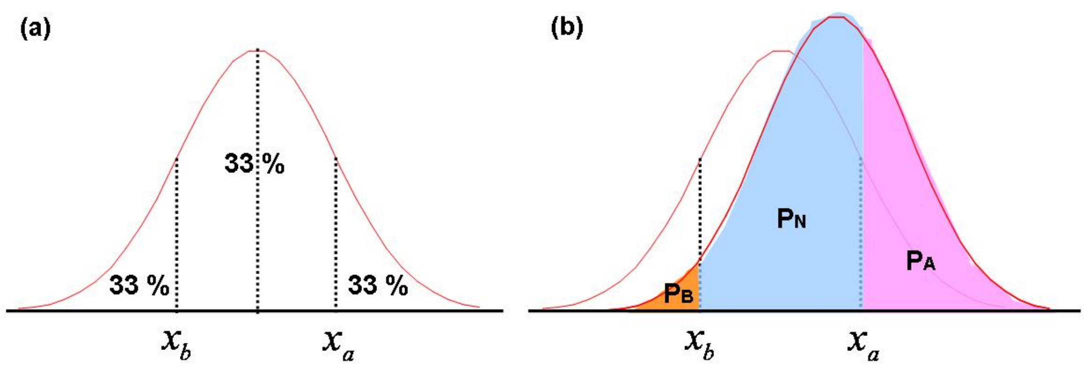

Fig. 3 (a). Definition of the tercile borderlines using the climatological PDF. (b). Forecast probabilities of below-normal (P_B), near-normal (P_N), and above-normal (P_A).

For each grid point, in order to merge three category probabilistic forecasts (above-normal, near-normal, and below-normal) the chi-square (χ^2) test is applied. We estimate statistic

$$\chi^2 * = \sum_{i=1}^{3} (O_i - E_i)^2 / E_i \quad ,$$

(2.18)

where *O* is observed frequency and *E* is expected frequency equal to one third of ensemble size. Under the Null hypothesis (uniform probability distribution – forecast is uncertain) this statistic has χ^2 probability distribution. We set significance level at 0.05 and treat forecast certain and associated with maximal probability out of three categories if Null hypothesis is rejected.

The participants were also trained on the hindcast and forecast verification methods follwed at APCC, which are essentially the WMO's recoomeded level 3 skills.

2.b. 6 Statistical Downscaling

APCC has successfully developed and implemented a regression-based statistical downscaling technique for Korea. It is based on multi-predictor optimal selection and coupled pattern projection method (Kang et al, 2008). Since Feb. 2008, the predictions of precipitation and temperature based on the downscaling scheme have been operationally provided for 60 Korean stations for every month.

Experimental probabilistic interpretation of multi-model downscaled forecasts was carried out for one season. APCC plans to continuously make efforts on probabilistic downscaling based on accounting for combined uncertainty associated with regression and model spread. Moreover, development of a temporal downscaling method based on weather generator is initiated for fine-scale temporal information (e.g., wet/day days, rainfall amount, etc.).

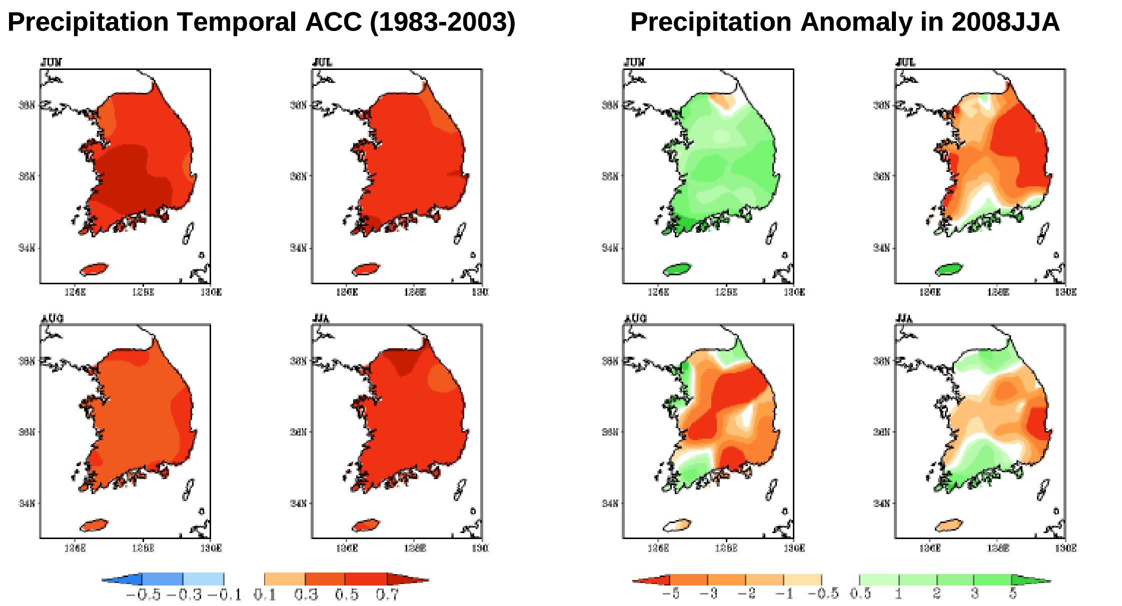

Fig.1 Temporal correlation coefficients of downscaled precipitation during 1983 to 2003 JJA (left) and predictions of downscaled precipitation in 2008 JJA (right)

Interactive on line climate information (CLIK) tools: In order to promote better utilization of climate information, APCC has recently developed a web-based tool kit. This online product, named CLIK (CLimate Information tool Kit), aids users in retrieving and utilizing climate prediction data and information available from APCC data servers in a user friendly manner.

The data processing engines powering CLIK at the backend are built on the NCAR Command Language (NCL) a powerful suite of libraries for climate data manipulation and visualisation.

The web interface of CLIK is built on the popular web building framework known as Ruby on Rails (RoR). Both RoR and NCL are powerful frameworks , includes an extensive API (Application Program Interface) and allows easy incorporation of existing Fortan/C codes.

Both frameworks are being extensively used at APCC. The automated forecast system(AFS), APCCi¯s semi-automated operational framework is built upon NCL and has been in operational use at APCC since January 2008.

Ruby on Rails (RoR) is a relatively new entry into the APCC workflow. RoR is an open-source web framework written in Ruby. Ruby in turn is a dynamic, open source, object oriented programming language with a focus on simplicity and productivity.

It has an elegant syntax that is natural to read and easy to write. Ruby is a language of careful balance. Its creator, Yukihiro Matsumoto, blended parts of his favorite languages (Perl, Smalltalk, Eiffel, Ada, and Lisp) to form a new language that balanced functional programming with imperative programming.

RoR is based on the the Model-View-Control pattern of separation and provides a full stack web-application and persistence framework that includes everything needed to create databasebacked web-applications.

It enforces good design principles, consistency of code across your organization, and proper release management. Rails swept to world-wide attention in the spring of 2005. Since then, it has become a serious and popular alternative to traditional web development environments such as Java and .NET. From the Ajax in the view, to the request and response in the controller, to the domain model wrapping the database, Rails gives you a pure-Ruby development environment.

Results and Discussion

The main results from the Training Course could be combined into three groups:
1. Theoretical knowledge in downscaling theory and techniques and in multi-model combination.
2. Practical experience in access to and processing of the APCC basic data – global model outputs.
3. Practical experience in the usage of the APCC CLIK for the purposes of downscaling.

1. In the theoretical part of the training course the participants were given the lectures and seminars on the theory of downscaling, downscaling techniques and peculiarities of downscaling from multi-model ensemble forecasts. Particular lectures cover: deterministic and probabilistic approaches to downscaling, nuances of statistical applications for the downscaling from the model outputs, the basics of multi-model climate forecasting, and many other downscaling-related matters.

2. APCC provides access to its data via Internet. During the course the participants got the skill in downloading large volumes of model output data, perform the data preprocessing procedures such as quality check, estimate of ensemble mean, spread, bias correction, anomalies, etc. These model outputs are used as predictors in downscaling procedures.

3. APCC developed the software, CLIK (Climate Prediction and Information Toolkit),

for data processing and analysis. This software provides the users with the ability to develop their own applications by using the toolkit. The participants experienced in the development of the user applications for particular downscaling methods and so, they become able to develop the downscaling applications by themselves.

The training course has been conducted on the basis of the model simulated global seasonal climate prediction data. However, the results from the course are not restricted to only the seasonal climate prediction. Downscaling approaches and general downscaling procedures are the same in both seasonal climate prediction and multi-decadal climate change projection (IPCC FAR, 2008), with the requirements posted to downscaling methods in the seasonal climate prediction framework being more strict and methods being verified more precisely. Therefore, the obtained knowledge and experience can be applied in the framework of the regional climate change assessments.

4. Conclusions

The goal of the Training Course "Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction" has been achieved. The representatives of the developing countries of the Asia-Pacific region have got the knowledge in the downscaling theory and techniques and experience in performing of the downscaling procedures in application to their country needs. Furthermore, the participants have got access to the APCC multimodel ensemble dataset and to the ready to use CLIK tools developed by the APCC science team. Thus, it was achieved the main goal of the CAPaBLE program, i.e., the capacity building and enhancement for sustainable development in developing countries.

5. Future Directions

Future directions of regional cooperation in the enhancement of capacity of climate prediction and adaptation imply two future directions of development. The first one is improvement of the reliability of the existing downscaling methods and development of the new methods (e.g., probabilistic). The second direction is development of the regional decision supporting applications based on the downscaled predictions, however, this direction implies much closer integration within the region than it is today. So, the second directions is rather a proposal for the future, meanwhile, the development of the first direction, actually, provision of the countries in the region with the improved climate prediction tools can be started nowadays.

APCC developed the CLIK software in 2008. APCC provides free access to its data and user-friendly CLIK interface via Internet for the specialists from NMHSs of the Asia-Pacific region. Owing to the training course the participants become able to perform downscaling from the APCC forecasts via the Internet interface in the real-time mode (operational forecast) using existing methods. Furthermore, within the framework of CLIK software, there is a potential for development and implementation of new advanced downscaling methods, which provides the bases for further cooperation between APCC and NMHSs and between NMHSs – the users of the APCC data and software.

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Appendix I – Funding outside the APN

APEC Climate Center:

Financial: In-kind contributions $100,000 (toward staff time, data handling costs, software development costs etc.).

Appendix II – The Program of the training course

APN DETAILED PROGRAM SCHEDULE

Course Title : **Training Course on Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction**

Duration : **September 22(Monday) - November 10(Monday), 2008**

Place : **APEC Climate Center**

Practice class

Date/Time	Activities	Responsible	Location
Sep 22 (Mon)	**Lecture**		**APCC**
09:30-11:30	Orientation	Dr. Gun-Kyo Jung	
12:00-13:00	Lunch		
13:30-15:30	Seminar "WMO LRF framework"	Dr. Vladimir Kryjov	
18:00	Dinner		
Sep 23 (Tue)	**Lecture**		
09:30-11:30	Country Report / brain storming on Challenges in local climate prediction	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-14:30	Branstorming continues	Dr. Vladimir Kryjov	
14:30-15:30	Global Climate Prediction System	Dr. Bong-Geun Song	
15:30-16:30	APCC Seasonal Prediction System	Dr. Karumuri Ashok	
16:30-17:30	Further discussion, if necessary	Dr. Vladimir Kryjov	
18:00	Welcoming Party		
Sep 24 (Wed)	**Lecture**		
09:30-11:30	APCC Computing System I (Hardware)	Mr. Hanse Yi	
12:00-13:00	Lunch		
13:30-15:30	APCC Computing System II (Software)	Mr. Sang-Cheol Kim	
18:00	Dinner		
Sep 25 (Thu)	**Lecture**		
09:30-11:30	Introduction to Grads	Ms. Hye-In Jeong	
12:00-13:00	Lunch		
13:30-15:30	Introduction to NCL	Ms. Soo-Jin Sohn	
18:00	Dinner		

Sep 26 (Fri)	**Lecture**		
09:30-11:30	Climate Information tool Kit (CLIK)	Dr. Saji N. Hameed	
12:00-13:00	Lunch		
13:30-15:30	APCC Data Service System (ADSS)	Mr. Doo-Young Lee	
18:00	Dinner		
Date / Time	**Activities**	**Responsible**	**Location**
Sep 27 (Sat)			
Sep 28 (Sun)			
Sep 29 (Mon)	**Lecture**		
09:30-11:30	(1) Potential of downscaling techniques for climate applications	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	(2) Graphic tools	Dr. Vladimir Kryjov	
18:00	Dinner		
Sep 30 (Tue)	**Lecture**		
09:30-11:30	Probabilistic climate prediction. Basics and different approaches to probabilistic multimodel prediction	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Overview of multivariate statistical approaches: EOF, SVDA, CCA analysis	Dr. Ashok Karumuri	
18:00	Dinner		
Oct 1 (Wed)	**Lecture**		
09:30-11:30	Introduction to Fortran	Ms. Hye-In Jeong	
12:00-13:00	Lunch		
13:30-15:30	Overview of Downscaling tools	Dr. Saji N. Hameed	
18:00	Dinner		
Oct 2 (Thu)	**Lecture**		
09:30-11:30	Probabilistic climate prediction. Basics and different approaches to probabilistic multimodel prediction	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		

13:30-15:30	Downscaling applications	Dr. Vladimir Kryjov Dr. Saji N. Hameed	
18:00	Dinner		
Oct 3 (Fri)	Korea National Holiday		
Oct 4 (Sat)			
Oct 5 (Sun)			
Date / Time	**Activities**	**Responsible**	**Location**
Oct 6 (Mon)	**Interim Report**		
09:30-11:30			
12:00-13:00	Visiting KMA		
13:30-15:30			
18:00			
Oct 7 (Tue)	**Interim Report**		
09:30-11:30			
12:00-13:00	Visiting KMA		
13:30-15:30			
18:00			
Oct 8 (Wed)	**Interim Report**		
09:30-11:30	Interim Report		
12:00-13:00	Lunch		
13:30-15:30	Interim Report		
18:00	Dinner		
Oct 9 (Thu)	**Interim Report**		
09:30-11:30	Interim Report		
12:00-13:00	Lunch		
13:30-15:30	Interim Report		
18:00	Dinner		
Oct 10 (Fri)	**Interim Report**		
09:30-11:30	Interim Report		
12:00-13:00	Lunch		
13:30-15:30	Interim Report		

18:00	Dinner		
Oct 11 (Sat)			
Oct 12 (Sun)			
Date/Time	**Activities**	**Responsible**	**Location**
Oct 13 (Mon)	**Lecture**		
09:30-11:30	Deterministic downscaling : Coupled Pattern selection and projection	Dr. Hongwen Kang	
12:00-13:00	Lunch		
13:30-15:30	Deterministic downscaling : Multi predictor optimal selection	Dr. Hongwen Kang	
18:00	Dinner		
Oct 14 (Tue)	**Lecture**		
09:30-11:30	Research I (The tropical controls of the Asian monsoon)	Dr. Ashok Karumuri	
12:00-13:00	Lunch		
13:30-15:30	Research II (The tropical controls of the Asian monsoon)	Dr. Ashok Karumuri	
18:00	Dinner		
Oct 15 (Wed)	**Lecture**		
09:30-11:30	APCC Monitoring System	Ms. Soo-Jin Sohn	
12:00-13:00	Lunch		
13:30-15:30	Supercomputing at APCC	Dr. Bong-Geun Song	
18:00	Dinner		
Oct 16 (Thu)	**Lecture**		
09:30-11:30	Deterministic downscaling: Introduction to downscaling methods	Dr. Hongwen Kang	
12:00-13:00	Lunch		
13:30-15:30	Deterministic downscaling: Strategy	Dr. Hongwen Kang	
18:00	Dinner		
Oct 17 (Fri)	**Lecture**		
09:30-11:30	Probabilistic downscaling: Uncertainty of the forecast and its assessment; multimodel peculiarities	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Code writing and implementation for probabilistic downscaling for different regions	Dr. Vladimir Kryjov Ms. Young-Mi Min	
18:00	Dinner		

Oct 18 (Sat)			
Oct 19 (Sun)			
Oct 20 (Mon)	**Lecture**		
09:30-11:30	Probabilistic downscaling: Bayes theorem: basics, likelihood function, multivariable case	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Code writing and implementation for probabilistic downscaling for different regions	Dr. Vladimir Kryjov Ms. Young-Mi Min	
18:00	Dinner		
Date/Time	**Activities**	**Responsible**	**Location**
Oct 21 (Tue)	**Lecture**		
09:30-11:30	Probabilistic downscaling: verification methods and metrics	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Code writing and implementation for probabilistic downscaling for different regions	Dr. Vladimir Kryjov Ms. Young-Mi Min	
18:00	Dinner		
Oct 22 (Wed)	**Lecture**		
09:30-11:30	Probabilistic downscaling: multimodel probabilistic prediction methods based on Bayes theorem	Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Code writing and implementation for probabilistic downscaling for different regions	Dr. Vladimir Kryjov Ms. Young-Mi Min	
18:00	Dinner		
Oct 23 (Thu)	**Lecture**		
09:30-11:30	Research III	Dr. Bong-Geun Song	
12:00-13:00	Lunch		
13:30-15:30	Research ☐	Ms. Young-Mi Min	
18:00	Dinner		
Oct 24 (Fri)	**Lecture**		
09:30-11:30	Research ☐	Mr. Doo-Young Lee	
12:00-13:00	Lunch		
13:30-15:30	Research ☐	Ms. Kyong-Hee An	
18:00	Dinner		

Oct 25 (Sat)			
Oct 26 (Sun)			
Oct 27 (Mon)	**Lecture**		
09:30-11:30	Deterministic downscaling: Implementations and code writing □	Dr. Hongwen Kang	
12:00-13:00	Lunch		
13:30-15:30	Deterministic downscaling: Implementations and code writing □	Dr. Hongwen Kang	
18:00	Dinner		
Date / Time	**Activities**	**Responsible**	**Location**
Oct 28 (Tue)	**Lecture**		
09:30-11:30	MME Forecast with CLIK	Dr. Saji N. Hameed Ms. Kyong-Hee An	
12:00-13:00	Lunch		
13:30-15:30	MME Forecast with CLIK	Dr. Saji N. Hameed Ms. Kyong-Hee An	
18:00	Dinner		
Oct 29 (Wed)	**Lecture**		
09:30-11:30	Downscaling Forecast with CLIK	Dr. Saji N. Hameed Ms. Kyong-Hee An	
12:00-13:00	Lunch		
13:30-15:30	Downscaling Forecast with CLIK	Dr. Saji N. Hameed Ms. Kyong-Hee An	
18:00	Dinner		
Oct 30 (Thu)	**Lecture**		
09:30-11:30	Extending CLIK Functionality I	Dr. Saji N. Hameed	
12:00-13:00	Lunch		
13:30-15:30	Extending CLIK Functionality II	Ms. Kyong-Hee An	
18:00	Dinner		
Oct 31 (Fri)	**Lecture**		
09:30-11:30	Analisys of forecast	Dr. Ashok Karumuri	
12:00-13:00	Lunch		
13:30-15:30	Verification	Dr. Vladimir Kryjov	

18:00	Dinner		
Nov 1 (Sat)			
Nov 2 (Sun)			

Date / Time	Activities	Responsible	Location
Nov 3 (Mon)	**Lecture**		
09:30-11:30	Downscaling of NDJ Forecast of station levels	Dr. Hongwen Kang	
12:00-13:00	Lunch		
13:30-15:30	Verification	Ms. Young-Mi Min	
18:00	Dinner		
Nov 4 (Tue)	**Lecture**		
09:30-11:30	Final report	Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
12:00-13:00	Lunch		
13:30-15:30	Final report	Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
18:00	Dinner		
Nov 5 (Wed)	**Lecture**		
09:30-11:30	Final reports	Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
12:00-13:00	Lunch		
13:30-15:30	Final reports	Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
18:00	Dinner		
Nov 6 (Thu)	**Lecture**		
09:30-11:30	Final reports	Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
12:00-13:00	Lunch		
13:30-15:30	Review and evaluation	Dr. Woo-Jin Lee Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
18:00	Dinner		

Nov 7 (Fri)	**Lecture**		
09:30-11:30	Review and evaluation	Dr. Woo-Jin Lee Dr. Ashok Karumuri Dr. Saji N. Hameed Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Review and evaluation	Dr. Woo-Jin Lee Dr. Vladimir Kryjov Dr. Ashok Karumuri Dr. Saji N. Hameed	
Nov 10 (Mon)	**Lecture**		
09:30-11:30	Review and evaluation	Dr. Woo-Jin Lee Dr. Ashok Karumuri Dr. Saji N. Hameed Dr. Vladimir Kryjov	
12:00-13:00	Lunch		
13:30-15:30	Review and evaluation Report writing	Dr. Ashok Karumuri Dr. Saji N. Hameed Dr. Vladimir Kryjov	
18:00	Farewell Party		

Appendix III – List of participants

Training Course

"Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction"

List of Foreign Participants

	Position	Affiliation	Address
Vladimir Kryjov (Kryzhov)	Leading Research Scientist	Hydrometeorological Research Centre of the Russian Federation	Bol.Predtechensky Per. 11-13, Moscow, 123242 Russia Tel. 7-499-255226 e-mail: kryjov@mecom.ru; kryjov@yahoo.co.uk
Mongkol Prongsungnoen	Meteorogist	Climate Group, Meteorological Developement Bureau, Thai Meteorological Department, Thailand	4353 Thai Meteorological Department, Bangna Bangkok Thailand 10260 Tel. 662-398-9929 e-mail: m_prong@yahoo.com
Nguyen Dang Quang	Researcher, Division of Research and Development	Vietnam National Center for Hydrometeorological Forecastings	4 Dang Thai Than, Hoan Kiem District, Hanoi, Vietnam. Tel. : 84-4-9330942 Email : quangvnes@yahoo.com quangnd@vnu.vn
Rosalina G. De Guzman	Supervising Weather Specialist	Philippine Atmospheric, Geophysical & Astronomical Administration (PAGASA)	Agham Road, Diliman, Quezon City, Philippines 1100 Tel No. 063(2)-4340955 e-mail : rdeguzmanph@yahoo.com

Appendix IV – Country Reports

Downscaling of Precipitation in the Type 1 Climate for the Philippines

Rosalina G. De Guzman
Philippine Atmospheric, Geophysical & Astronomical Services Admnistration (PAGASA)

Abstract

This paper presents the use of CLIK technique to establish the statistical relationship between station rainfall in the Philippines under the Type 1 climate and the larger-scale atmospheric circulation from GCM outputs for 4 target seasons (MAM, JJA, SON, DJF). The downscaling is carried out for each station in the Type 1 climate for each model in a cross-validation manner. This downscaling technique is based on linear regression models and makes use of long-term GCM hindcasts data to derive the dynamic relationship between observations and model outputs. The purpose of downscaling is to obtain high-resolution detail as accurately as possible over the area of interest. The CLIK was designed to take only significantly correlated areas which are taken into account in the downscaling procedure. Analysis showed that downscaled GCM model outputs have significant skill in most of the target seasons evaluated. The improvement gained when using the statistical downscaling tool is significant Downscaled MME distinctly showed to have better prediction skill than the original one for all the target seasons. The results indicate that the large-scale circulation pattern from current GCMs muti model outputs have the potential in predicting station-scale precipitation in the Philippines using CLIK.

1. Introduction

The Philippines is situated just off the southeastern portion of the Asiatic continent in an almost north to south orientation. The island extends from about 4.7°N to 22.5°N and 117°E to 127°E in their longest and broadest dimensions. The complexity of terrain varies a great deal. From extensive mountainous regions in Luzon and Mindanao to land-sea mix in the Visayas that produces large spatial variability in the rainfall. The topographic features of the country play an important role in the seasonal variations of the climate. The country's climate is tropical and maritime and is influenced by large-scale atmospheric patterns that bring in substantial amount of rains almost all year round. It is characterized by a relatively high temperature, high humidity and abundant rainfall. The spatial distribution of precipitation varies regionally and is largely dependent on the direction of the moisture-bearing winds and the location of the mountain ranges. Mean annual rainfall varies from 965 to 4,064 millimeters annually, with the eastern parts of the country receiving the greatest amount of rainfall and the southernmost part of Mindanao receiving the less.

During the summer monsoon (southwest monsoon) heavy rains are concentrated over the western coastal areas of Luzon and the Visayas known as the Type 1 climate. Thus, aside from typhoons, it is responsible for about 50% of the rainfall during the rainy season in these areas. The southwest monsoon is characterized by so much variability to create periods of dry and wet spells that varies significantly from year to year. In winter, the climate is dominated by the winter monsoon (northeast monsoon). It originates in the cold intense Asiatic Winter Anticyclone and spirals outward across Japan towards the Northwestern Pacific Ocean. It finally reaches the country as a Northeasterly air stream. It starts affecting the Philippines during the later part of October, attains its maximum intensity in January and gradually recedes in the later part of April. This air stream is responsible for the relatively cold weather spell and heavy rainfall along the eastern coastal regions of the country during the winter season of the year.

Seasonal variability of rainfall in the Philippines is greatly influenced by the El Nino Southern Oscillation (ENSO) (Jose 2002). El Nino conditions lead to drier seasons caused by suppressed tropical cyclone activity in the western equatorial Pacific and weak monsoon activity which is characterized by delayed onset, dry periods or monsoon breaks and early termination. La Nina conditions are characterized by earlier to near-normal onset, above normal rainfall and longer rainy seasons. Abnormalities in the local climate as manifested by the ENSO phenomenon have both negative and positive impacts on the various sectors of the society but experience would show that there are more adverse impacts than the beneficial ones. Not only is the relationship between ENSO and climate understood by the Philippine scientific community, the knowledge is being used operationally, especially in the context of disaster prevention and climate risk management. Thus, the reliability of seasonal climate forecasts is of great concern especially to the user community. The ability to understand and predict these variations has an immense value especially for the management of the agriculture and water resources sectors in order to anticipate and mitigate associated impacts of monsoon variability such as drought and flood. Identifying and understanding the influence of the large-scale atmospheric circulation patterns which produce variations of rainfall in different time scales over the Philippines is therefore of crucial and great importance in seasonal forecasting in the country.

Seasonal climate forecasting is essentially based on the premise that the slowly evolving sea surface temperature (SST) anomalies influence seasonal mean weather conditions (Palmer & Anderson 1994; Goddard et al. 2001). Variability in SST provides the main source of atmospheric predictability at seasonal time-scales. Therefore, estimation of the evolution of SST anomalies, which are often relatively predictable, and subsequently employing them as input to an atmospheric GCM, potentially provides the means of generating forecasts of seasonal average weather (Grahamet al. 2000). Seasonal forecasts are generally provided by leading global climate centers using General Circulation Models (GCMs). Direct application of output from General Circulation Models (GCMs) is often insufficient because of the limited representation of mesoscale atmospheric processes, topography and land-sea distribution in GCMs [e.g. Cohen, 1990; von Storch et al., 1993]. GCMs can provide skillful seasonal forecast of mean circulation particularly in the tropics (e.g. Stockdale et al 1998; Charney and Shukla 1981) and such information may be used to forecast the rainfall at a certain area of interest. Local climate is greatly influenced by local features such as mountains, which are not well represented in GCMs because of their coarse resolution. Hence, seasonal forecasts from GCMs may have limited predictability since it cannot capture the influence of small scale synoptic features. It has been shown from previous studies that dynamical models can provide skilful seasonal forecasts, i.e. forecasts that are better than climatology, particularly in the tropics (Stockdale et al. 1998, Feddersen et al, 1999), but it has also been demonstrated that the prediction skill, particularly for precipitation, can be further improved using statistical techniques to correct the raw model output.

The most critical variable in the Philippines that is often poorly predicted on local scale is precipitation which is also one of the most important variables for many applications One approach to improve poor predictions of precipitation is that of statistical downscaling (Feddersen,et al 2004). Statistical downscaling aims at specifying the local field (the predictand, e.g. precipitation) from a large scale field (the predictor) which is accurately predicted by the dynamical model. There is a significant skill improvement when statistical downscaling of GCMs model outputs were used to forecast the precipitation in selected areas in the Philippines and Thailand as shown in the results of Kang et al (2007).

A combination of forecast of various different dynamical predictions, the so called multi-model ensemble (MME) prediction, has emerged as one of the more popular techniques in climate prediction (Barnston et al. 2003; Palmer et al. 2000, 2004; Shukla et al. 2000). The objective of multimodel ensemble prediction is to reduce the uncertainty in model errors by combining forecasts of various independent models. Kang et al (2007) showed that downscaled MME forecasts for the Philippines and Thailand using six GCMs were more skillful compared to any individually downscaled GCM forecast. The same findings were also documented in the downscaling of rainfall in Korea and the study of Chu et al (2008) for seasonal prediction of precipitation in Taiwan.

2. Objective

The study had two main objectives:

- To obtain the statistical relationship between station rainfall in the Philippines and the larger atmospheric circulation.
- To apply the use of CLIK as a downscaling tool and evaluate its ability in predicting seasonal rainfall in the Philippines.

3. Data and Methodology

3.1 Data

The datasets used in this study include historical hindcast data of 500 hPa geopotential height (Z500), sea level pressure (SLP), and zonal wind (u850 ,u200) from six different GCMs, with the target four seasons of DJF, MAM, JJA and SON which are used as predictors for statistical downscaling. The predictor variables are GCM gridded output data with a spatial resolution of 2.5º latitude x 2.5º longitude. The observed rainfall data are taken from the Philippine Atmospheric Geophysical and Astronomical Services Administration (PAGASA) from 1982 -2002. Similarly, the reanalysis data also covers the same period. The predictand to be downscaled were observed monthly precipitation at selected stations over the Philippines. Their locations are shown in Figure 1.

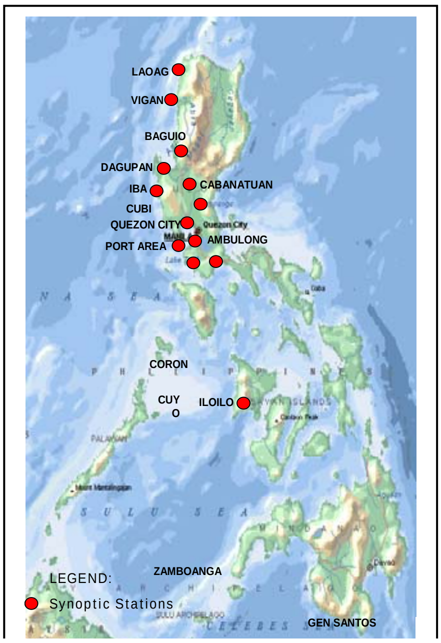


Figure 1: Stations under the Type 1 Climate

The descriptions of the individual model and hindcast datasets are tabulated in Table 1. Hindcast datasets of the GCMs include the u-component of wind at 850 and 200 hPa, geopotential height (z500), sea level pressure (slp) and temperature at t850.

Model	**Institution (Member Economy)**	**Data Type**	**Ensemble Size**	**Training Period**
CWB	Central Weather Bureau (Chinese Taipei)	SMIP	5	1979-2004
GCPS	Korea Meteorological Administration (Korea)	SMIP	10	1979-2003
GDAPS_F	Korea Meteorological Administration (Korea)	SMIP	10	1979-2003
GDAPS_O	Korea Meteorological Administration (Korea)	SMIP	10	1979-2003
HMC	Hydro-meteorological Central of Russia (Russia)	SMIP	6	1979-2003
JMA	Japan Meteorological Agency (Japan)	SMIP	6	1983-2003
METRI	Meteorological Research Institute / KMA (Korea)	SMIP	10	1979-2004
MGO	Main Geophysical Observatory (Russia)	SMIP	6	1979-2004
NCC	National Climate Center (China)	SMIP	8	1979-2005
NCEP	Climate Prediction Center/NCEP (United States)	CMIP	10	1981-2003

Table 1: Description of Hndcast Data Set from participating GCM models

3.2 Choice of Predictors

Selecting the suitable predictors for the predictand is a fundamental part of the downscaling exercise. An initial set of predictor variables was chosen based on the following criteria:

a) an assessment of which GCM are most reliable,
b) it must have a stable relationship between the predictor and the predictand,
c) the predictor should be well predicted by the dynamical model (Wilby et al. 1999)

In addition to identifying the best predictor, another important consideration taken into account is the choice of domain for which the predictor values are selected. One of the basis for the domain selection is that it should be large enough to resolve the relevant large-scale pattern and encompass corresponding observations

(Feddersen et al. 2005). Predictors were examined over the region 45 ºS 45 ºN and 60 ºE 300 ºE . This is large enough to capture the large scale pattern affecting the Philippines during the target season.

3.3 The CLIK Downscaling Scheme

A statistical downscaling method developed by APCC known as the Climate Information Kit (CLIK) was used to empirically relate large scale atmospheric circulation variables with seasonal precipitation. This method is regression based and is constructed by deriving empirical relationships between the large-scale GCM predictors and the station-scale predictands. This downscaling method makes use of long-term GCM hindcasts data to derive the dynamic relationship between observations and model outputs. Downscaling techniques allow the mapping of the low-resolution global predictions to a high-resolution set of forecasts as accurately as possible for a network of stations over an area of interest. It also bridged the gap between the low-resolution global ensemble predictions and the high-resolution end-user requirements for seasonal climate prediction.

Different approaches have been devised to deal with the model uncertainty problem (see e.g. Palmer et al., 2005): multi-model, stochastic physics and perturbed parameter approaches. CLIK incorporates the multi model ensemble system (MME) to the downscaling tool to reduce uncertainty and correct raw model outputs from GCMs. The multi-model approach consists of performing simulations with different prediction models. It is a practical solution to the problem that can be combined with the ensemble method to perform multi-model ensemble simulations. This system produces more skilful and reliable estimates of future states of the atmosphere and the ocean than any single model (Palmer et al., 2004).

3.4 Methodology

The first step that was carried out in this study is to identify large-scale atmospheric predictors that drive local rainfall. This is done by two methods: The first one is by eyeball verification and if it is not recognizable by human eye, the CLIK technique was applied to get the correlation pattern for each GCM outputs. The choice of predictors has to be limited to the most credible fields from climate models. There are 6 model data sets used for statistical downscaling. Several predictors were tested: synoptic atmospheric fields, such as mean sea level pressure (MSLP), geopotential height at mid (500 hPa) levels; low level air flows (U850); zonal wind (U200) and thermal variables such as T850. Models with good performance in predicting the predictors are selected.

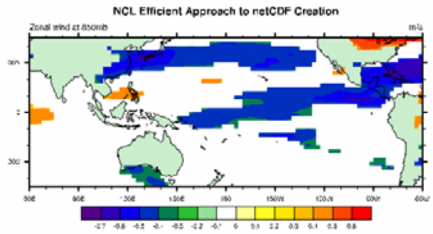
Correlation coefficient between observed and predicted field are calculated for each season before downscaling. Correlation coefficient analysis between observed station precipitation and the observed predictors is carried out for each station under the Type 1 climate and target season in searching for the large range of coupled pattern. The observed pattern provide a solid basis for the choice of the predictor and its domain. The CLIK was designed to take only significantly correlated areas which are taken into account in the downscaling procedure. The basic idea of precipitation downscaling is that local precipitation is related to large scale patterns of model variables. After downscaling each model, a MME is made to further improve the prediction skill.

4.0 Results and Discussion

4.1 MAM Season

The spring season (MAM) is the transition season in the Philippines. During the latter part of the season farmers start plowing their fields in preparation for the rainy season. There are two predictors that can be used during the season. Maps showed that there are consistent pattern for both GCPS u850 and GDAPS_F z500 with station rainfall under the Type 1 climate.

The left panel in Figure 2 shows the spatial distribution of correlation coefficient between Type 1 climate precipitation and GCPS u850 in MAM; right panel displays the result for GDAPS_F Z500.



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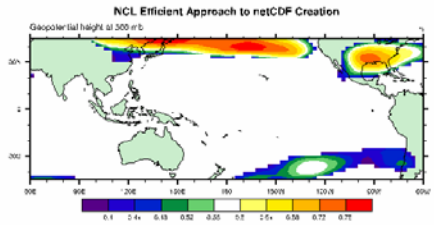

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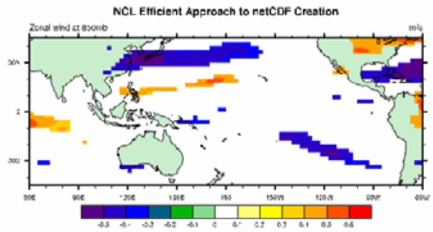

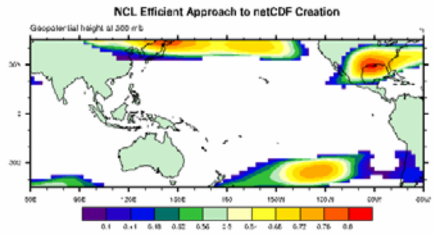

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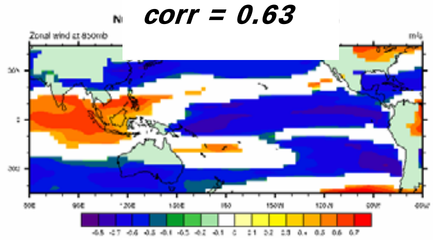

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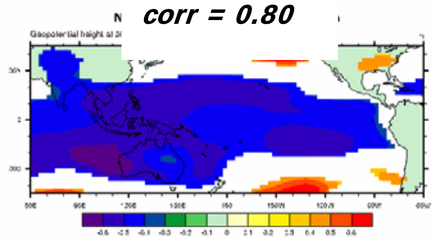

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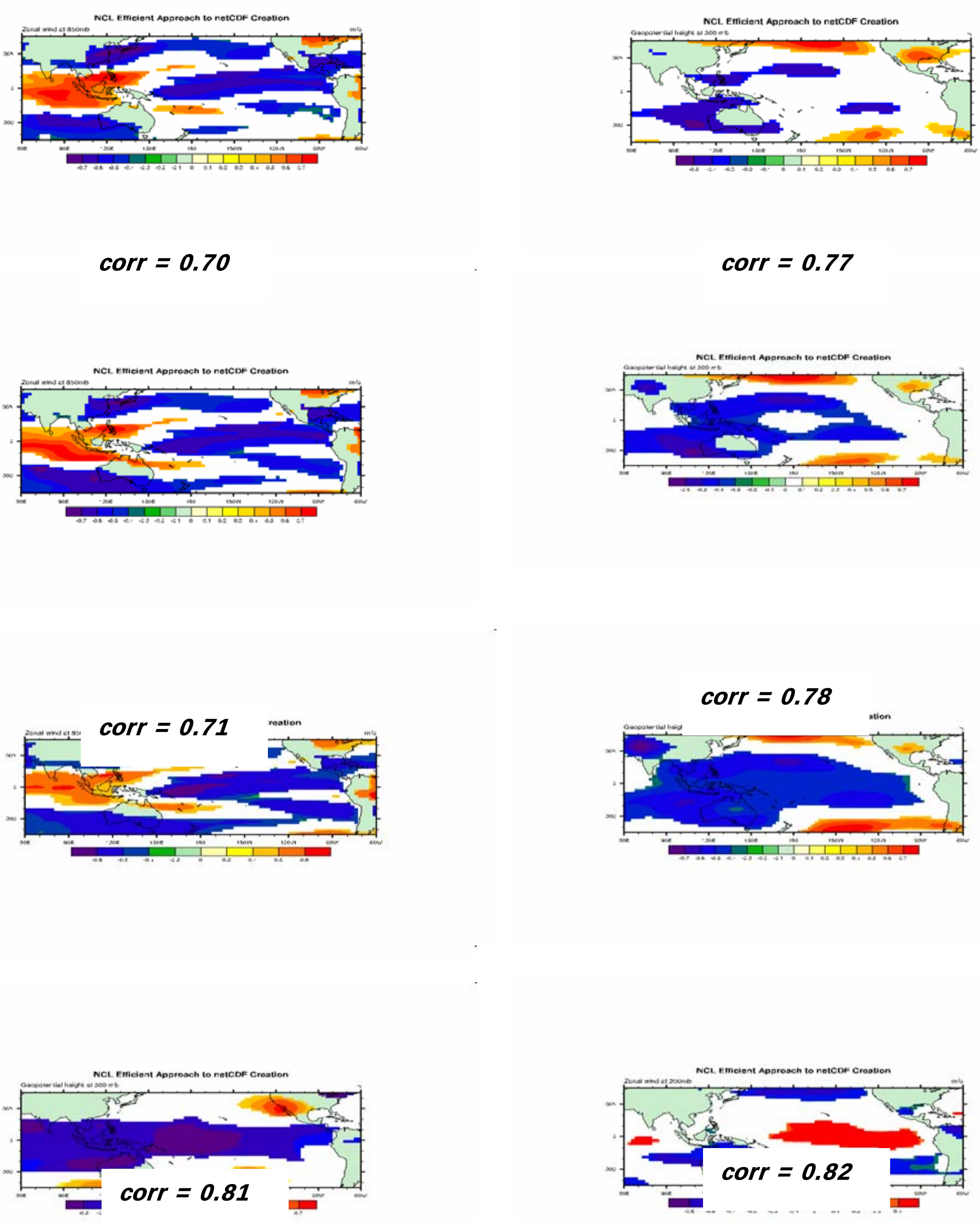
Figure 2: Correlation pattern between observed rainfall and GCPS u850 and GDAPS_F z500 in MAM under the Type 1 climate



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corr = 0.78

corr = 0.81

corr = 0.82

corr = 0.51

corr = 0.64

Figure 2: Correlation pattern between observed rainfall and GCPS u850 and GDAPS_F z500 in MAM under the Type 1 climate

Table 2 shows the summary results of correlation coefficient between observed rainfall and models GCPS u850 and GDAPS_F z500 for individual station under the Type 1 Climate during the target season MAM. It is found that GDAPS_Z500 has higher correlation coefficient above 90% confidence level than GCPS u850 in most of the stations under the Type 1 climate. However for station 637 models GCPS u200 and CWB z500 are the models that showed significant correlation. Raw GCM outputs showed good correlation in most of the stations under the Type 1 climate. Results also showed that after using MME downscaling technique the correlation between the predictand and predictor further improved.

Table 2: Summary of correlation coefficient pattern for MAM

Station	GCPS u850	GDAPS_F z500	MME
222	0.52	0.56	0.58
324	0.63	0.80	0.81
325	0.57	0.77	0.73
328	0.73	0.76	0.76
330	0.70	0.77	0.75
430	0.71	0.78	0.77
432	0.81	0.82	0.84
	GCPS u200	CWB z500	MME
637	0.51	0.64	0.64

4. 2 JJA Season

The most important season for seasonal climate prediction in the Philippines is the summer monsoon season. This is largely due to the fact that the Philippines is predominantly an agriculture country. Majority of the agricultural lands in the country are located in the Type 1 climate wherein the planting season starts in June. Predicting what will be the performance of the southwest monsoon is of great concern especially to the agricultural and water resources sectors during this season. When monsoon rainfall fails it create great problems for these climate sensitive sectors.

Correlation analysis between the observed station rainfall and the global predictors were carried out for this season. The spatial distribution of the correlation coefficients is shown in Figure 3. Results showed that geopotential height at 500 mb level have a strong negative (-) correlation over most parts of the tropics. This pattern may suggest that the decrease in geopotential height at 500mb level in the western Pacific is associated with enhanced rainfall activity in the Philippines. Kang et al (2007) also found significant correlation in the observed rainfall in the Philippines using this predictor. Of all the seasons evaluated, JJA showed the most promising results in terms of the consistency of all the global models used most especially for z500. A combination of five models can also be used for statistical downscaling for this season. Although raw GCM outputs can reliably simulate the observed rainfall in the Philippines there is also much improvement when MME technique was applied.

Results of experiments showed that JJA can be well simulated by GCM outputs. A consistent pattern is depicted in all the maps for JJA using geopotential height (z500) for all the station evaluated. Composite analysis of rainfall during El Nino years showed that above normal rainfall is observed in most parts of Luzon during El Nino in JJA. This large convergence area is associated with enhanced precipitation during the JJA season in most parts of the country during the onset of an El Nino. Figure 3 shows strong association of Type 1 Climate to various global GCM predictor variables with geopotential height for JJA and MJJ.

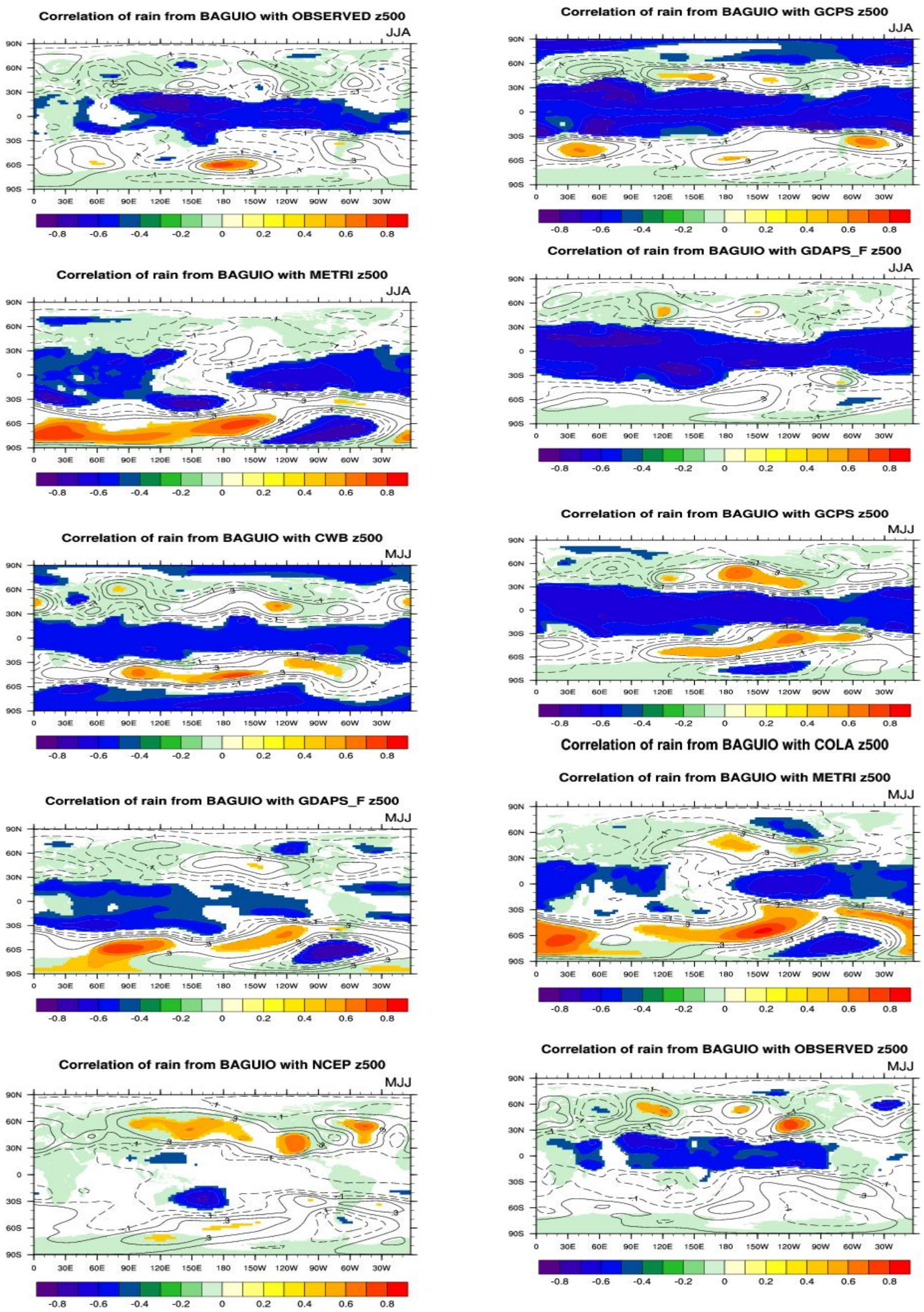


Figure 3 shows the correlation pattern of Geopotential Height (z500) and observed rainfall during JJA and MJJ for station 328 (Baguio)

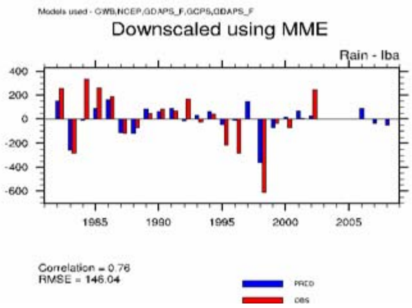
Table 3 shows the summary Correlation Pattern of different GCM and Philippine Rainfall

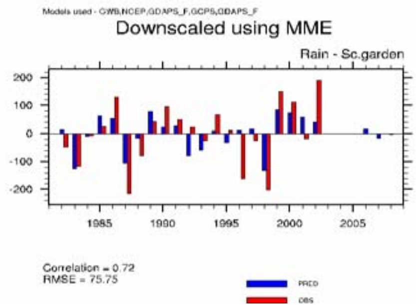
for JJA using different predictors from GCM outputs

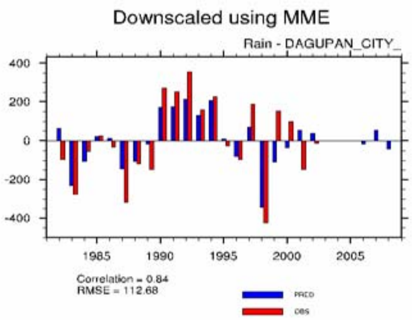
Stations	CWB Z500	NCEP U850	GDAPS_F T850	GCPS SLP	GDAPS_U200	MME
222	0.78	0.78	0.74	0.59	0.60	0.76
324	0.64	0.62	0.72	0.71	0.62	0.76
325	0.71	0.82	0.61	0.72	0.69	0.84
328	0.80	0.71	0.77	0.72	0.66	0.82
430	0.65	0.69	0.62	0.72	0.65	0.72
432	0.78	0.70	0.83	0.62	0.56	0.75
637	0.70	0.64	0.76	0.68	0.67	0.77
	GDAPS_F Z500	GCPS T 850	NCEP SLP			MME
330	0.58	0.53	0.71			0.68

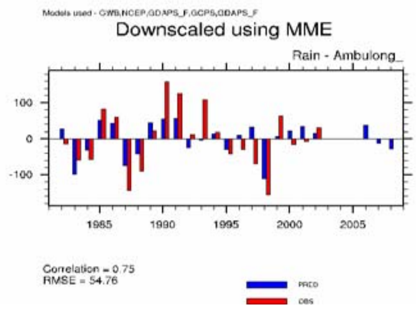
As shown in the table most of the GCMs model outputs such as CWB z500, NCEP u850, GDAPS_F FT850, GCPS slp, and GDAPS_F u200 have strong correlation with observed station rainfall under the Type1 climate. After MME downscaling technique was applied to the raw GCM outputs improvements in the skill were noted in all the stations evaluated. This showed that GCM outputs can reliably simulate the large-scale circulation pattern.

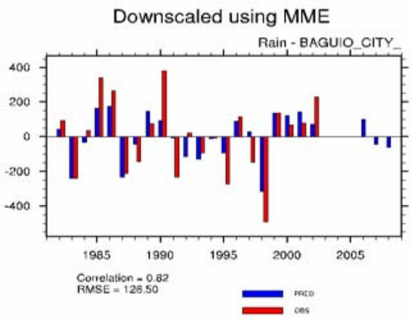
The graphs shown in Figure 4 also confirmed the results of the simulation. The El Nino signal was strong in the Philippines and this maybe one reason why that during ENSO years the models was able to simulate well the observed station rainfall in the Philippines. In most ENSO years 1982-83,1986-87, 1991-92, 1997-98, 1998-99 the observed and predicted are well captured in most of the station rainfall in the Type 1 climate.











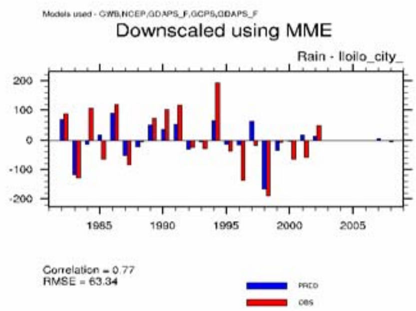
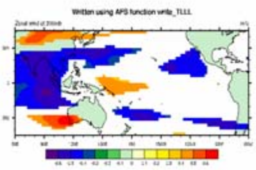


Figure 4 Correlation Coefficient between observed and predicted rainfall after MME downscaling

4. 3 SON Season

Results of analysis for this season showed that observed station rainfall during this season has strong relationship between the three predictors namely GDAPS_F u850, CWB t850 and GDAPS_F u200. Results are significant above the 90% confidence level. Figure 5 shows the different maps showing the correlation pattern of the predictors for each stations under the Type 1 climate.



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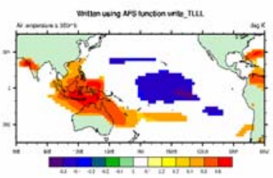

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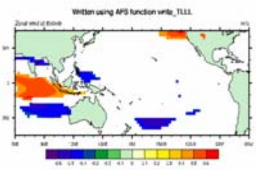

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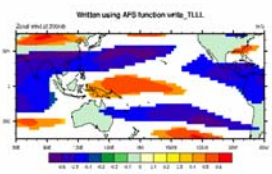

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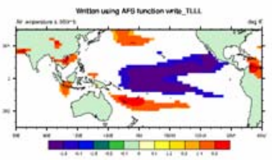

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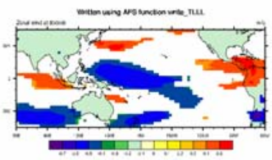

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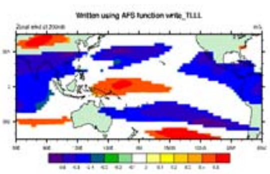

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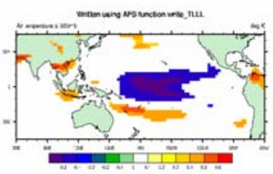

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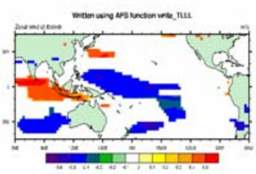
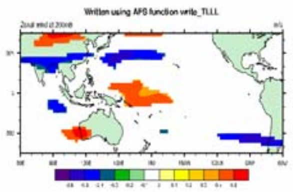


corr = 0.55

Figure 5 Correlation coefficient between observed rainfall and GDAPS_F u850, CWB t850 and GDAPS_F u200



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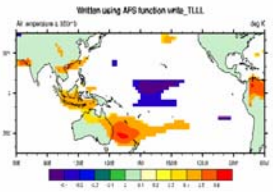

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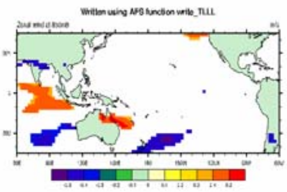

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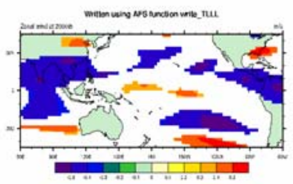

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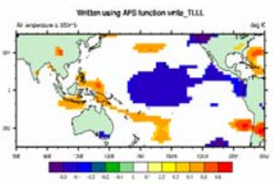

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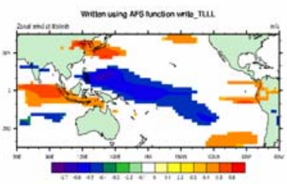

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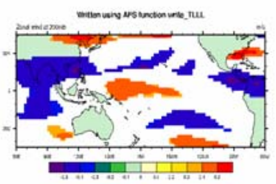

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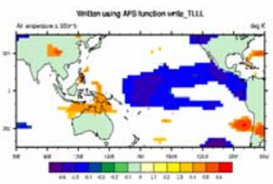
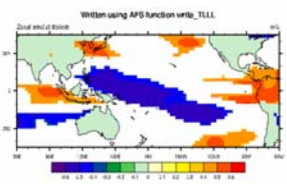


corr = 0.55



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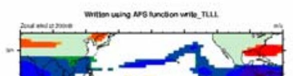
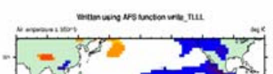
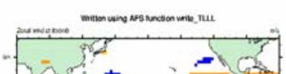






corr = 0.58 *corr = 0.52* *corr = 0.60*

Figure 5 Correlation coefficient between observed rainfall and GDAPS_F u850, CWB t850 and GDAPS_F u200 for SON for Type 1 climate stations

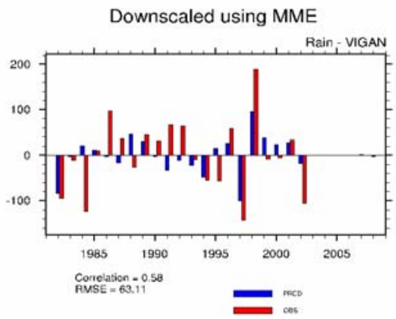
A summary of the correlation coefficient between the observed station rainfall and predictors from GCM outputs is presented in Table 4 before and after downscaling. Results show that downscaled GCM outputs can also reliably capture the large scale circulation during the season. Improvements are seen after downscaling technique is applied in the simulations.

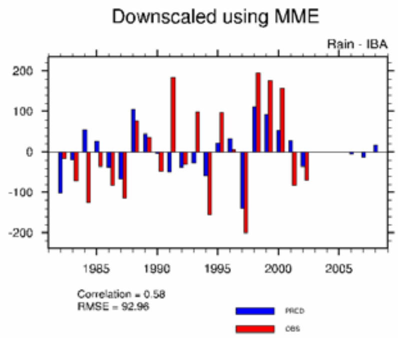
Table 4

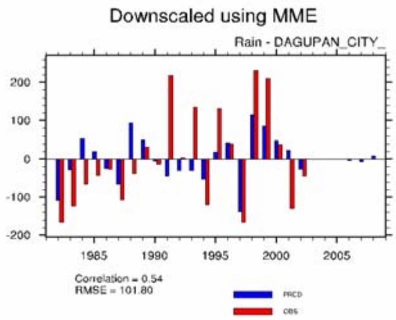
shows the summary of correlation coefficient between before and after downscaling corrected prediction for each station for SON.

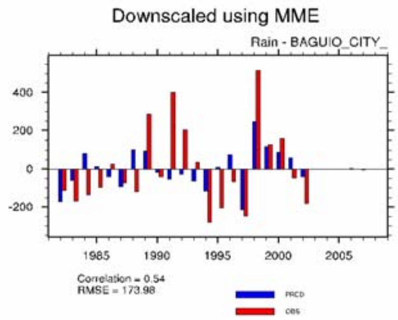
Station	GCPS u850	CWB t850	GDAPS_F u200	MME
222	0.54	0.59	0.56	0.58
324	0.57	0.57	0.58	0.58
325	0.52	0.52	0.55	0.54
328	0.58	0.54	0.48	0.54
330	0.56	0.58	0.57	0.61
430	0.52	0.55	0.56	0.55
432	0.57	0.58	0.59	0.59
637	0.58	0.57	0.60	0.60

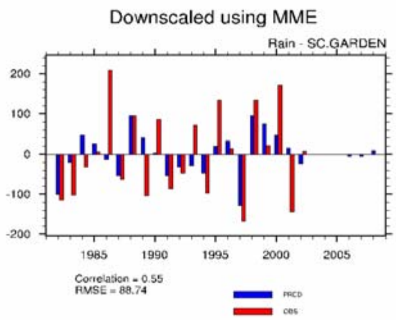
The graphs (Fig 6) shown below present that after downscaling most of the years can be reliably simulated as depicted by the difference between the observed and predicted rainfall. Majority of the years evaluated between the observed and predicted rainfall gave quite satisfactory results. The 1997 El Nino year was well predicted in most of the stations during the season. Similar years with good prediction include 1983, 1987, 1988
to name a few.

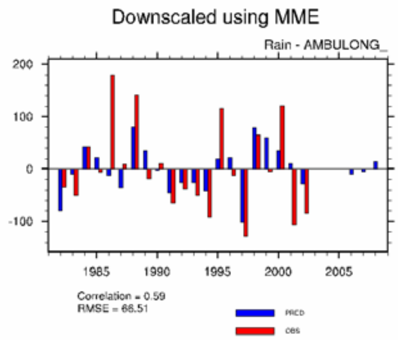

Downscaled using MME
Rain - VIGAN
Correlation = 0.58
RMSE = 63.11
PRCD
OBS


Downscaled using MME
Rain - IBA
Correlation = 0.58
RMSE = 92.96
PRCD
OBS


Downscaled using MME
Rain - DAGUPAN_CITY_
Correlation = 0.54
RMSE = 101.80
PRCD
OBS


Downscaled using MME
Rain - BAGUIO_CITY_
Correlation = 0.54
RMSE = 173.98
PRCD
OBS


Downscaled using MME
Rain - SC.GARDEN
Correlation = 0.55
RMSE = 88.74
PRCD
OBS


Downscaled using MME
Rain - AMBULONG_
Correlation = 0.59
RMSE = 68.51
PRCD
OBS

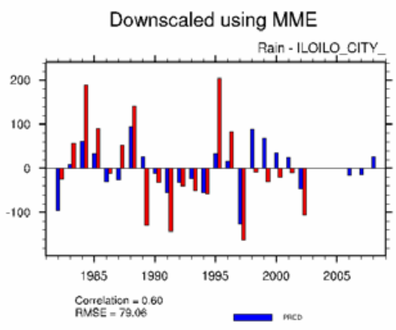

Downscaled using MME
Rain - ILOILO_CITY_
Correlation = 0.60
RMSE = 79.06
PRCD

Figure 6 Correlation Coefficient between observed and predicted rainfall after MME downscaling during SON

4.4 DJF Season

The season is the peak of the northeast monsoon season. Based on earlier studies the impact of ENSO is often manifested during this season. GCM outputs using sea level pressure (slp) and zonal wind (u200) as predictors can provide good skill between the predictand (observed station rainfall) during DJF.

Table 5 shows the correlation pattern of different GCM models for SLP and station ranfall during DJF

Station	GCPS slp	GDAPS_F slp	CWB slp	NCEP	MGO
222	0.57				
324	0.58		0.55		0.52
325			0.70		
328	0.75	0.59	0.65	0.57	0.59
330	0.66	0.68	0.63		0.52
425					
430	0.63	0.69	0.66		0.63
432	0.65	0.68			0.68
637					

Table 6 shows the correlation pattern of different GCM models for u200 and station ranfall during DJF

Station	GCPS u200	GDAPS_F u200	CWB u200	NCEP u200	MGO u200
222					
324					0.57
325					
328	0.52	0.51	0.62	0.59	0.65
330	0.58	0.56	0.55	0.53	0.65
425	0.53	0.54			0.59
430	0.58	0.52		0.59	0.58
432					0.50
637					

4. 5 Conclusion

This study demonstrated that the Multi Model Ensemble developed by APCC based on simple composite method can be used as a downscaling tool to translate large-scale atmospheric anomalies into local scale rainfall anomalies. Applying statistical correction to downscale rainfall in the Philippines can increase the predictive skill of GCM outputs. Statistical downscaling done on Philippine rainfall showed strong correlation on observed rainfall in the Type 1 climate for all the 4 target seasons (MAM, JJA, SON, DJF). The choice of predictors is dependent on the drivers of climate for a particular season. Predictors used vary from season to season. The following predictors are identified to have good correlation for the different seasons: MAM (GCPS u850 and GDAPS_F z500), JJA (CWB z500, NCEP u850, GDAPS_F FT850, GCPS slp, and GDAPS_F u200) SON (GDAPS_F u850, CWB t850 and GDAPS_F u200) and for DJF (GCPS slp & MGO u200). This suggests that the predictors used in the different seasons can capture the large scale synoptic features which characterize the climate over the particular area of interest. This suggests that the predictors used in the different seasons can capture the large scale synoptic features which characterize the climate over the area of interest. Of all the seasons tested JJA showed the most promising results. This suggests that monsoon rainfall can reliably be predicted using the MME technique. A significant number of predictors can be used to downscale the station rainfall during the JJA season. MAM, SON and DJF is predicted as well after downscaling. Statistical downscaling of GCM outputs with that of station rainfall has a very good potential to enhance the skill of seasonal climate prediction in the Philippines. The we based CLIK technique when implemented can be use for operational seasonal prediction of rainfall in the country.

Acknowledgement

This research was supported by the Asia Pacific Network under the CAPaBLE grant. The simulations were performed at the APPC Climate Center in Busan, Korea. This paper is not possible without the help of the following persons. I am extremely grateful to Dr. Kryjov, Dr. Ashok and Dr. Saji for their assistance and encouragement; Special thanks is also given to the Executive Director of APCC, Dr. Lee and to all the staff of APCC for all their valuable support.

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APN / APCC Joint Training Course

Training Course on Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction

September 22 - November 10, 2008

APEC Climate Center

Mongkol Prongsungnoen

Climate Group, Meteorological Development Bureau,

Thai Meteorological Department , Thailand

Background

The Asia Pacific Network for Global Change Research (APN) and APEC Climate Center (APCC) conducted a joint Training Course on Regional Downscaling for Asia-Pacific Region using APEC Climate Center Global Seasonal Climate Prediction in Republic of Korea on September 22 - November 10, 2008

The training course provided participants with an overview of seasonal forecasting methods, with a focus on statistical downscaling. The central was the tailoring of forecast and other climate information for risk management application, for which practical statistic approaches were introduced.

The training course was hosted by APCC and the project fund sponsored by APN.

Participants

The climate participants were come from three countries (Thailand, Philippines and Vietnam). The Experts from Russian Federation and staff of APCC attended the training course. Training course aimed to enhance the technical capacity in three countries in tailoring seasonal climate forecasts for risk management in important sectors such as agriculture, tropical storm, water resources and public health. The active participation in training course by three countries underlies the importance of technical expertise in this area, which is vital in mitigating impacts of extreme climate such as droughts and flood.

The 50 days training course provided participants with knowledge, skill and tools in seasonal forecasting methods, with a focus on downscaling of MME (CLIK) output to areas of interest and on customize forecasts that would allow useful actions to be taken to enhance national resilience in areas such as agriculture, water resource management and public health.

Training Course Structure

Training course was lectures about hardware, software, Grads, NCL, CLIK

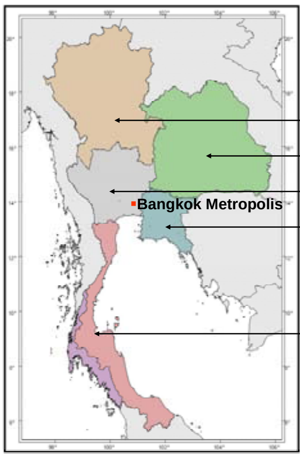
(Climate information tool Kit), how to forecast in local climate, how to used the best of MME for region, downscaling approaches, probabilistic climate prediction, downscaling application, deterministic downscaling. The participants learned about the available methods for tailoring forecast information and how the downscaling methods fit in this context.

However, there were lectures that illustrated the use of tailored information in risk management in a range of sectors including agriculture and water resources. The participants had the opportunity to share the idea approaches to the challenge of provide climate information for different application. The participants also undertook practical exercises, in which they analyzed their own data, by applying some of the statistical tailoring methods that were introduced in the lectures. These analyses were intended to be both learning experiences for the participants.

At the end of training course, the participants were provided presentation about product in each country.

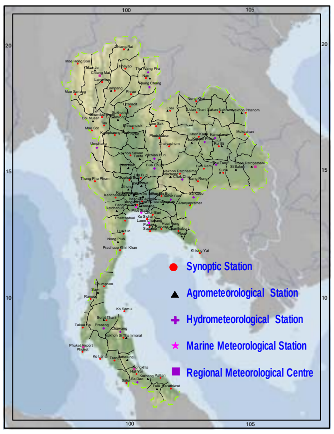
Introduction to Thailand

Thailand is located in the tropical area between
latitudes :
5 ° 37 ′N to 20 ° 27 ′N
longitudes :
97 ° 22 ′E to 105 ° 37 ′E



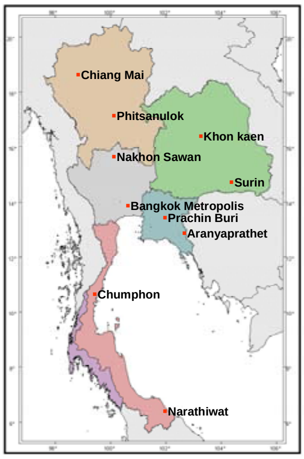
Thailand is divided into 76 provinces and 5 Parts
Northern Part (16)
Northeastern Part (19)
Central Part (17)
Eastern Part (8)
Souththern Part (16)

Meteorological Station in Thailand



TMD 114 stations and 4 centers

-69 Synoptic stns.
-29 Agromet. stns.
-16 Hydromet. Stns.



Choose 10 stations from 5 parts to look for
- good models
- good predictors

Practical Training Course Results

For Thailand, the MME (CLIK) forecasted temperature and rainfall in each station, multi stations, each part, multi parts and country. Choose 10 stations for substitute 5 parts in Thailand. Data base used in 1982-2002 years. GCPS, GDAPS_F and NCEP were good model. SLP, t850, u850, v850 and z500 were good predictors. Example in Figures 1, 2, 3 and 4

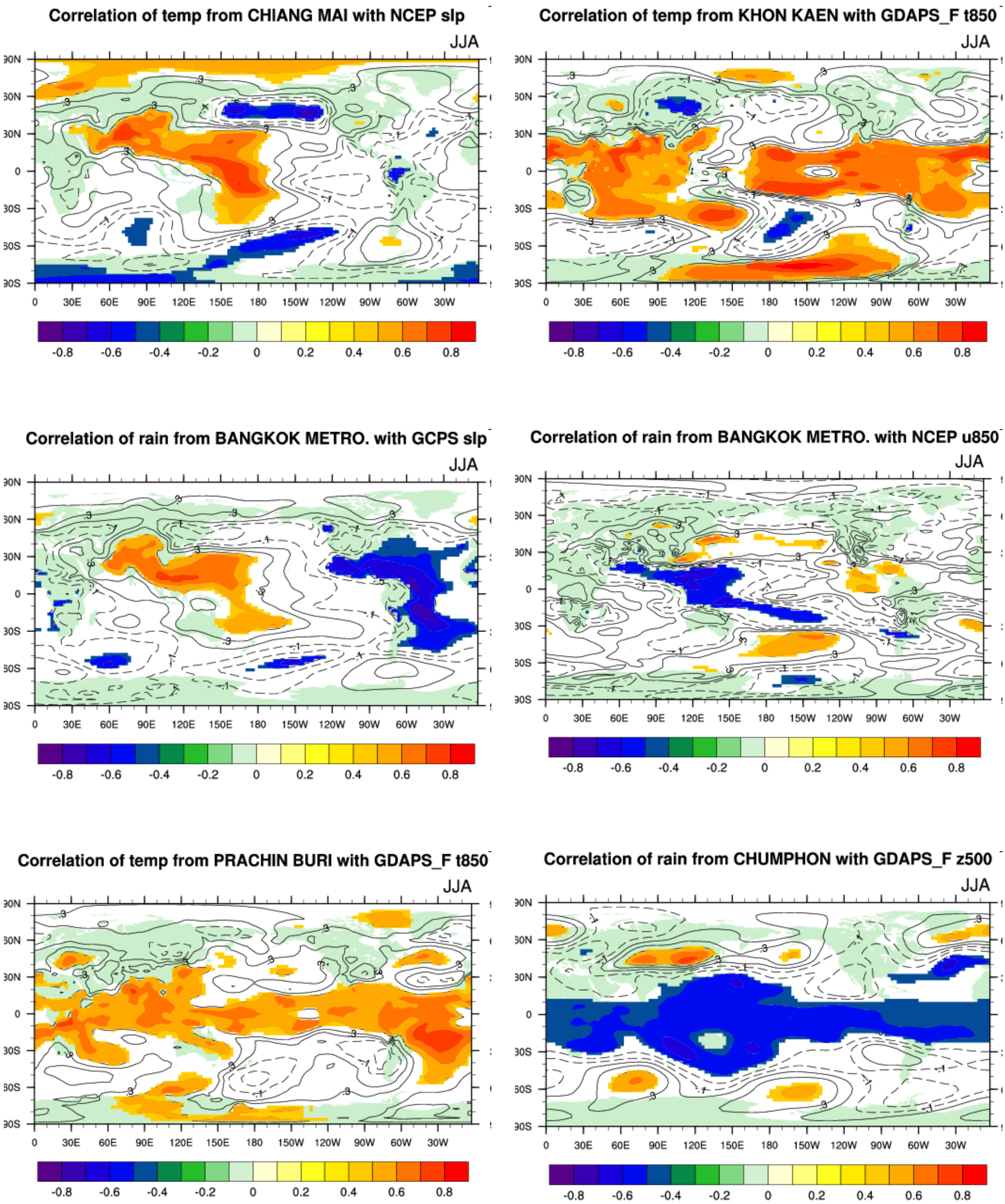


Figure 1 The correlation for each station in Thailand was shown. It used GCPS, GDAPS_F and NCEP for models and some predictors.

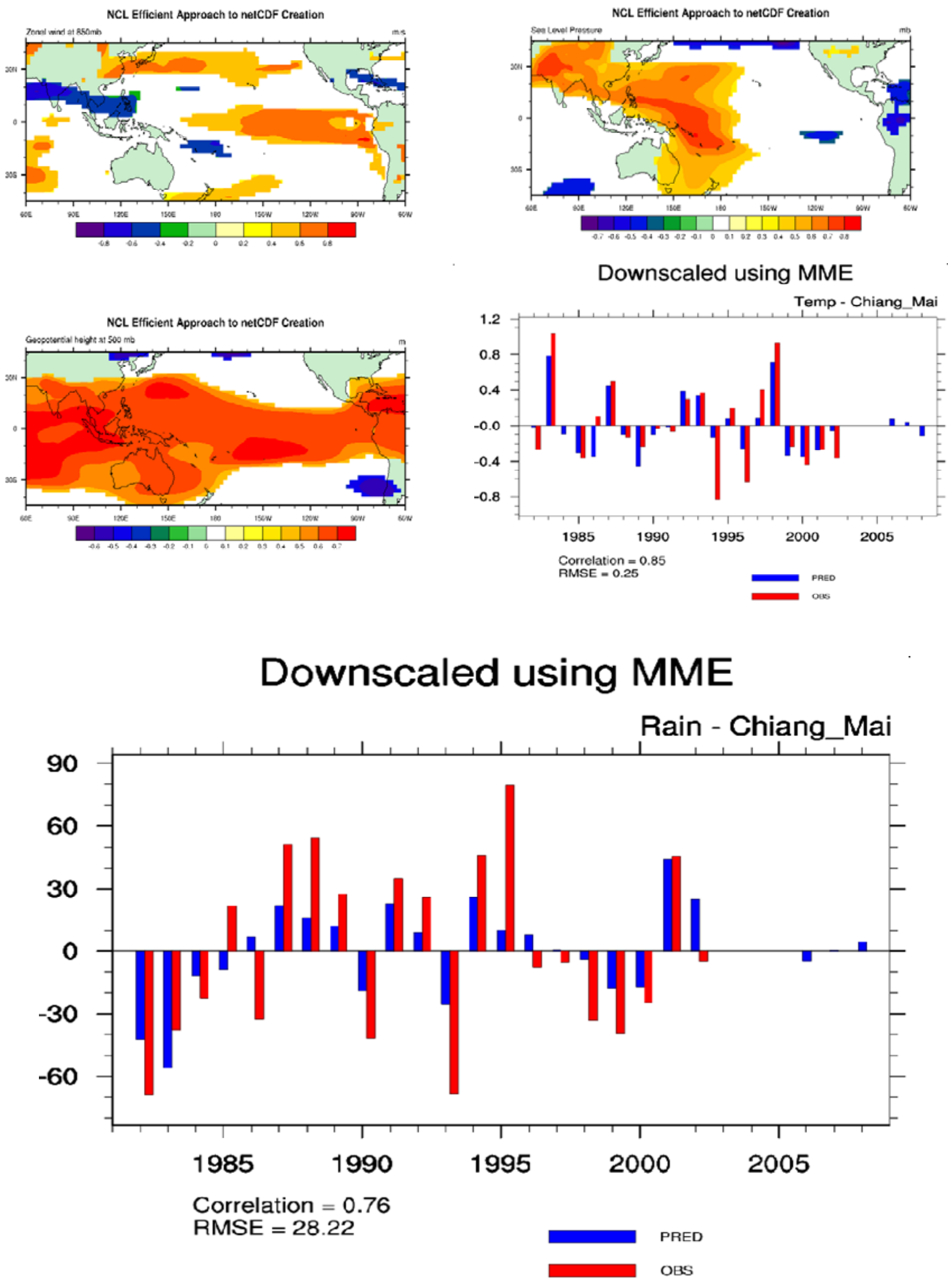


Figure 2 The correlation for downscaling used MME in Chiang Mai province. It was forecasted temperature and rainfall seasonal in 2006, 2007 and 2008

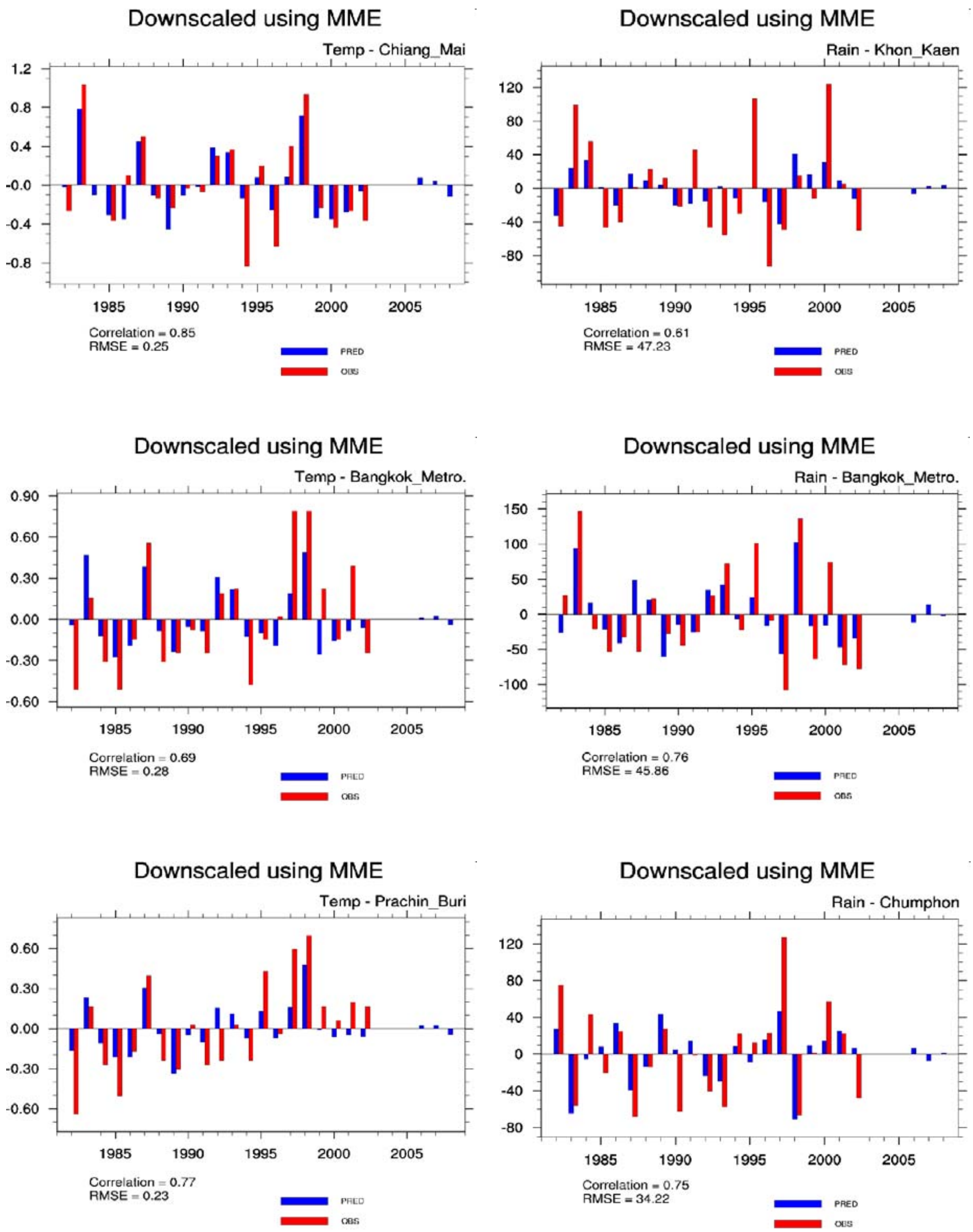


Figure 3 The correlation for downscaling used MME in each stations. It was forecasted temperature and rainfall seasonal in 2006, 2007 and 2008

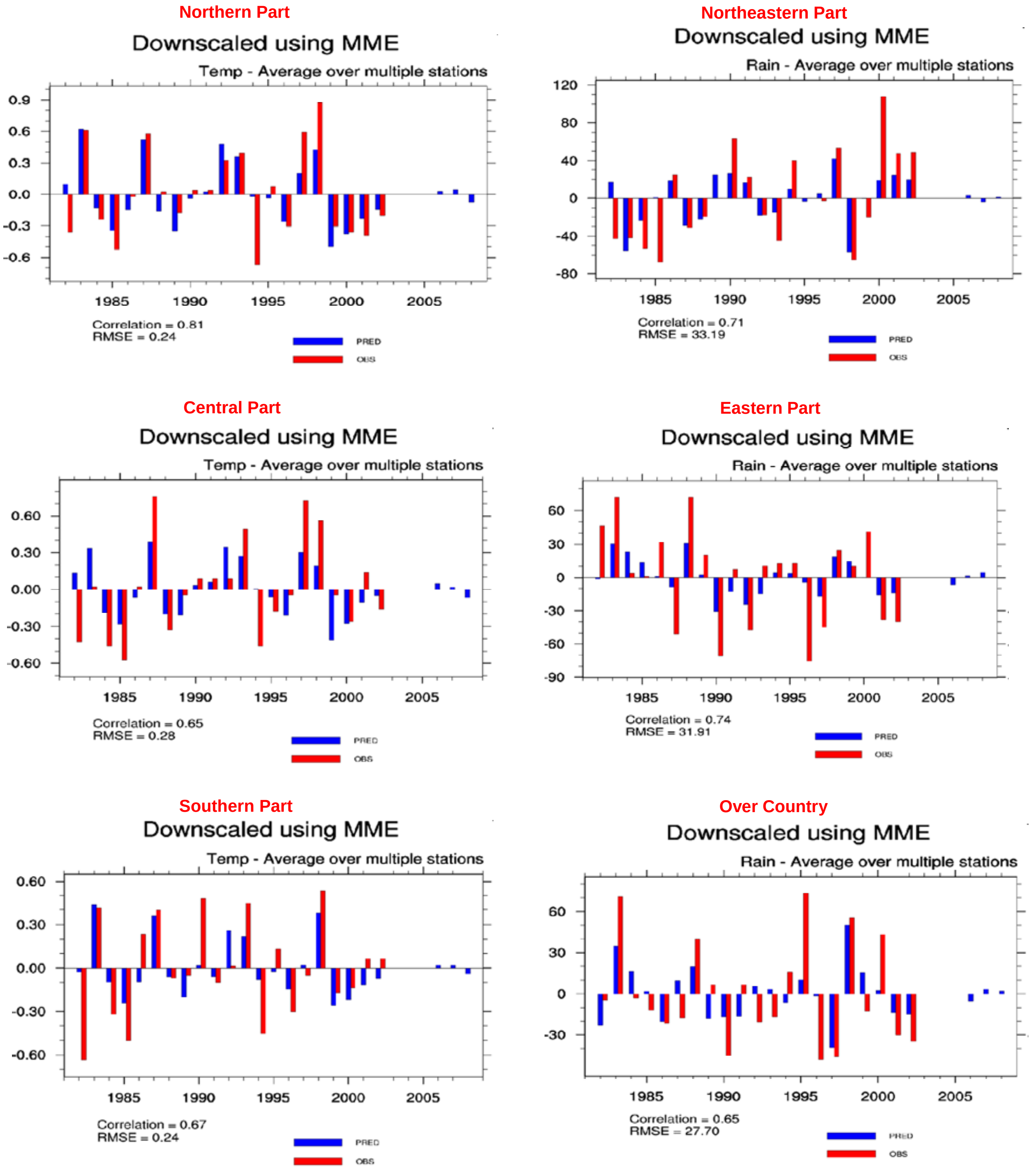


Figure 4 The correlation for downscaling used MME in each parts and country. It was forecasted temperature and rainfall seasonal in 2006, 2007 and 2008

Summary of Result

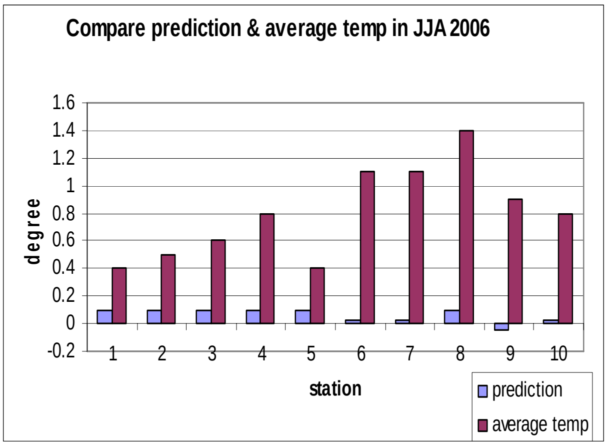
The results of training course are summarized as follows:

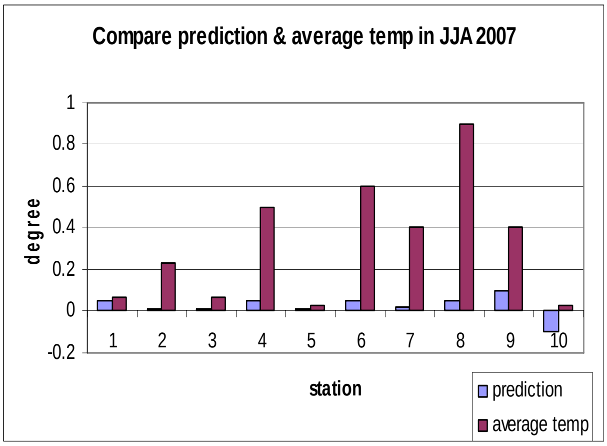
1) The correlation of each station, each parts and country was around 0.6-0.8. It is emphasized that skill of CLIK model is good and it can be used in Thailand.

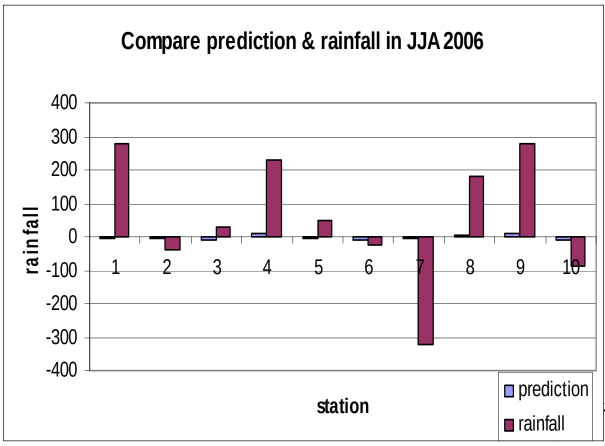
Correlation	MME	
	temp	rain
Chiang Mai	0.85	0.76
Phitsanulok	0.76	0.61
Khon Kaen	0.81	0.61
Surin	0.79	0.74
Nakhon Sawan	0.66	0.67
Bangkok Metropolis	0.69	0.76
Prachin Buri	0.77	0.65
Aranyaprathet	0.76	0.60
Chumphon	0.74	0.75
Narathiwat	0.63	0.66

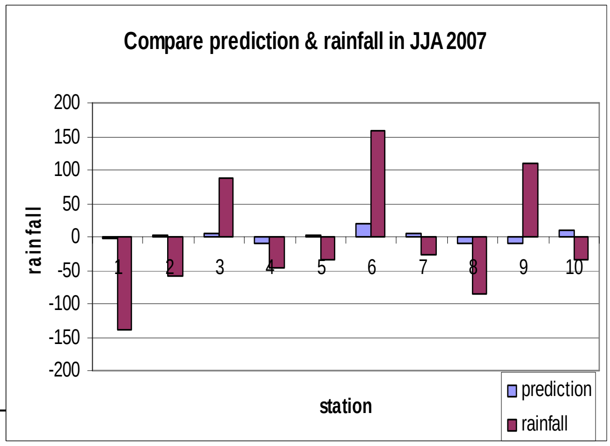
Correlation	MME	
	temp	rain
Northern Part (N)	0.81	0.73
Northeastern Part (NE)	0.76	0.71
Central Part (C)	0.65	0.73
Eastern Part (E)	0.70	0.74
Southern Part (S)	0.67	0.76
Over Country	0.75	0.65

2) The Compared CLIK model prediction and observed from 10 stations in 2006 and 2007 years. The results were rather to be contented.









Participants

Name	Country
Mongkol Prongsungnoen	Thailand
Nguyen Dang Quang	Vietnam
Rosalina de Guzman	Philippines

Lecturers

Name	Position / Nationality
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Dr. Vladimir Kryjov	Russian Federation
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Dr. N. H. Saji	Senior Research Scientist (APCC) India
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Ms. Young Mi Min	Climate Model Specialist (APCC) Korea
Ms. Kyong Hee An	Climate Model Specialist (APCC) Korea

The Climate of Thailand

1. Geographical Situation

Thailand is located in the tropical area between latitudes 5 ^{o} 37 ′ N to 20 ^{o} 27 ′ N and longitudes 97 ^{o} 22 ′ E to 105 ^{o} 37 ′ E. The total area is 513,115 square kilometers or around 200,000 square miles.

The boundaries of Thailand with adjacent areas are :

- North : Myanmar and Laos.
- East : Laos, Cambodia and the Gulf of Thailand.
- South : Malaysia.
- West : Myanmar and the Andaman Sea.

2. Topography

According to the climate pattern and meteorological conditions Thailand may be divided into 5 parts i.e. Northern, Northeastern, Central, Eastern and Southern Parts. The topography of each part is quite different as follows :-

2.1 Northern Part

This part is divided into 15 provinces i.e. Chiang Rai, Mae Hong Son, Chiang Mai, Phayao, Lamphun, Lampang, Phrae, Nan, Uttaradit, Phitsanulok, Sukhothai, Tak, Phichit, Kamphaeng Phet and Phetchabun. Most areas of the part are hilly and mountainous which is the source of several important rivers. These north-south oriented hill ridges are parallel from west to east and intersected by a number of major valleys, particularly those near Chiang Mai, Chiang Rai, Lampang and Nan provinces. The highest mountain, about 2,595 meters high above mean sea level, is Doi Inthanon in Chiang Mai. Along the eastern border with the Northeastern Part is mountainous called central highlands. The area in the southern portion between the western mountains and the central highlands is a central valley.

2.2 Northeastern Part

This region is naturally a high level plain called northeast plateau. Northwest-southeast oriented Phu Phan ridge in the northeastern portion separates this part into two basins. One is a large high level plain in the west. The another is smaller and slope towards the east. This part is divided into 19 provinces i.e. Nong Khai, Loei, Udon Thani, Nong Bua Lam Phu, Nakhon Phanom, Sakon Nakhon, Mukdahan, Khon Kaen, Kalasin, Maha Sarakham, Roi Et, Chaiyaphum, Yasothon, Amnat Charoen, Ubon Ratchathani, Sri Sa Ket, Nakhon Ratchasima, Buri Ram and Surin.

2.3 Central Part

Central Part is divided into 18 provinces i.e. Nakhon Sawan, Uthai Thani, Chai Nat, Sing Buri, Lop Buri, Ang Thong, Sara Buri, Suphan Buri, Ayutthaya, Pathum Thani, Kanchanaburi, Ratchaburi, Nakhon Pathom, Nonthaburi, Bangkok Metropolis, Samut Prakan, Samut Sakhon and Samut Songkhram. This part is a large low level plain where the Ping, Wang, Yom and Nan Rivers originated in the Northern Part join together to be the Chao Phraya River at Nakhon Sawan provine. However the western mountains in the Northern Part extend to this part along the western portion.

2.4 Eastern Part

The south and southwest of the part is adjacent to the Gulf of Thailand. Farther in land, most areas are plains and valleys but there are some small hills in the northern, central and eastern portions. This part is divided into 8 provinces i.e. Nakhon Nayok, Prachin Buri, Sra Kaeo, Chachoeng Sao, Chon Buri, Rayong, Chanthaburi and Trat.

2.5 Southern Part

The topography of this part is the peninsula between the Andaman Sea which is on the western side of the part and the South China Sea which is on the eastern side. The long ridge of western mountains in the Northern and Central parts also extend to this part. Phuket ridge along the west coast and Nakhon Si Thammarat ridge in the central of lower portion forming the backbone of the Southern Part separate this part into two regions, Southern Thailand East Coast and Southern Thailand West Coast. Ten provinces from north to south which are Phetchaburi, Prachuap Khiri Khan, Chumphon, Surat Thani, Nakhon Si Thammarat, Phatthalung, Songkhla, Pattani, Yala and Narathiwat belong to Southern Thailand East Coast while there are 6 provinces i.e. Ranong, Phang Nga, Krabi, Phuket, Trang and Satun in Southern Thailand West Coast.

3. General Climatic Conditions

The climate of Thailand is under the influence of monsoon winds of seasonal character i.e. southwest monsoon and northeast monsoon. The southwest monsoon which starts in May brings a stream of warm moist air from the Indian Ocean towards Thailand causing abundant rain over the country, especially the windward side of the mountains. Rainfall during this period is not only caused by the southwest monsoon but also by the Inter Tropical Convergence Zone (ITCZ) and tropical cyclones which produce a large amount of rainfall. May is the period of first arrival of the ITCZ to the Southern Part. It moves northwards rapidly and lies across southern China around June to early July that is the reason of dry spell over upper Thailand. The ITCZ then moves southerly direction to lie over the Northern and Northeastern Parts of Thailand in August and later over the Central and Southern Part in September and October, respectively. The northeast monsoon which starts in October brings the cold and dry air from the anticyclone in China mainland over major parts of Thailand, especially the Northern and Northeastern Parts which is higher latitude areas. In the Southern Part, this monsoon causes mild weather and abundant rain along the eastern coast of the part.

The onset of monsoons varies to some extent. Southwest monsoon usually starts in mid-May and ends in mid-October while northeast monsoon normally starts in mid-October and ends in mid-February.

4. Season

From the meteorological point of view the climate of Thailand may be divided into three seasons as follows :

- *Rainy or southwest monsoon season* (mid-May to mid-October). The southwest monsoon prevails over Thailand and abundant rain occurs over the country. The wettest period of the year is August to September. The exception is found in the Southern Thailand East Coast where abundant rain remains until the end of the year that is the beginning period of the northeast monsoon and November is the wettest month.
- *Winter or northeast monsoon season* (mid-October to mid-February). This is the mild period of the year with quite cold in December and January in upper Thailand but there is a great amount of rainfall in Southern Thailand East Coast, especially during October to November.
- *Summer or pre-monsoon season*, mid-February to mid-May. This is the transitional period from the northeast to southwest monsoons. The weather becomes warmer, especially in upper Thailand. April is the hottest month.

5. Surface Temperature

Upper Thailand i.e. the Northern, Northeastern, Central and Eastern Parts usually experiences a long period of warm weather because of its inland nature and tropical latitude zone. March to May, the hottest period of the year, maximum temperatures usually reach near 40 ^{o}C or more except along coastal areas where sea breezes will moderate afternoon temperatures. The onset of rainy season also significantly reduces the temperatures from mid-May and they are usually lower than 40 ^{o}C. In winter the outbreaks of cold air from China occasionally reduce temperatures to fairly low values, especially in the Northern and Northeastern Parts where temperatures may decrease to near or below zero.

In the Southern Part temperatures are generally mild throughout the year because of the maritime characteristic of this region. The high temperatures common to upper Thailand are seldom occur. The diurnal and seasonal variations of temperatures are significantly less than those in upper Thailand.

Seasonal temperatures (^{o}C) in various parts of Thailand

Temperature	Region	Winter	Summer	Rainy
Mean	North	23.1	28.0	27.3
	Northeast	23.9	28.5	27.7
	Central	26.1	29.6	28.3
	East	26.4	28.9	28.1
	South			
	- East Coast	26.3	28.1	27.7
	- West Coast	26.8	28.3	27.4
Mean maximum	North	30.8	35.8	32.2
	Northeast	30.3	35.0	32.3
	Central	31.7	35.5	32.8
	East	31.7	33.9	32.1
	South			
	- East Coast	29.9	32.8	32.1
	- West Coast	31.9	34.0	31.4
Mean Minimum	North	17.1	21.4	23.7
	Northeast	18.3	23.0	24.2
	Central	21.1	24.6	24.8
	East	21.8	25.0	25.0
	South			
	- East Coast	22.0	23.2	23.7
	- West Coast	22.9	23.7	24.1

Extreme maximum temperatures (^{o}C) in Summer

Region	Maximum	Date / Month / Yea	Province

	temperature	r	
North	44.5	27 Apr	Uttaradit
Northeast	43.9	1960	Udon Thani
Central	43.5	28 Apr	Kanchanaburi
		1960	
		29 Apr	
East	42.9	1958	Prachin Buri
South		14 Apr	
- East	41.2	1983	Prachuap Khiri
Coast	40.5	14,20 Apr	Khan
- West		1992	Trang
Coast		23 Apr	
		1990	
		15 Apr	
		1998	
		29 Mar	
		1992	

Based on 1951-2005 period

Extreme minimum temperatures (^{o}C) in winter

Region	Minimum temperature	Date/Month/Year	Province
North	0.8	27 Dec	Tak
Northeast	-1.4	1999	Sakon Nakhon
Central	5.2	2 Jan	Kanchanaburi
East	7.6	1974	Sra Kaeo
South		27 Dec	
- East	6.4	1993	Prachuap Khiri
Coast	13.7	16 Jan	Khan
- West		1963	Ranong
Coast			
		26 Dec	
		1999	
		21 Jan	
		1956	

Based on 1951-2005 period

6. Rainfall

Upper Thailand usually experiences dry weather in winter because of the northeast monsoon which is a main factor that controls the climate of this region. Later period, summer, is characterized by gradually increasing rainfall with thunderstorms. The onset of the southwest monsoon leads to intensive rainfall from mid-May until early October. Rainfall peak is in August or September which some areas are probably flooded. However, dry spells are commonly occur for 1 to 2 weeks or more during June to early July due to the northward movement of the ITCZ to southern China.

Rainy season in the Southern Part is different from upper Thailand. Abundant rain occurs during both the southwest and northeast monsoon periods. During the southwest monsoon the Southern Thailand West Coast receives much rainfall and reaches its peak in September. On the contrary, much rainfall in the Southern Thailand East Coast which its peak is in November remains until January of the following year which is the beginning of the northeast monsoon.

According to a general annual rainfall pattern, most areas of the country receive 1,200 - 1,600 mm a year. Some areas on the windward side, particularly Trat province in the Eastern Part and Ranong province in the Southern Thailand West Coast have more than 4,000 mm a year. Annual rainfall less than 1,200 mm occurs in the leeward side areas which are clearly seen in the central valleys and the uppermost portion of the Southern Part.

Seasonal rainfall (mm) in various parts of Thailand

Region	Winter	Summer	Rainy	Annual rainy days
North	105.5	182.5	952.1	123
Northeast	71.9	214.2	1,085.8	117
Central	124.4	187.1	903.3	113
East	187.9	250.9	1,417.6	131
South				
- East Coast	759.3	249.6	707.3	148
- West Coast	445.9	383.7	1,895.7	176

Based on 1971-2000 period

7. Relative Humidity

Thailand is covered by warm and moist air in most periods of the year except the areas farther in land the relative humidity may significantly reduces in winter and summer. For example, the extreme minimum relative humidity values shows only 9 % at Loei and Chiang Rai on 23 March 1983 and 23 April 1990, respectively. In the Southern Part which is maritime characteristic the humidity is relatively higher.

Relative humidity (%) in various parts of Thailand

Region	Winter	Summer	Rainy	Annual
North	74	64	81	75
Northeast	69	66	80	73
Central	70	69	79	75
East	71	75	81	76
South				
- East Coast	80	77	79	79
- West Coast	78	76	84	80

Based on 1971-2000 period

8. Cloudiness

Cloud cover is normally less from November to March. Perfectly clear skies are generally found that is a reason why extreme temperatures usually occur. Most clouds in this period are high clouds but cumulus and cumulonimbus may be seen on some occasions. During the southwest monsoon, most clouds in the sky are convective clouds. Clear skies are seldom occur in this period except during June which have a few days.

9. Thunderstorms

Thunderstorms in upper Thailand often occur in the period from April to October while those in the Southern Part will occur in March to November. The maximum frequency of thunderstorms in upper Thailand is in May. Convection and the confluence of two different air streams, cold and warm, are the main factor of thunderstorms. The afternoon and evening thunderstorms occur from the convection while the other from the confluence of winds of different airstreams.

10. Surface Wind

The pattern of surface wind directions is characterized by the monsoon system. The Prevailing winds during the northeast monsoon season are mostly north and northeast in upper Thailand and east or northeast in the Southern Part while they are south, southwest and west over the country during the southwest monsoon. In summer, prevailing wind are mostly south, especially in upper Thailand.

11. Tropical Cyclones

Tropical cyclone affecting Thailand usually moves from the western North Pacific Ocean or the South China Sea. Considering its strength it may be characterized by wind speed as follows :

* Tropical Depression : the maximum sustained winds less than 34 knots (63 kilometers per hour)
* Tropical storm : the maximum sustained winds up to 34 and less than 64 knots (63 and less than 118 kilometers per hour)
* Typhoon : the maximum sustained winds 64 knots and above (118 kilometers per hour and above)

Thailand normally receives the effect of tropical depressions because of its location farther in land and some mountain ranges which obstruct and decrease the wind speed before moving into Thailand except the Southern Part has a relatively high risk of tropical storms and typhoon. For instance, the tropical storm "HARRIET" hit Nakhon Si Thammarat province in October 1962 and the typhoon "GAY" hit Chumphon province in November 1989 and the latest one was the typhoon "LINDA" which hit Prachuap Khiri Khan province in November 1997 as it was tropical storm. By considering the annual mean, tropical cyclones usually move across Thailand about 3 - 4 times a year. During January to March, Thailand has never received the effect. According to the historical data, it can be seen that April is the first month which tropical cyclone move across Thailand. The relatively higher frequencies are found from May, particularly September and October. They usually pass through the Northern and Northeastern Parts in early southwest monsoon season and will move across the southern Thailand from October to December.

The frequency of tropical cyclones moving through Thailand during 56 years (1951 - 2007)

Region	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
North	-	-	-	-	5	2	9	17	25	15	1	-	74
Northeast	-	-	-	-	1	6	4	17	29	23	4	-	84
Central	-	-	-	-	2	1	1	-	7	9	2	-	22
East	-	-	-	-	1	1	1	-	3	12	2	-	20
South	-	-	-	1	-	-	-	-	3	15	23	9	51

Climatological Group
Meteorological Development Bureau
Meteorological Department

Statistical downscaling over the Vietnam: Application of APCC/Climate Information tool Kit (CLIK).

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This report introduces a statistical downscaling method for temperature seasonal prediction in Vietnam by using CLIK. Monthly 2-metres temperature at eleven stations was used in this study. The strategy for multi-model output downscaling prediction is described as two steps: first is choice of predictor and second is downscaling. One procedure for selecting suitable predictor has been implemented and stable lead predictors have been found as the result. For stations having stable predictor those can have good forecast. JJA temperature forecast shows better than that of DJF. This web-based CLIK result can be used toward to operational seasonal prediction at National Hydro-Meteorological Services such as Vietnam, Thailand and Philippines.

1. Introduction

Located in the centre of two main tropical monsoon areas, the South and the East Asia monsoon, Vietnam is extremely affected by natural disasters, such as flood, drought, cold surge, typhoon… In summer, Vietnam climate is dominated by the South Asian monsoon those hot and wet summer in the South, in winter, climate is affected by the East Asian monsoon those cold and dry in the North and Central. The coastal line extending more than 3000kms, from 8.4N to 21.5N, complex non-homogeneous geographical are formed several sub-regional climate regions.

Seasonal prediction is one of the most challenge issues in a developing country like Vietnam. Since information provided by General Circulation Models (GCM) is insufficient based on its coarse grid resolution, the approach of using statistical downscaling was carried out in this study. Statistical downscaling methods establish an empirical statistical relationship between the atmospheric circulation and predictands (in the current study, predictands is temperature in both JJA and DJF), and then infer local changes by means of sensibly projecting the large scale information on the local scale [Zorita and von Storch, 1999]. Kang et al. [2007] showed potential skill in rainfall prediction at Philippines and Thailand stations.

Toward the goal of capacity building for exchange and utilization of climate information, the Asia Pacific Economic Cooperation Climate Center (APCC) has been developing a web-based tool, called CLIK (Climate Information tool Kit), which allow retrieving data and make predictions. In this report, we limit at the part of using CLICK for seasonal climate prediction.

The focus of this study is the application of statistical downscaling for climate prediction over Vietnam. Specifically, CLIK downscaling result based on various GCM hindcast experiment will be preliminary analysed. Section 2 introduces the models data and the method of downscaling. Analyses and results are described in section 3. Some conclusions are presented in section 4.

2. Data and Methodology

2.1 Data

The observed station monthly temperature used in this research was taken from Vietnam National Center for Hydrometeorological Forecastings (NCHMF); these were collected during the period from 1971 to 2007. Statistically, from North to South, nine sub-region climates were built by distribution of temperature, rainfall, topography, sunny hours and land surfaces; hence, excepting two island stations, last nine selected stations have representative character of nine sub-regional climates over Vietnam.

APCC's CLIK uses hindcast and forecast data from several institutions around the world. They are Central Weather Bureau (CWB) of Chinese Taipei, Japan Meteorological Agency (JMA); Global Climate Prediction System (GCPS) of the Seoul National University, Korea; Global Data Assimilation and Prediction System (GDAPS) of Korea Meteorological Administration, Korea; Russian Federal Service for Hydrometeorology and Environmental Monitoring, Main Geophysical Observatory (MGO) of Russia and National Centers for Environmental Prediction (NCEP) of USA. The predictors are taken from these six operational seasonal model outputs. The hindcast data cover the period of 21-year from 1983 to 2003 and have the spatial resolution of 2.5^{o} x 2.5^{o}.

2.2 Methodology

There are two main steps in multi-model outputs downscaling prediction for temperature:

a. Choice of Predictors

CLIK offers two options, one based on correlation analysis, the other based on pattern analysis which shows correlation of station with observed predictor and correlation of station with simulated predictor. In this part, we can also modify the optimal area of study. For the current study, we choose area from 60S-60N, 60E-60W. This domain contains the large scale circulation information from the whole Pacific Ocean, East of India Ocean, Tibet permanent high pressure and Asia-Australia monsoon area.

In addition, our approach is searching as much as possible predictor(s) in models which have the consistent stable correlation with local station variable. The detail is described as below. We will choose models, e.g. six models, with one predictor; if both these six models show a good correlation then we can select that predictor as the most suitable predictor. Unfortunately, none of predictor satisfied all models. Our concept is just only predictor(s) show good results in at least haft of selected models, in this study is three per six models, will be chosen. Moreover, first leading predictor is the predictor having most suitable with the sign of observed anomaly, and we also put priority on general circulation variable such as SLP, Z500 in the procedure of predictor selection.

b. Statistical Downscaling Method

The prediction scheme in CLIK based on pointwised regression method. The detail of the method of downscaling can be found in Kang et al. [2007]. Shortly, suppose the predictand and predictor are Y(t) and X(I,j,t), respectively. Y(t) is observed station precipitation and X(i, j, t) is model predicted large-scale variable.

$$Y(t) = \alpha X_p(t) + \beta$$

Where $X_p(t)$ is the projection of the predictor in the selected area

$$X_p(t) = \sum_{i,j} COR(i,j).X(i,j,t)$$

The correlation coefficient is obtained as:

$$COR(i,j) = \frac{\frac{1}{N}\sum (Y(t) - Y_m).(X(i,j,t) - X_m(i,j)}{\sigma_x(i,j).\sigma_Y}$$

Where N is the training year, the subscript m is the average of the average of the variable during the training period, σ is the variance. Regression coefficient α, β are calculated in training period.

3. Results

3.1 Selection predictors

The table 1 shows prevail predictor(s) which is founded by CLIK. The predictand is temperature in summer (JJA) and winter (DJF). There are three per six models show the consistent predictor(s). For the purpose of operational forecast, such stable leading predictors can be used in Vietnam.

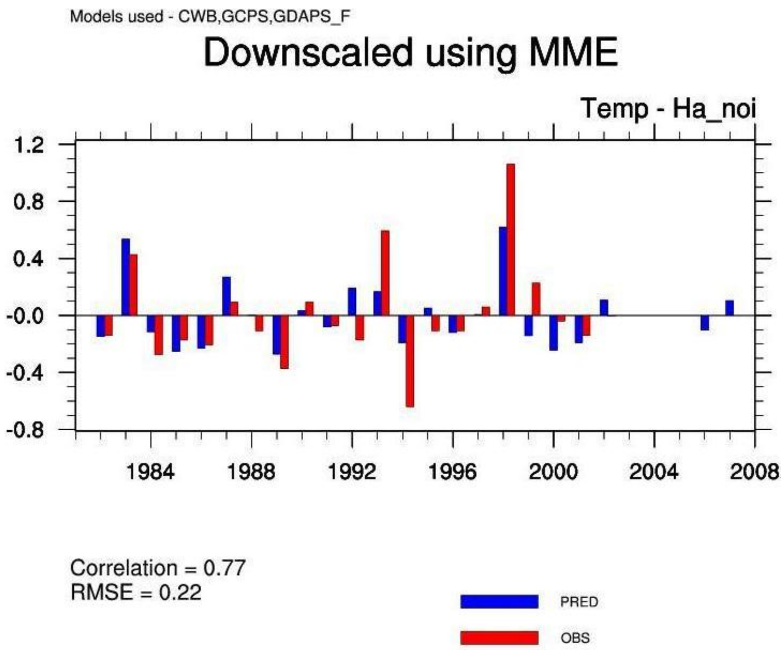
Table 1: Lead predictor for 11 stations in CWM, GCPS and GDAPS_F models, region: 60S-60N, 60E-120W

Station name and ID	JJA		DJF	
	Predictor 1	Predictor 2	Predictor 1	Predictor 2
Lai Chau (48800)	T850	V850	///////////	///////////
Ha Giang (48805)	V850	Z500	SLP	T850
Lang (48820)	Z500	V850	Z500	T850
Phu Lien (48826)	Z500	V850	Z500	T850
Vinh (48845)	Z500	V850	SLP	T850
Da Nang (48855)	///////////	///////////	T850	///////////
Plei Ku (48866)	Z500	V850	Z500	V850
Quy Nhon (48870)	V850	Z500	T850	///////////
Phu Quoc (48917)	Z500	V850	V850	T850
Chau Doc (48909)	///////////	///////////	T850	///////////
Bach LV (48839)	V850	U850	Z500	SLP

Interestingly, while most of stations have at least one stable predictor some of them show nothing. The similar thing has occurred in studying on downscaling stations in Philippines and Thailand. Therefore we can assume that there are two types of stations, type one is those that has downscaling predictability and the type two is the rest. The reasonable explanation for the type two can be solved on its local characteristic such as topography and climate regime. Take Danang (48855) station as an example. It located in the south of White Horse Mountain; Danang has a special climate condition. Typically, White Horse Mountain has been used as the climate frontier between the North and the South in Vietnam. A coherent contrast temperature in summer between the south and north mountain sides is recorded in observed data. The Laichau station (48800), it located in 243m high altitude above sea level in the Northwestern region. In general, winter temperature in Laichau is much less colder than that of in the Northeastern region because of blocking of the highest mountain, named HoangLienSon, in the East. The winter then shows great effect by cold surges from the South China within ridge, trough and valleys around station (Figure 2, Appendix 1). The ChauDoc (48909) station, is beside the Delta Mekong, the biggest river in the Indochina region, has an agreeable temperature in summer; it normally keeps at about 27.5^{o}C year by year. Overall, in such complex areas, correlation analysis probably may not have skill in predictor detect-ability.

3.2 Forecast and some preliminary assessment.

After selecting the predictor, the downscaling procedure is carried out at each station for each model. In general, correlation coefficient of downscaling and observed reaches at 0.7, the root mean square error varies from 0.15 to 0.3^{o}C. Figure 1 is the prediction for the station 48820 (Lang or HaNoi station). By using regression equations for seasonal prediction, we would be better to look at the sign of anomaly than that of quantity. For stations those have predictor, the tendency training skill of CLIK is at 85%. This skill is simply calculated by the number of wrong predictions in the training period.



As the rest part of study, we performed some preliminary assessment for predictions. In figure 1, two right blue columns are forecasts for 2006 and 2007. Combination of climatology temperature, real-time observed temperature in 2006, 2007 and the downscaling forecast at stations, we can find out some significant features (Appendix 3).

In winter, forecast skill just stands at level of about 50%, five correct forecasts per ten stations. In summer 2007, only one forecast failed at station 48839 and the percentage of correct forecast is 90%. However, summer 2006 showed an abnormal less-skill in most stations. This is an interesting result because when we look back to the climatology summary in summer 2006 that was the most active Pacific hurricane season since the 2000 season. The 2006 season started by the typhoon Chanchu (Caloy) on 5 May, ended by the typhoon Trami (Tomas) on 19 December and there were total 23 typhoon/tropical storm activating in South West pacific region [JMA, 2006]. Obviously, this extreme season had huge impact to the temperature and rainfall distribution in the study area; hence it should be an important source to explain the failed forecasts in temperature in JJA 2006.

4. Conclusions

In this study, downscaling technique has been accomplished for two-metres temperature prediction in eleven stations in Vietnam. In particular, finding prevail predictor then making prediction for each station are carried out. Of lead predictor as general circulation variables, Z500 and SLP, CLIK show the ability in studying phenomena like ENSO.

By using CLIK, this is the first time seasonal forecast at station scale in Vietnam has been performed and this allows us have hopes toward on operational forecast in the near future.

However, there are still some remain questions. Why DJF downscaling shows less good quality than that of in JJA? How to improve forecast in extreme typhoon seasons (a case study from 2006 season)? Studying in rainfall as the predictand, working with as much as possible number observed stations also need be carried out in the next studies.

Acknowledgement:

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Appendix 1: Vietnam topographical and 11 selected stations

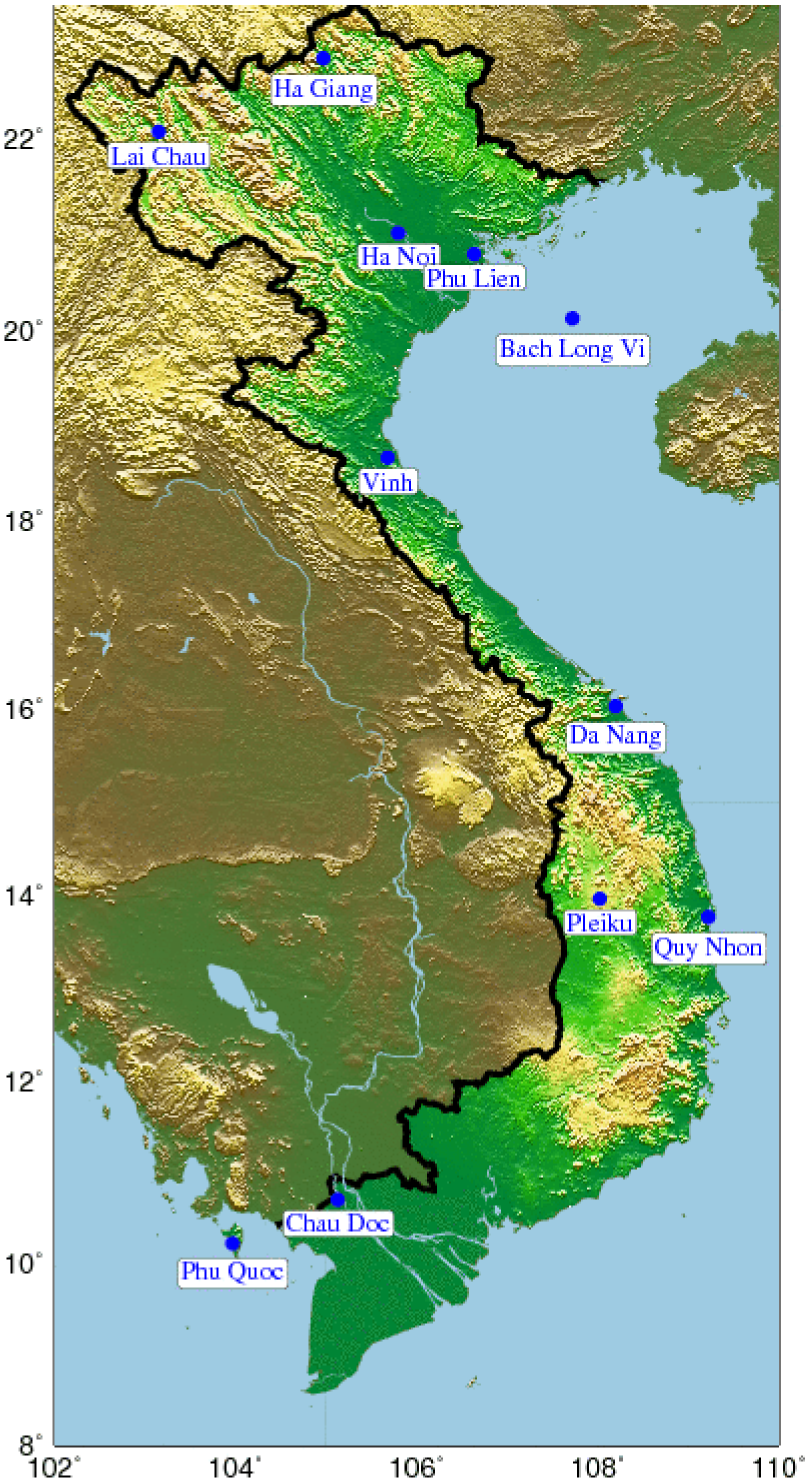


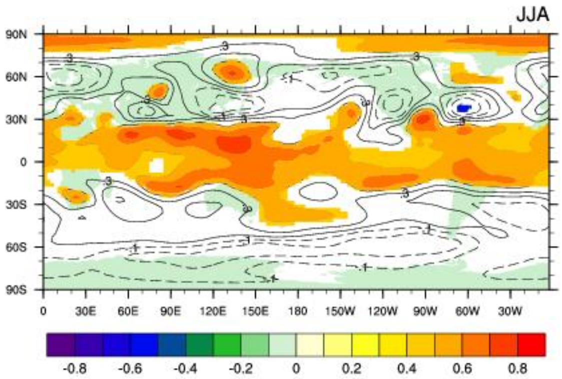
Figure 1: Eleven stations and Vietnam topography.

Figure 2: Laichau station (48800) geographical position. Photo copyright by Google Earth.

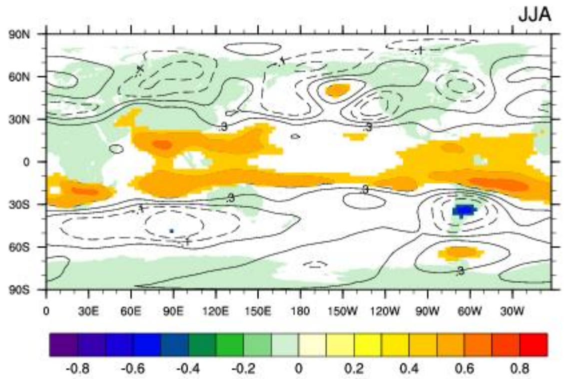
Appendix 2: Correlation maps

Station 48820 (Hanoi): Correlation maps of Z500 in models with T2m.

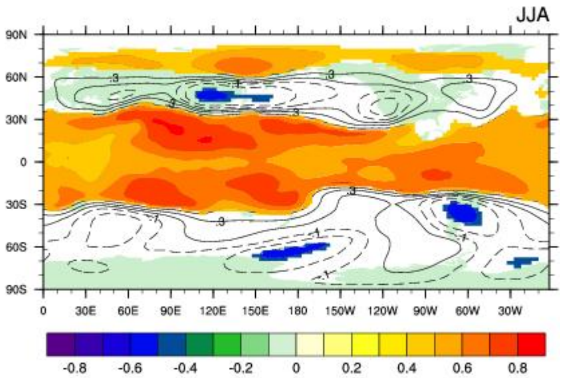
Correlation of temp from LANGTTB with OBSERVED z500



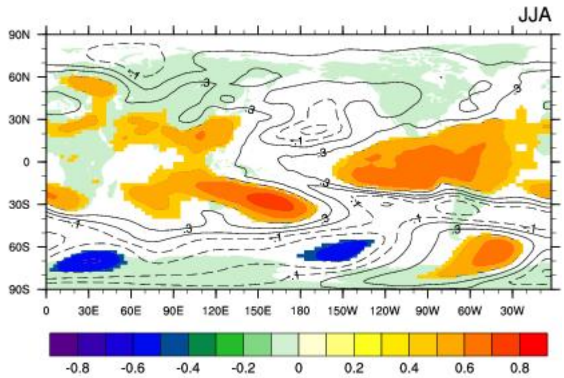
Correlation of temp from LANGTTB with CWB z500



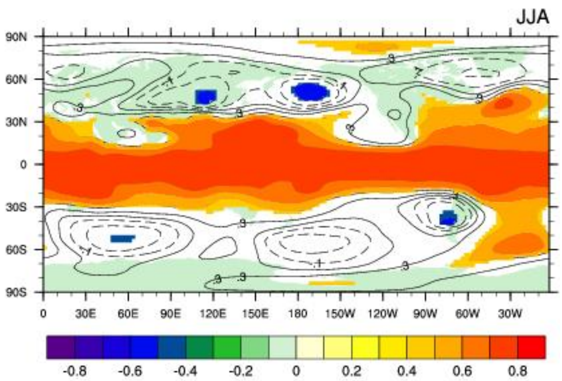
Correlation of temp from LANGTTB with GCPS z500



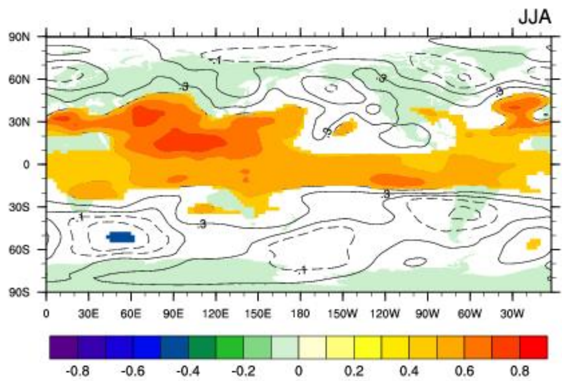
Correlation of temp from LANGTTB with METRI z500



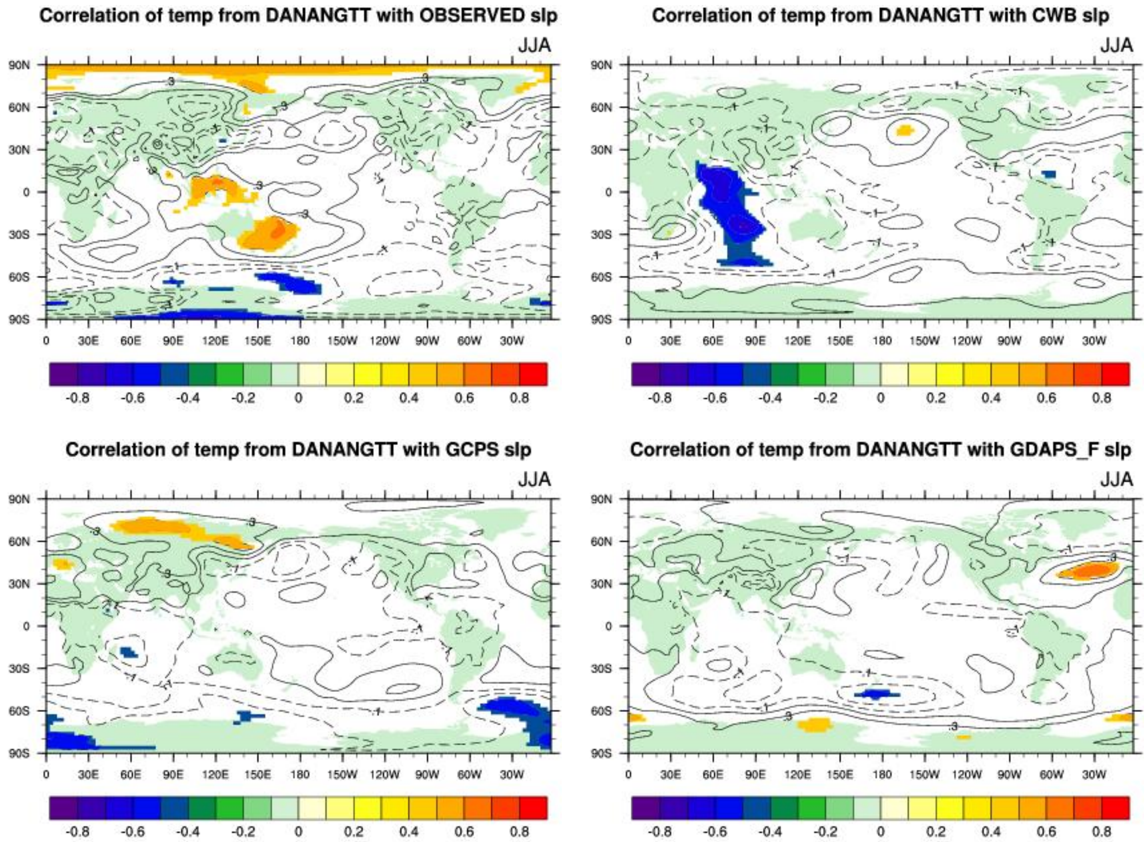
Correlation of temp from LANGTTB with GDAPS_F z500



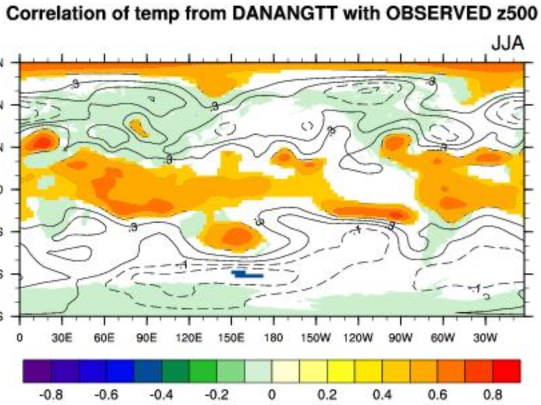
Correlation of temp from LANGTTB with MGO z500

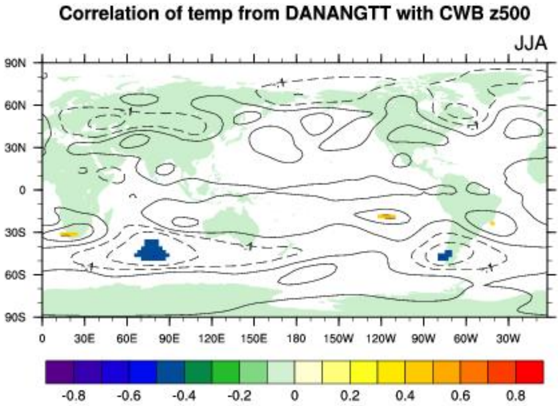


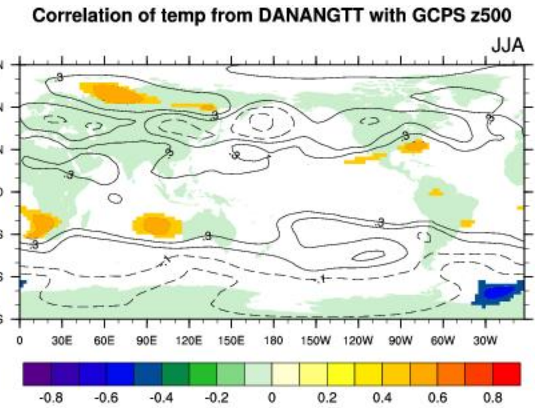
Station 48855 (DaNang): Correlation map of SLP in models with T2m.

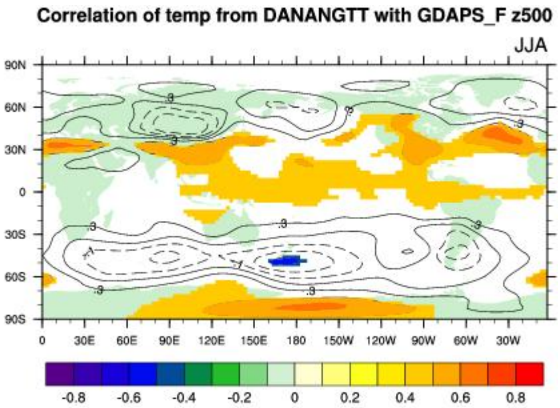


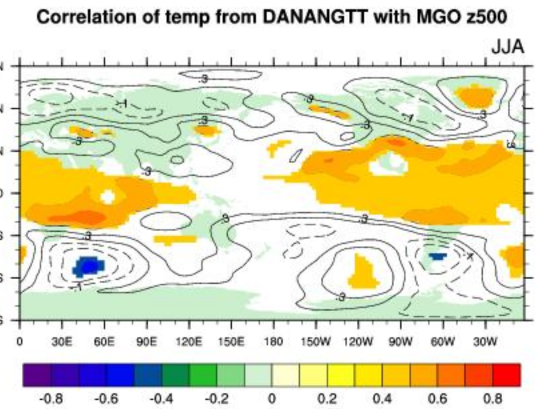
Station 48855 (DaNang): Correlation map of Z500 in models with T2m.

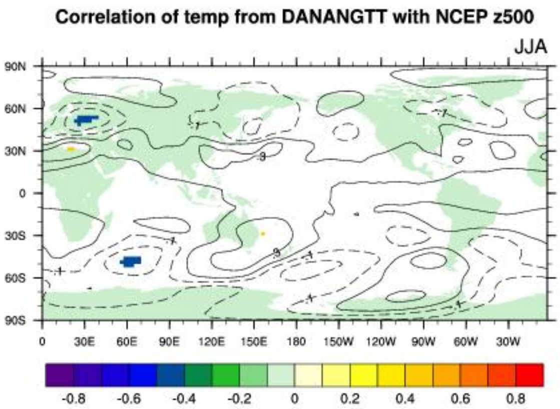




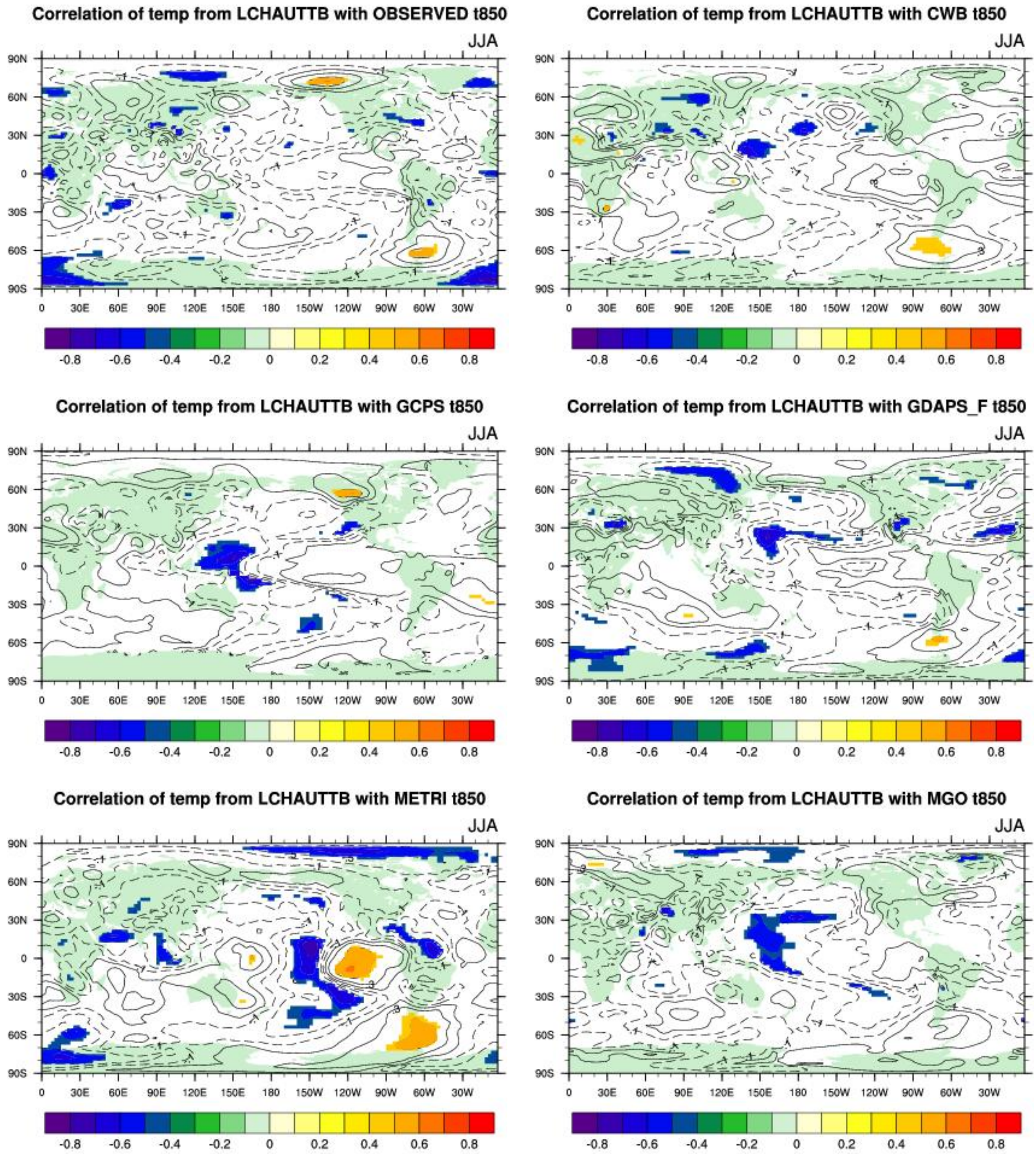




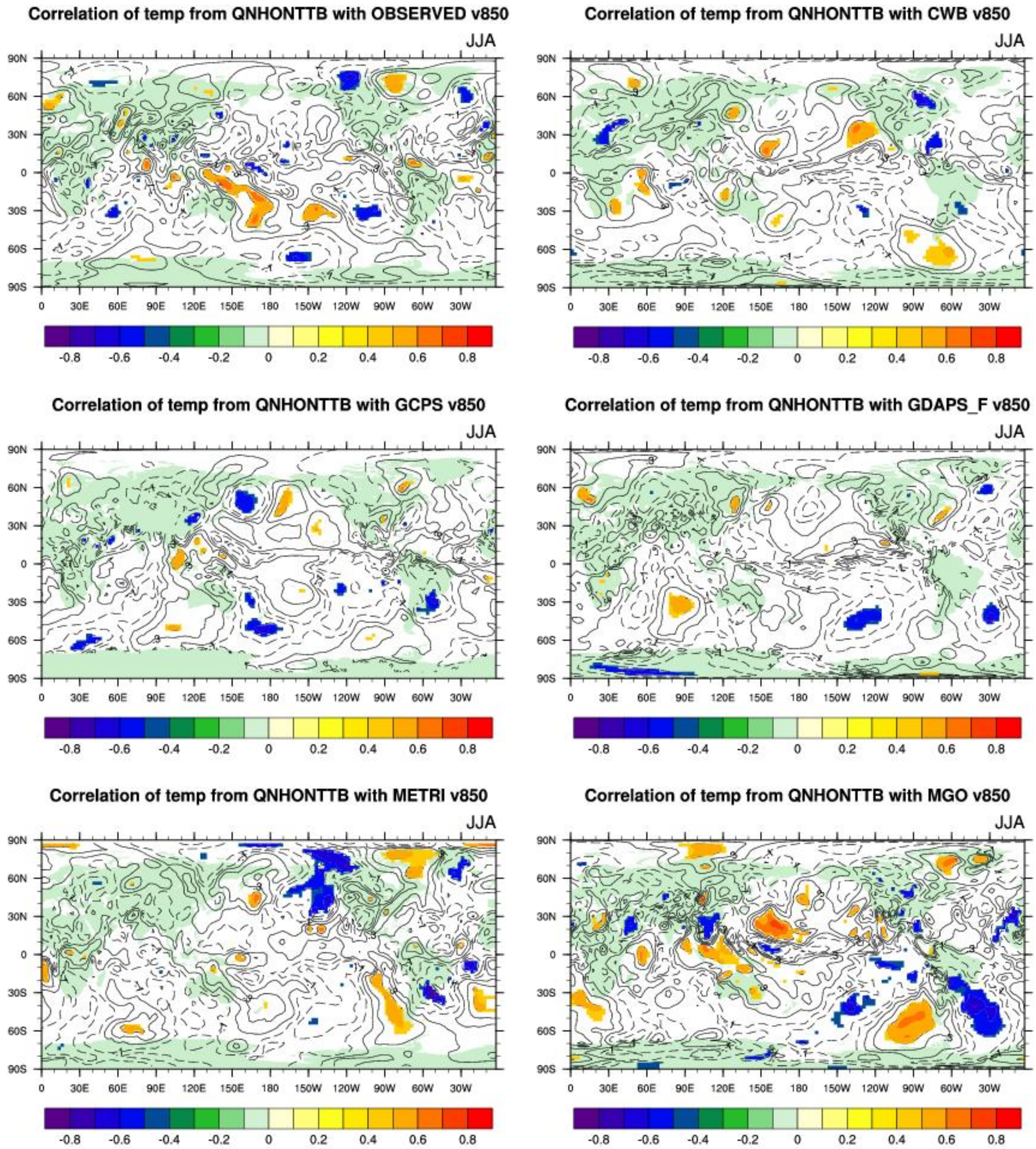




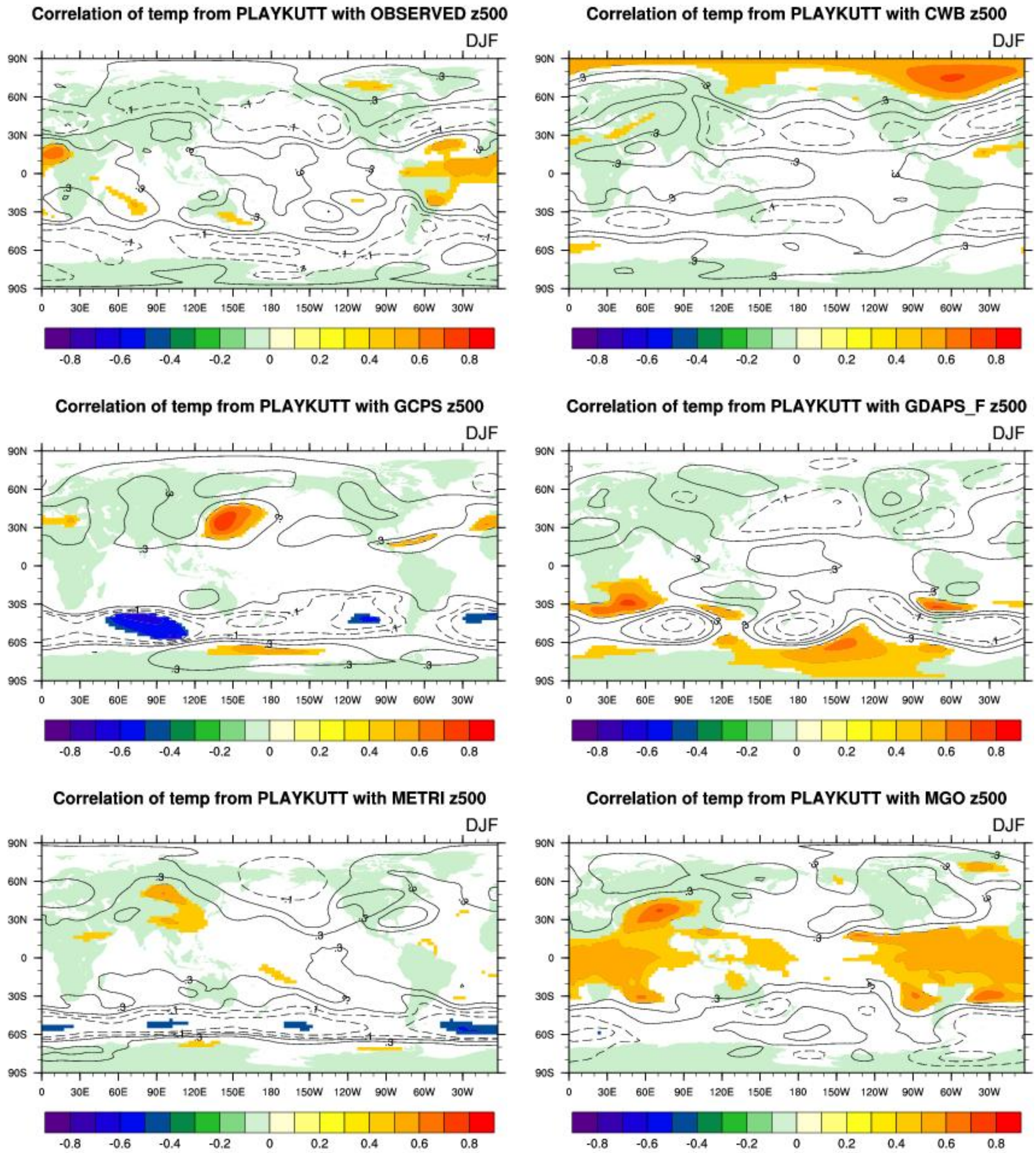
Station 48800 (LaiChau): Correlation map of T850 in models with T2m (JJA)



Station 48870 (QuyNhon): Correlation map of V850 in models with T2m.



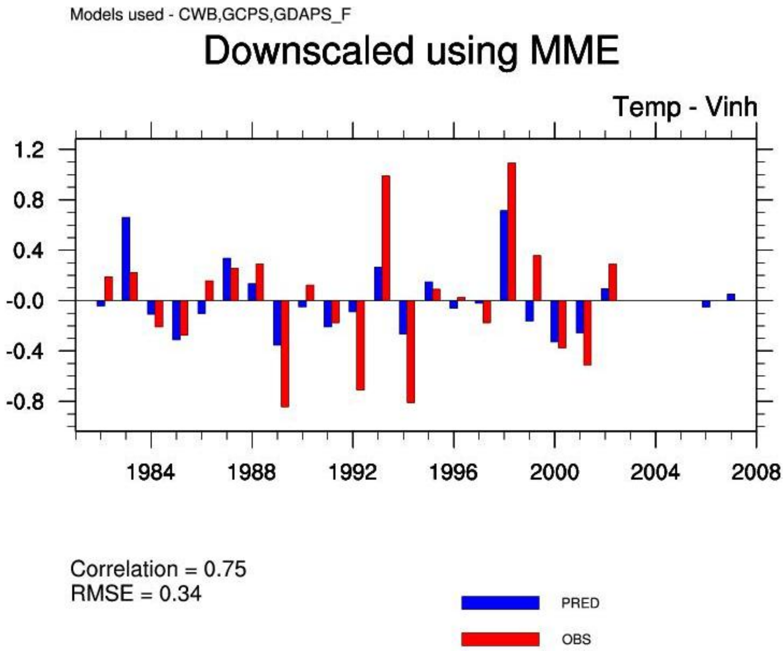
Station 48866 (PleiKu): Correlation map of Z500 in models with T2m (DJF).



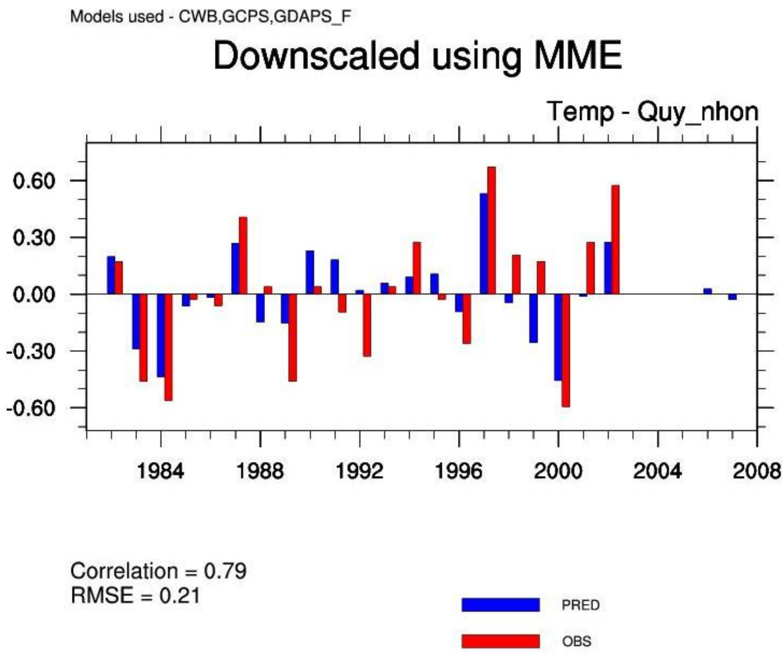
Appendix 3: 2006-2007 forecast assessment summary

A. Forecast results

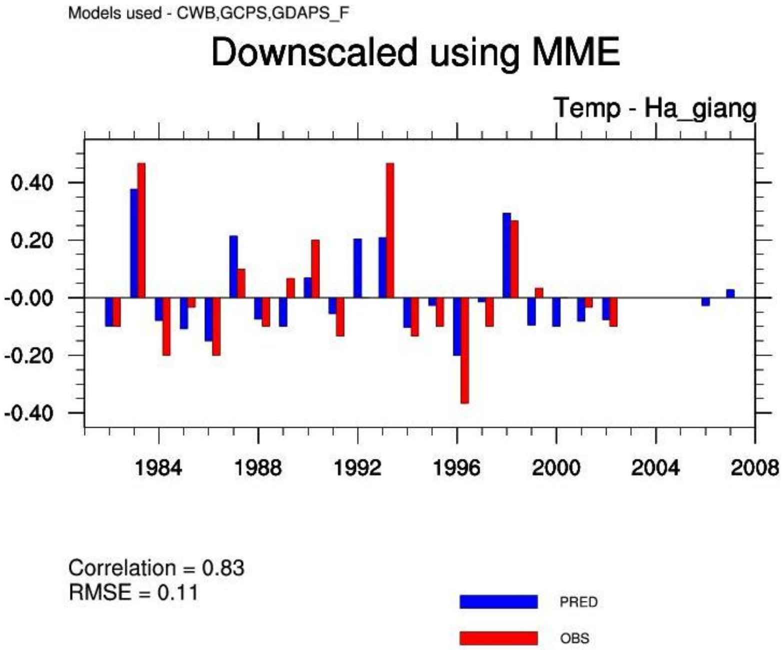
Station 48845 (Vinh): JJA



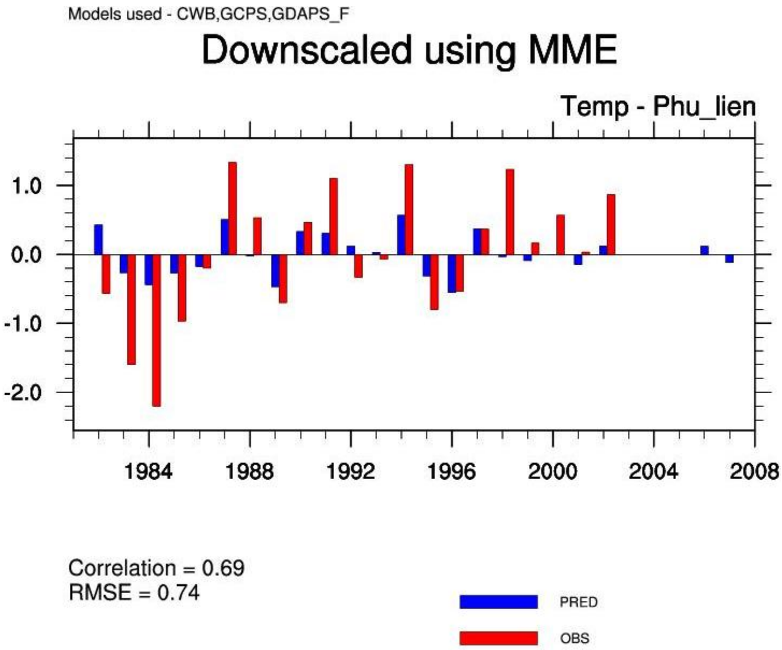
Station 48870 (QuyNhon): JJA



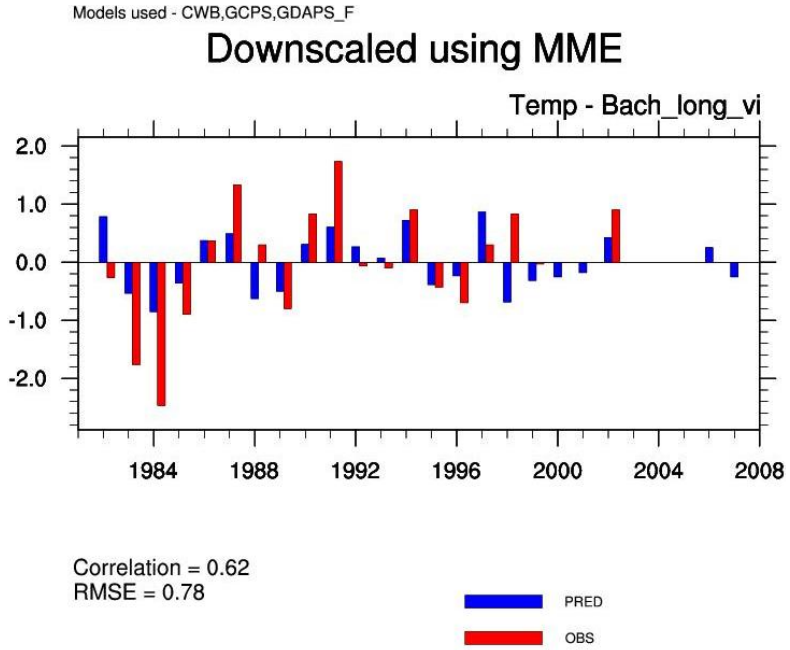
Station 48805 (HaGiang): JJA



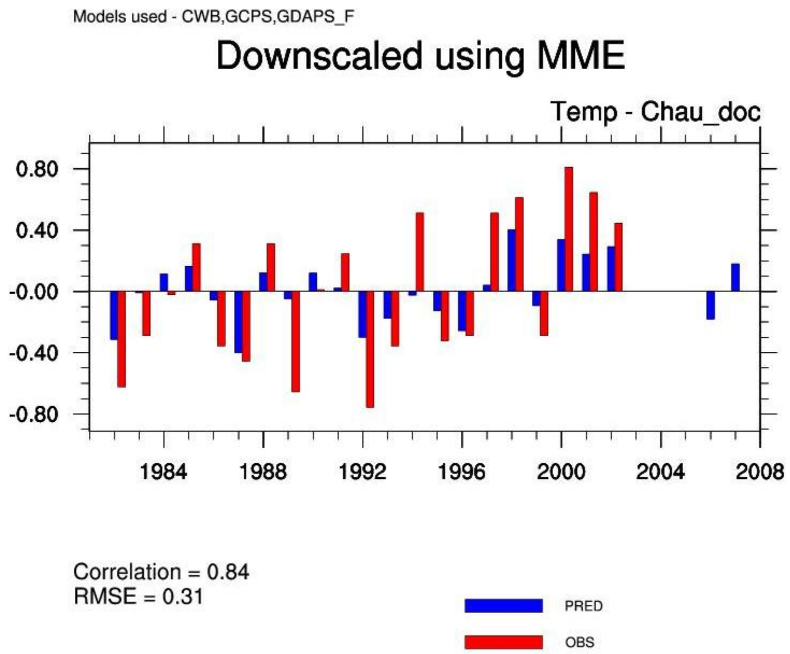
Station 48826 (PhuLien): DJF



Station 48839 (BachLongVy): DJF



Station 48909 (ChauDoc): DJF

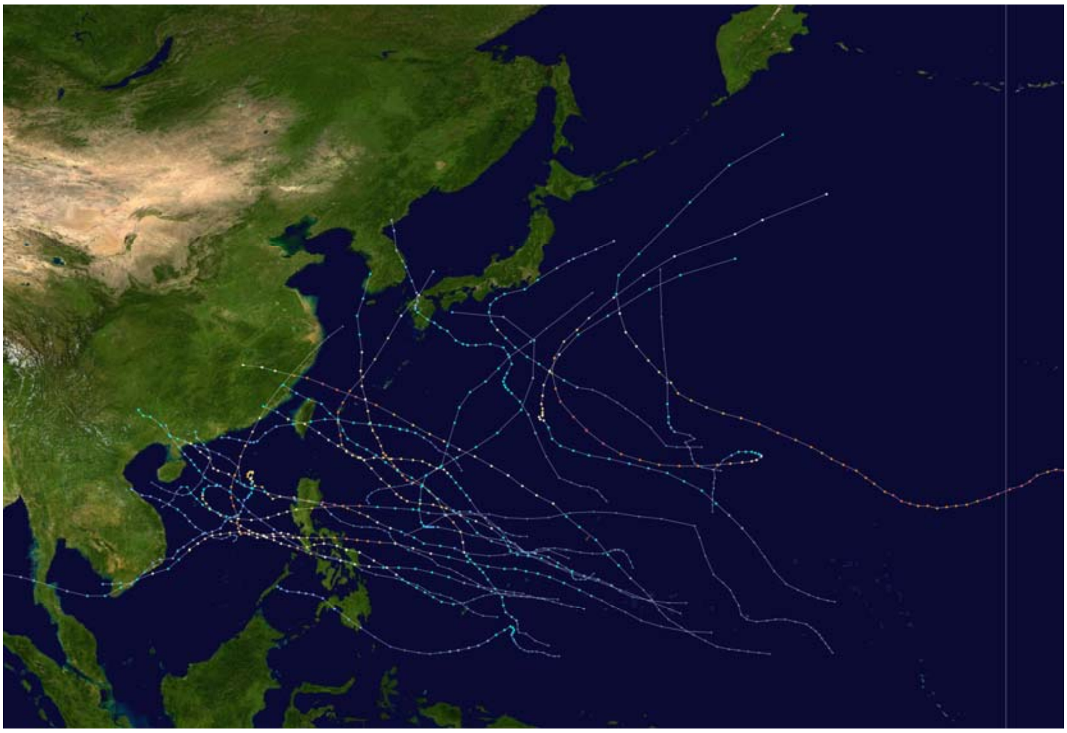


B.

Table 2: 2006, 2007 forecast assessment summary

Station name and ID	JJA		DJF	
	Correct	Wrong	Correct	Wrong
Lai Chau (48800)	2006, 2007		///////////////////	///////////////////
Ha Giang (48805)	2007	2006	2006	2007
Lang (48820)	2007	2006		2006, 2007
Phu Lien (48826)	2007	2006	2006	2007
Vinh (48845)	2007	2006	2006	2007
Da Nang (48855)	///////////////////	///////////////////	2007	2006
Plei Ku (48866)	2007	2006	2007	2006
Quy Nhon (48870)	2006, 2007		2007	2006
Phu Quoc (48917)	2007	2006	2007	2006
Bach LV (48839)	2006	2007	2006	2007
ChauDoc (48909)	///////////////////	///////////////////	2007	2006

Appendix 4: 2006 NorthWest Pacific typhoon season summary



Source:

http://en.wikipedia.org/wiki/Image:2006_Pacific_typhoon_season_summary.jpg

http://sharaku.eorc.jaxa.jp/ADEOS2/JAXA_TYP_DB/TYP_DB_COMMON/ytrack/all_2006s_WPh.gif

STATISTICAL DOWNSCALING FROM THE GLOBAL CIRCULATION MODEL OUTPUTS

Vladimir Kryjov

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Introduction

Seasonal climate prediction for the extratropical areas is one of the greatest challenges of the modern meteorology and climatology. The skill of the raw model seasonal forecasts for the most of the extratropical area is quite poor nowadays. The skill of the forecasts, based on the statistical relationships between the objects of synoptic climatology, also hardly exceed the skill of climatological forecasts and only for restricted areas. Many NMHSs of extratropical countries, and NMHS of Russia among them, restrict practical long range forecasting to the only monthly forecast with zero lead time.

The possible way of the improvement of the seasonal prediction skills for the extratropical regions resides in finding of the robust relationships, expressed in a statistical form but underlied by physical dependencies, between the target variables at the target region and model predictions of the variables which prediction is skillful and which are physically related to the target variables. The mostly reasonable is to find linear dependencies and assess them with ordinary linear correlations.

The main problem of finding of the predictors resides in multiplicity of the performed correlations and, consequently, in the large probability of occasional obtaining of significant correlations. Particularly, the model output fields expressed on the 2.5^{o} by 2.5^{o} grid consist of more than 10000 grid-points. It means that at more than 500 grid-points the correlation coefficients significant at the 5% level may be obtained just by chance. Therefore, in the performed analysis the main attention was paid to the significance of the obtained relationships and robustness of the regression equations.

A number of hydrometeorological stations were selected for the tests of the downscaling methods for the development of the station seasonal forecast based on the global model outputs. These stations mainly represent the Far Eastern region of the Russian Federation because of two considerations. The first consideration resides in the Asia-Pacific regionality. The second consideration has more scientific basis. The climate of the Far Eastern region of the Russian Federation is affected by the El-Nino/Southern Oscillation phenomenon more strongly than any other part of Russia. The seasonal integrations of the global circulation models are governed by the boundary conditions mainly associated with the phase of the El-Nino/Southern Oscillation. Therefore, there is larger opportunity that the robust relationships between the observed variables and model outputs may be found just for the Far Eastern stations.

In Fig. 1 it is shown the first pair of the singular vectors from the maximum covariance analysis between rainfall and wind components at the 850 hPa surface. The tri-pole pattern shows the connection between the low troposphere wind components in the tropics, well predicted by the state-of-the-art global circulation models, and the rainfall in the Far Eastern regions of the Russian Federation. Such connection provides the hope on the success of the downscaling for this region from the global model outputs. However, it should also be noted that the fraction of the total rainfall variance, which is associated with the rainfall pattern shown in Fig. 1, is less than 30%. It means that even if the prediction of the pattern is quite successful, prediction of the station rainfall may contain large errors.

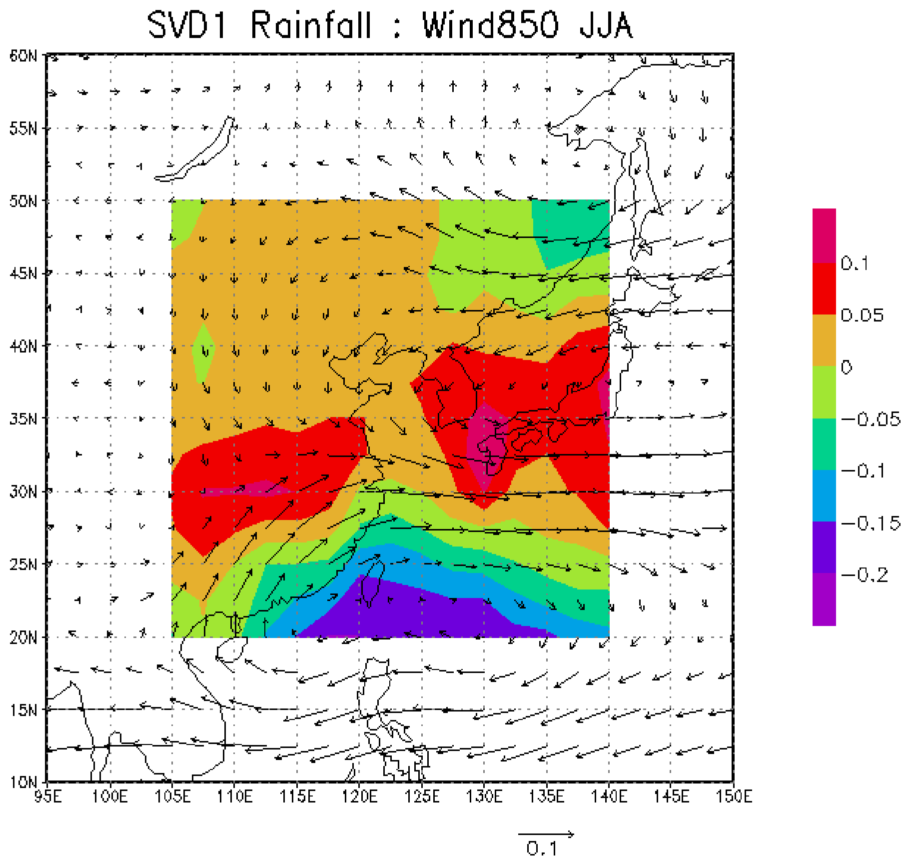


Fig. 1. The first pair of the coupled singular vectors from the maximum covariance analysis between rainfall and wind components at the 850 hPa surface.

Downscaling Experiments

A downscaling procedure consists of three stages. The firs stage is a searching for the potential predictors. In this stage, the correlation maps between a predictand (usually, a series of the target variable at a target station) and various model outputs are being constructed. Then, assessment of the statistical significance of the obtained dependencies with potential predictors is performed and, as a result of the first stage, selection and a list of potential predictors is formed.

In the second stage, the regression equation is being derived and assessed (significance of the regression coefficients, confidence intervals of the predictions, serial correlation in residuals, etc.) using the "dependent" series, that is the data from the training period.

The third stage for the real-time prediction is an estimation of the forecast using the model predicted variables as predictors and the derived regression equation.

APCC has developed a specialized Climate Information Tool Kit software which provides the users with the climate data processing and analyzing tools. The downscaling procedures have been written by the CLIK tools and implemented as a part of the CLIK software. The downscaling for the Far Eastern stations of Russia described below have been performed using the CLIK software.

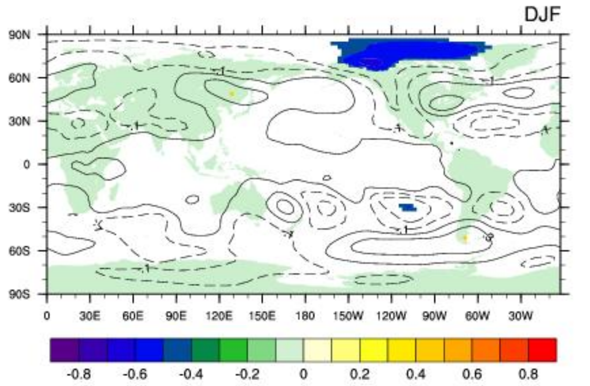
We have constructed correlation maps between the series of seasonal mean temperature and precipitation at a number of stations and the model output fields. Significance of the maps was assessed by means of the field significance test based on the Monte Carlo method, with significance of both local and global tests being set at the 10% level.

Results from the tests appear not too optimistic. For most of the stations and model output fields the correlation maps have not passed the field significance test, even with the 10% significance level having been set. Examples of such correlation maps are shown in Fig. 2. The spots of "significant" correlations are randomly dispersed throughout the globe, with the number of the grid-points which feature "significant" correlation being too small to be non-occasional.

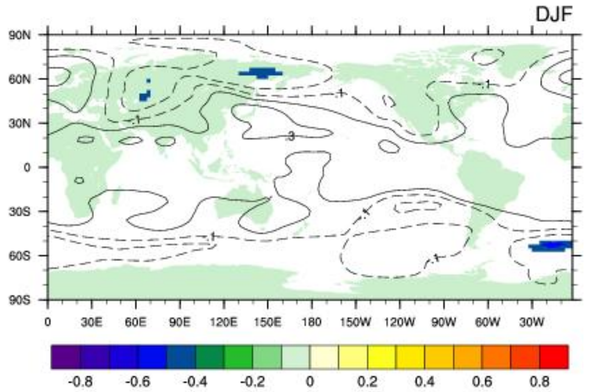
The best results have been obtained for summer temperature and precipitation predictions for Vladivostok station. Examples of the correlation maps for this station are shown in Fig. 3. It should be specially noticed that the areas of significant correlations between Vladivistok JJA temperature and model predicted Z500 for GCPS, GDAPS_F and NCEP models almost coincide with the areas of significant correlations with observed Z500.

Based on these correlation maps, the forecast methods have been developed. These methods have been assessed on well cross validated data from the period of the model historical forecasts. Year by year, one year data have been withheld, regression equations have been derived on the rest of the series and prediction for the withheld year has been performed. Then, the skill of the method has been assessed using these predicted and observed temperature and precipitation values.

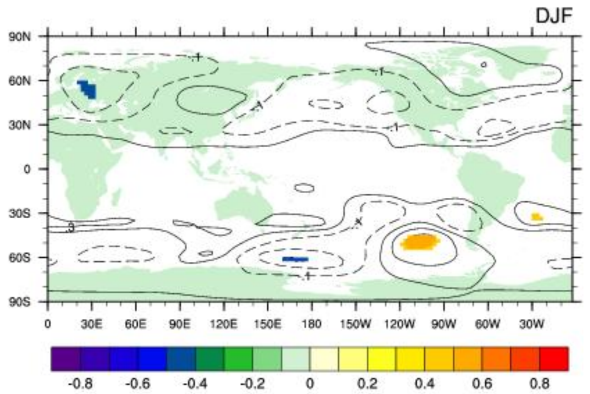
Correlation of temp from HABAROVSK with OBSERVED z500



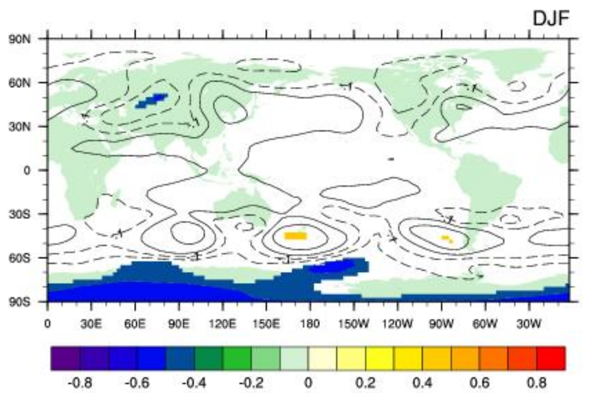
Correlation of temp from HABAROVSK with CWB z500



Correlation of temp from HABAROVSK with GCPS z500



Correlation of temp from HABAROVSK with GDAPS_F z500



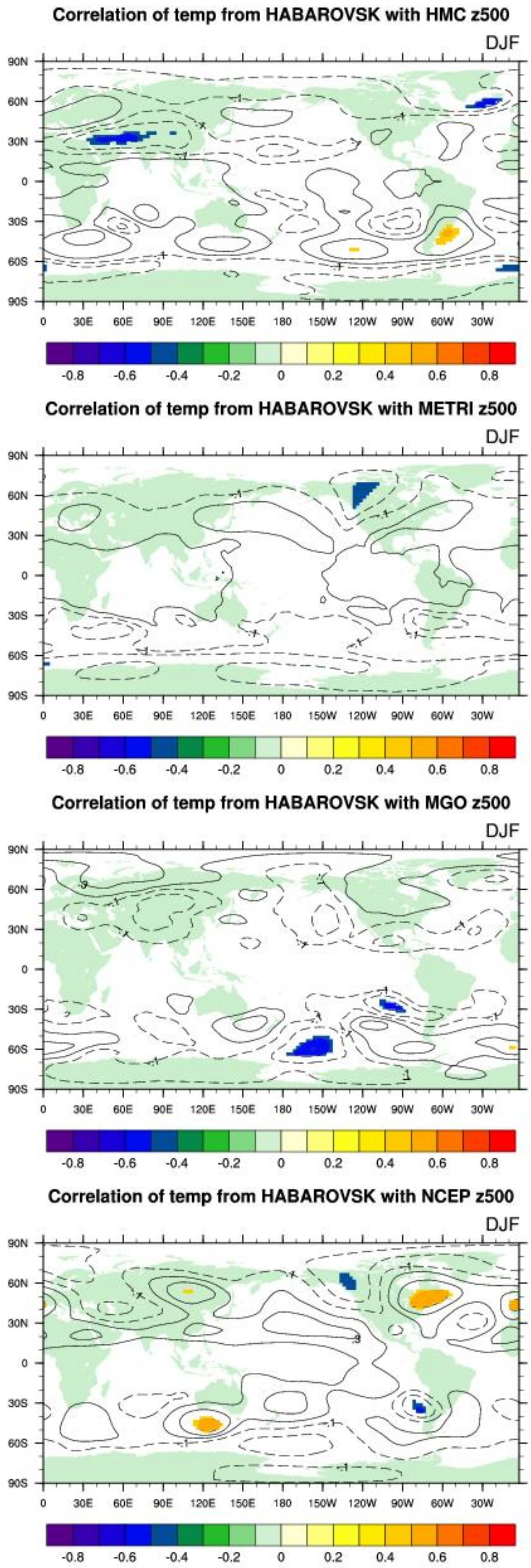
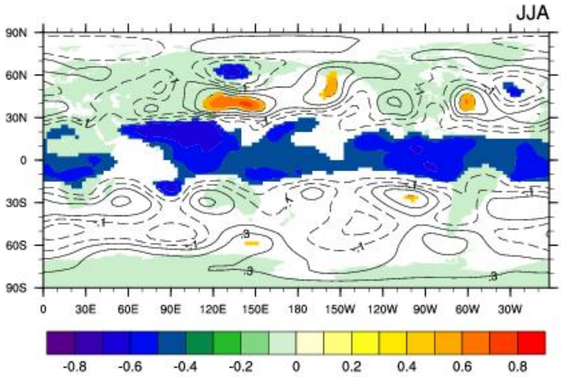
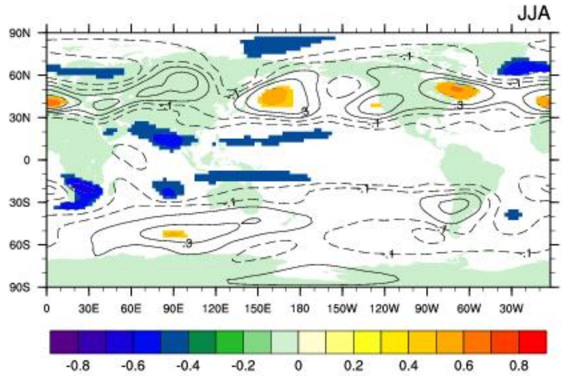


Fig. 2. Example of the correlation maps between DJF temperature at Habarovsk and observed Z500 and model simulated Z500.

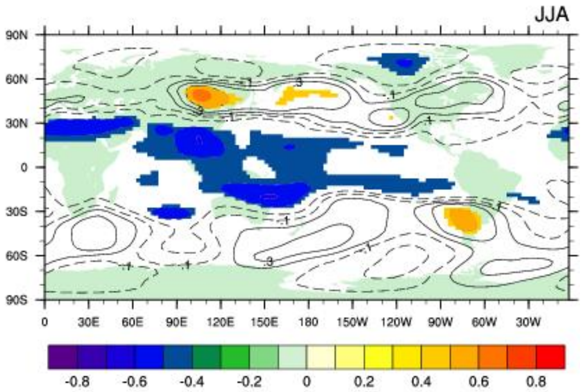
Correlation of temp from VLADIVOSTOK with OBSERVED z500



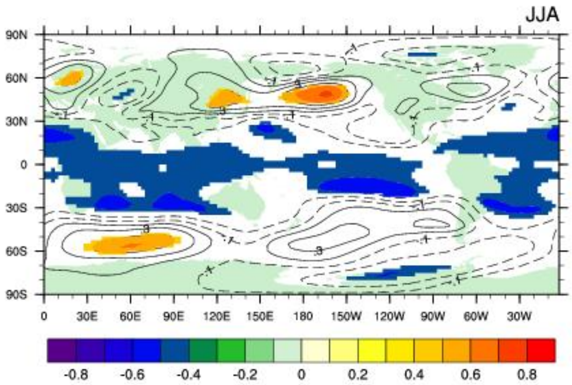
Correlation of temp from VLADIVOSTOK with CWB z500



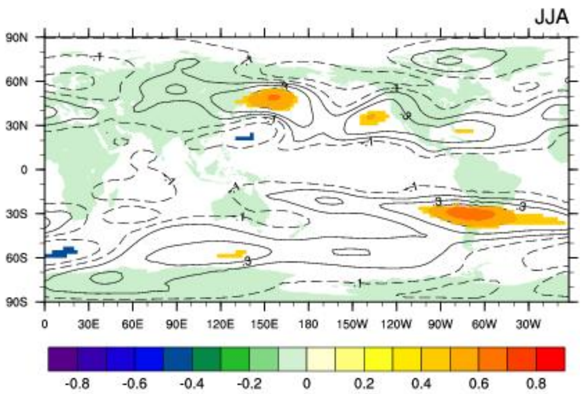
Correlation of temp from VLADIVOSTOK with GCPS z500



Correlation of temp from VLADIVOSTOK with GDAPS_F z500



Correlation of temp from VLADIVOSTOK with HMC z500



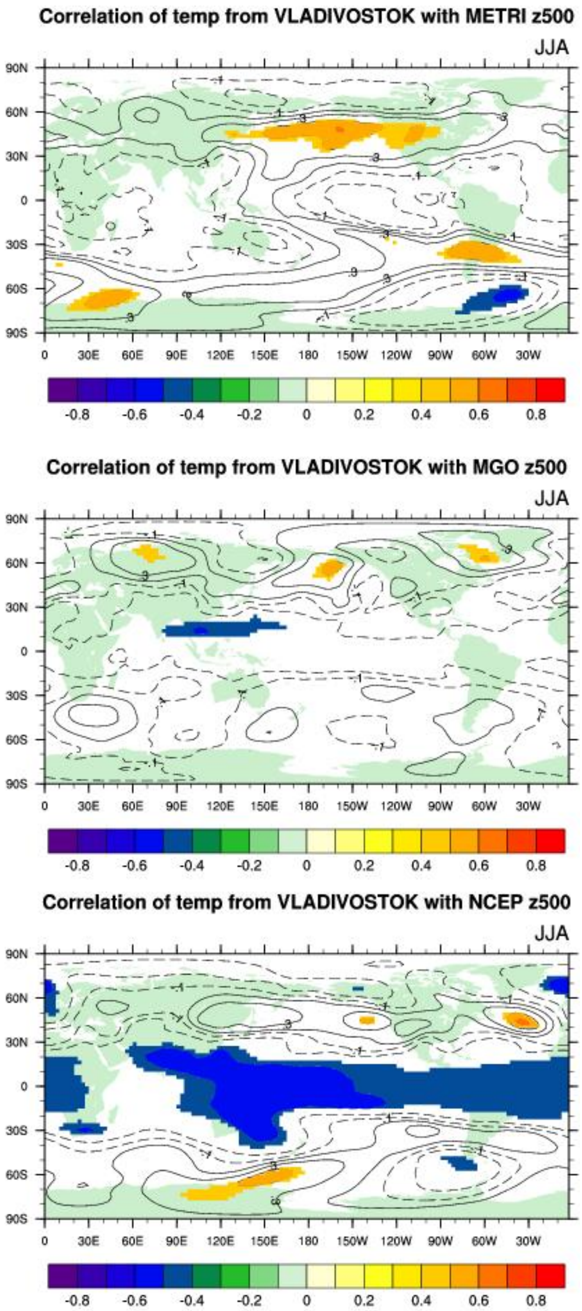


Fig. 3 Example of the correlation maps between JJA temperature at Vladivostok and observed Z500 and model simulated Z500.

Results from the prediction and prediction assessments are shown in Figs. 4 and 5.

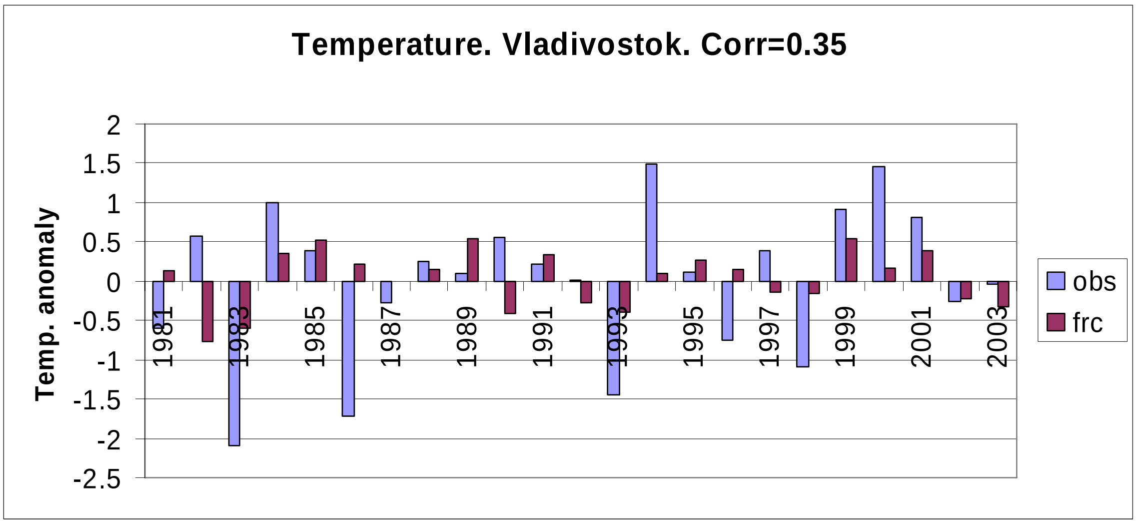


Fig. 4. Observed and forecast summer (JJA) temperature anomaly at Vladivostok.

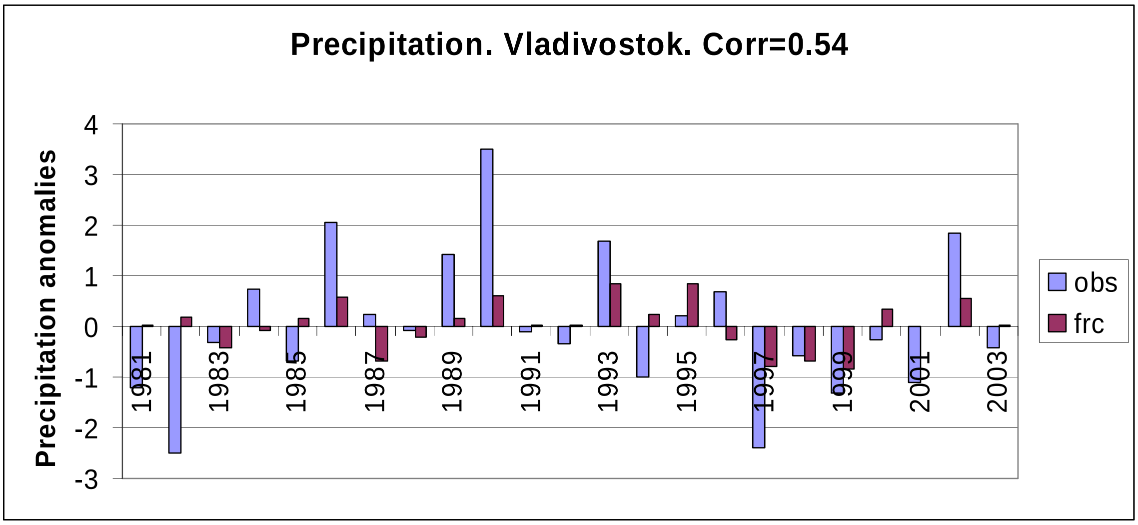


Fig. 5. Observed and forecast summer (JJA) precipitation anomaly at Vladivostok.

The obtained results strongly outperform raw model predictions for the station which suggest that downscaling from the model seasonal predictions to the stations may improve the forecasts. However, the level of the skill of the improved (downscaled) forecasts remains rather low. It is much lower than that for the tropical area.

The performed downscaling is a deterministic one. That is, the forecast is formulated in terms of anomalies. It is reasonable for the tropical regions, for which downscaling from the model outputs provide quite skillful forecasts. However, for the extratropical areas the skill even of the state-of-the-art models remains low and even downscaling improves the skill up to not too high level. So that, for the extratropics it reasonable to develop probabilistic forecast methods and probabilistic downscaling methods, which allow the users of the forecast to assess the uncertainty of the predicted values.

As a pilot project, we have developed a probabilistic downscaling method with optimization scheme based on the ignorance score (please see Lecture 4 given by V. Kryjov at the course). Assessment of the cross-validated probabilistic downscaled forecasts is shown in Fig. 6. The method outperforms climatological predictions and it outperforms the raw model forecasts. However, there are seven years of 23 when forecasts were not successful. Nevertheless, the results from this first experiment can be considered as promising. The method is planned to be upgraded and implemented in the CLIK software.

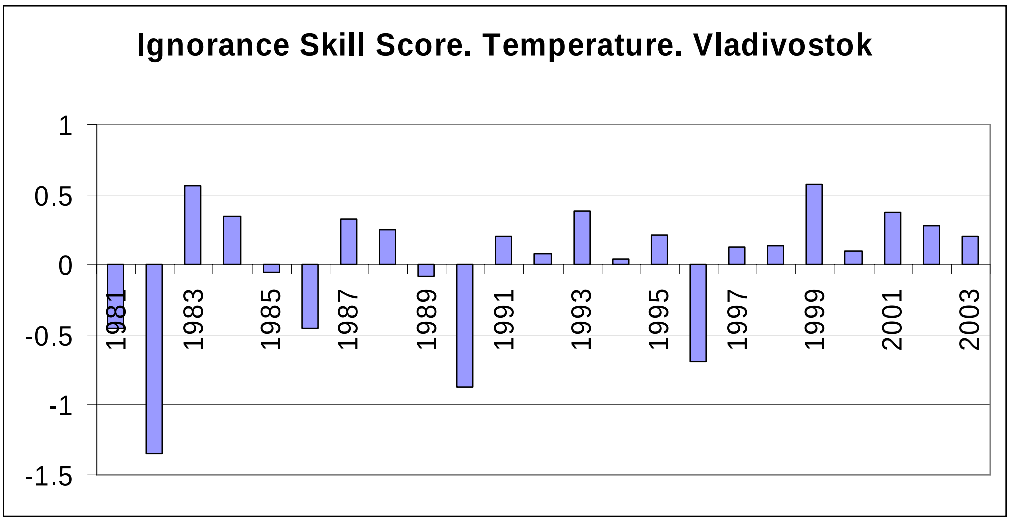


Fig. 6. Ignorance skill score for summer (JJA) temperature in Vladivostok.

Conclusions

The individual model forecasts as well as multimodel ensemble forecasts for the extratropical regions, particularly for North Eurasia, are rather poor. Their skill is at the same level as that of the statistical prediction methods.

Improvement of the forecast skill and reliability may be achieved by means of downscaling from the model predictions of the large scale circulation pattern down to station variables. However, the success of the downscaling methods is conditioned on the physical relationships between the large scale circulation patterns, which models are able to predict successfully, and the station variables. Therefore, actual forecast skill and reliability improvement by downscaling from the model outputs is restricted to the regions strongly affected by the large scale circulation patterns which models are able to predict.

Taking into account not high skill of the seasonal forecasts for extratropics even after downscaling, it is reasonable to develop probabilistic downscaling methods. One possible approach realized during the training course shows optimistic results. However, for the essential improvement of the method the further studies and works are necessary

The APCC developed software, CLIK, provides convenient user-friendly tools for processing and analyzing of the global model outputs, particularly, for the development of the statistical downscaling methods, both deterministic and probabilistic.

Acknowledgement

We are very grateful to Asia Pacific Network on Climate Change (APN), only owing to the funding provided by APN the training course has been carried out. We are very thankful to APCC who provided the basis for the course. Special thanks are to Dr. Woo-Jin Lee, Dr. Karumuri Ashok and the staff of APCC for their friendly support and valuable help in conducting of the course. And especially we are grateful to Dr. Saji N. Hameed who has developed the CLIK software and who helped us to work with it and who encouraged us to invent new downscaling schemes to be realized in it.