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Toward a Fire and Haze Early Warning System for Southeast Asia

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Toward a Fire and Haze Early Warning System for Southeast Asia

Final Report Submitted to APN

Part One: Overview of Project Work and Outcomes

Non-Technical Summary

Smoke haze from forest fires is among Southeast Asia's most serious environmental problems and there is a clear need for a fire and haze early warning system (EWS) for the region. APCC has been collecting monthly dynamic prediction data produced by 16 institutions and has been producing 6-month lead Multi-Model Ensemble (MME) climate forecasts every month. In this study, we developed 4 different statistical downscaling methods and assessed the forecast skill of each method over fire-prone regions in Southeast Asia. We developed a EWS prototype in which 3-month precipitation (August to October) is predicted during April to July and the forecasted precipitation amount is then translated into four fire danger ratings based on the relationship between precipitation amount and CO_2 emission. A needs assessment for early warning Information was conducted through the field survey with resource managers at three provinces in Indonesia. A two day workshop was held at the Malaysian Meteorological Department (MMD) with financial and logistical support from MMD for the improvement of the EWS. Finally, the forest fire early warning information on Southeast Asia created using the EWS will be provided though the hosting server in APCC.

Keywords

Fire danger, seasonal forecasts, statistical downscaling, dynamical downscaling, and seasonal drought

Objectives

- To assess forecast skill and downscale seasonal forecasts over fire-prone regions in Southeast Asia
- To develop new fire management decision triggers based on seasonal forecasts
- To create a prototype fire danger early warning system for Southeast Asia
- To formulate guidelines on integrating advance climate information into the standard operating procedures of fire management agencies
- To train stakeholders on understanding seasonal forecasts, downscaling, and the early warning system prototype

Amount Received and Number of Years Supported

The Grant awarded to this project was:

KRW23,547,176 for Year 1: to support dynamical and statistical downscaling experiments

KRW18,990,167 for Year 2: to support field survey and training workshop

Activity Undertaken

- Downscaling Experiments
  - Conduct dynamical and statistical downscaling experiments and assess skill levels of prediction over fire-prone regions in Southeast Asia

- Early Warning Information Needs Assessment and Fieldwork
  - Determine early warning information requirements with partner agencies
  - Conduct interviews and group discussions with land and forest managers for input on mainstreaming downscaled seasonal climate forecasts to preparedness and mitigation measures
- Prototype Development and Improvement
  - Develop the prototype early warning system at APCC
  - Amend the prototype early warning system according to test runs and feedback from training workshop participants
- Training Workshop and Tabletop Exercises
  - Conduct a training workshop to provide lectures on seasonal climate forecasting and statistical downscaling techniques
  - Demonstrate the prototype early warning system to fire and land managers and other stakeholders

Results

For the first year of the project, activities focused almost exclusively on a skill assessment of the different forecasting approaches. First, we compared the region-average of the August to October (ASO) period precipitation between observation (APHRODITE) and models (including ensemble members of each individual model) without any bias correction. Individual models predicted reasonably the temporal anomaly trend of ASO precipitation but they failed to predict the absolute precipitation amount for a specific month. Among the four regions, South Kalimantan (SKAL) region showed the most reasonable forecast performance. We applied both dynamical and statistical downscaling approaches over the maritime continent for June to August. Even though both dynamic and statistical downscaling approaches did not add further prediction skill during JJA on Southeast Asia region, it can be said that statistical downscaling using the MME forecast will be more appropriate for a real-world application toward Southeast Asian haze problems compared to dynamical. However, the moving window regression (MWR) method using MME as a predictor over all Southeast Asia showed limitations in representing yearly variations of 3-month total JJA precipitation. We also applied four different statistical downscaling methods over four regions in Southeast Asia for ASO period. Statistical downscaling methods including Simple Bias Correction (SBC), Moving Window Regression (MWR), Climate Index Regression (CIR), and Hidden Markov Chain (HMM) were compared. Temporal correlation coefficient (TCC) between observed precipitation and predicted precipitation using simple bias correction (SBC) increased within all regions as lead-time decrease. However, TCC value based on MWR and CIR downscaling methods did not always show the expected TCC trend by showing decrease in TCC as lead-time decrease. Comparison results showed the higher forecast skills within the Sumatra regions compared to the Kalimantan regions.

For the second year of the project, a needs assessment for early warning information was conducted through a field survey with resource managers. The field survey was conducted at three provinces where frequent land and forest fire occurred in Indonesia. The survey was conducted on their information requirements and preferred methods and timing of information delivery. All three study areas used a weather/climate forecasting and fire danger rating system with four criteria (low, moderate, high, and extreme) as an early warning system tool. The fire hot spot is the main indicator for fire occurrence that used widely from district, provincial to national level. All stakeholders need more reliable information related to weather conditions so they can have more anticipated prevention programs. For the development of the EWS prototype, we developed an integrated statistical downscaling package which uses Simple Bias Correction (SBC), Moving Window Regression (MWR), Climate Index Regression (CIR), and Integrated Time Regression (ITR) methods. The package is based on an open source license for further training workshops and free distribution of the developed prototype. The seasonal precipitation forecasts should be interpreted in terms of historical precipitation-fire relationships. Through the literature review and communication, we decide that methodology selected in the previous research by Field and Shen (2008) can be used for the interpretation of forecasted precipitation. Based on an earlier version of the prototype, APCC led a two day workshop in Petaling Jaya, Malaysia, June 9-10, 2015, which included hands-on training sessions on statistical downscaling and the prototype. The workshop had 32 participants including 12 participants from Indonesia and 17 participants from Malaysia. Finally, the EWS prototype was improved based on feedback from both field survey and training workshop participants. The forest fire early warning information on Southeast Asia created using the EWS will be provided though the hosting server in APCC.

Relevance to the APN Goals, Science Agenda, and to Policy Processes

Goals: The project supports the APN's primary goals of regional cooperation by involving eight organizations in six APN Member Countries in addressing one of Southeast Asia's most significant global change problems.

Climate Change and Climate Variability: The fires are triggered by below-normal dry-season precipitation, the result of several modes of climate variability.

Ecosystems, Biodiversity, and Land Use: One of the reasons for fire is the land use change, and have strictly negative impacts on Equatorial Southeast Asia's ecosystems and biodiversity.

Changes in the Atmospheric, Terrestrial and Marine Domains: Fires in the region rank among the single biggest contributors to inter-annual variability in global CO_2 composition in the atmospheric domain, and have completely transformed the landscape in the terrestrial domain.

Resources Utilisation and Pathways for Sustainable Development: Knowing in advance of severe burning conditions contributes directly to the appropriate use of fire in the region and sustainable development of these sectors.

Policy Processes: The ASEAN Regional Haze Action Plan identifies early warning systems as a cornerstone of fire management policy.

Self-Evaluation

The kick-off meeting was held on August 15th, 2012, in Singapore. During the meeting, the overall direction of the project was adjusted and all the issues are appropriately treated during the project period. A second meeting was held at Sapporo, Japan on August 1st, 2014. At this meeting, we shared the research results derived from the previous period of the project and discussed future plans for the success of the project.

Potential for Further Work

The prototype of the project covers four regions in Borneo Island focusing on ASO precipitation. However, dry season and the threshold level can be different region by region. In the future, the project team may consider creating a more comprehensive fire and haze EWS that covers all spatial regions and temporal period. In addition, integrated statistical downscaling packages can be used for various applications in different areas.

Publications

References

Field, R.D., and S.S.P. Shen, 2008: Predictability of carbon emissions from biomass burning in Indonesia from 1997 to 2006, Journal of Geophysical Research, 113.

Acknowledgments

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Preface

Smoke haze from forest fires is among Southeast Asia's most serious environmental problems. However, measures to prevent these fires and mitigate their impacts are limited by the absence of long-lead early warning systems. The project determined how seasonal forecasts can be used to predict drought conditions triggering forest fires. We evaluated the forecast skill of APCC's seasonal forecast, dynamical downscaling using WRF, and four different statistical downscaling methods. The presented prototype of fire danger early warning system (EWS) for Borneo Island can be used for land and forest managers to prepare mitigation measures in advance.

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1. Introduction

Smoke haze from forest fires is among Southeast Asia's most serious environmental problems and there is a clear need for a fire and haze early warning system (EWS) for the region. With industrial logging and agriculture as underlying causes, the trigger for severe fire and haze episodes in Southeast Asia is drought.

Severe burning in Indonesia occurs only during years with anomalously low rainfall; there is usually enough rain during the dry season to prevent serious burning. Anticipating a severe fire season largely consists of anticipating dry seasons. Severe haze has occurred in 1982, 1991, 1994, 1997 and 2006, with lesser events in 1987, 2002, 2004, 2009 and 2014. All events correspond to some combination of El Nino and positive Indian Ocean Dipole conditions and occur primarily between August and October.

The drought levels at which severe fires occur have been robustly quantified, and this information is now used in Indonesia and Malaysia to monitor fire danger.

Monitoring for these conditions is important, but has limited effectiveness because the burning is opportunistic; as soon as conditions are dry enough, burning will occur and cannot be prevented. When disturbed peat begins to burn, it cannot realistically be put out until the return of the monsoon rains. However, measures to prevent these fires and mitigate their impacts remains limited by the absence of long-lead EWSs. Severe burning conditions, therefore, need to be forecast weeks to months in advance for any prevention to be effective.

In this context, little of the progress made in seasonal forecasting has been applied to fire early warning in Indonesia. Recently over southern Kalimantan, previous research showed that most major fire events since 1997 could have been anticipated three months in advance using ECMWF System 4 precipitation forecasts, demonstrating a necessary step in fire prediction and management over Indonesia.

For simplicity, the focus of this project will be on the rainfall prediction during the primary August to September dry season by examining the precipitation forecast skill over the main fire prone regions of Indonesia using a multi-model ensemble maintained at the APEC Climate Center (APCC). The project builds upon current fire danger rating systems by providing forecasts at a longer lead-time, a time scale that is more relevant and useable for decision-makers. This two-year project consisted of two parts: 1) a forecast skill assessment of current and downscaled products supplied by the APCC, and 2) the development of a prototype fire danger EWS by considering field survey and workshop.

2. Methodology

The overall research procedure for this project is shown in Figure 1. It consists of two main parts: 1) evaluating forecast skill of APCC's MME and downscaling methods, and 2) assessing needs from forest fire managers and developing a prototype of early warning system (EWS).

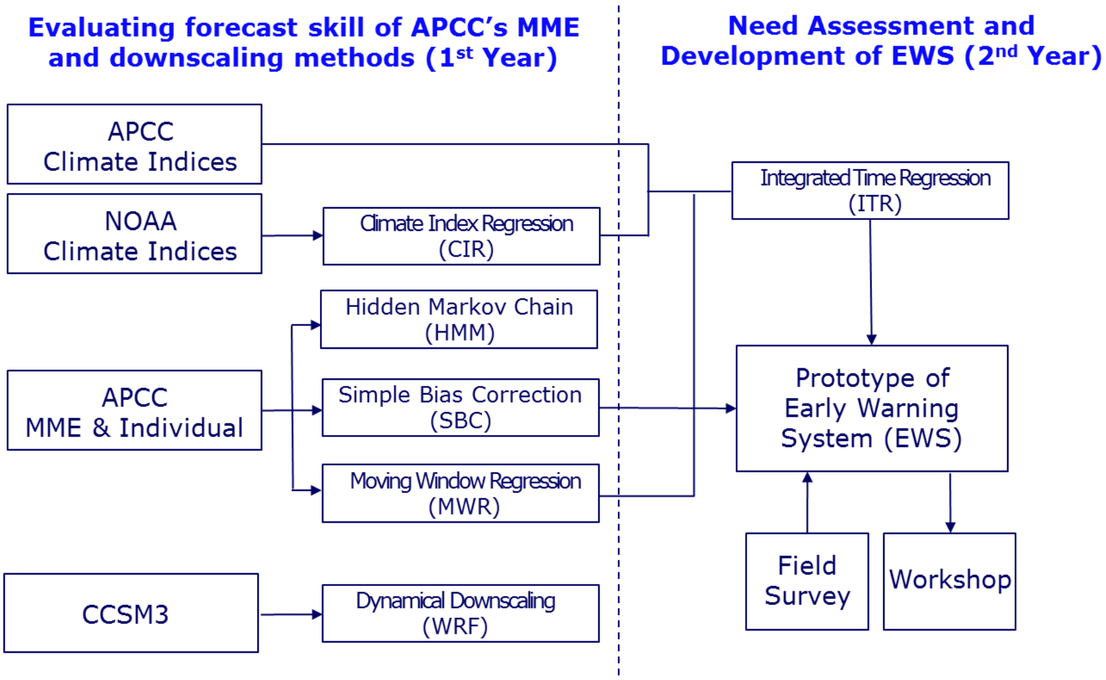


Figure 1. Overall research procedure

2.1. Evaluating Forecast Skill of APCC's MME and Downscaling Methods

2.1.1. Evaluation of APCC's Seasonal Forecasts

In this research, we focused on connecting the downscaled seasonal forecasts and drought conditions that trigger forest fires. Previous research on biomass burning in Indonesia was reviewed. Field[1] and Shen (2008) reported that 3-month total precipitation was determined to be the best predictor for predicting the severe biomass burning carbon emissions in equatorial Southeast Asia. As a result, we decided to analyse the predicted 3-month (August to October, AOS) total precipitation using APCC's seasonal forecast. Figure 2 shows the regions used in the analysis, namely Southern Sumatra (SSUM), Central Sumatra (CSUM), Eastern Kalimantan (EKAL) and Southern Kalimantan (SKAL).

[1] Dr. Robert Field is one of the team members for this project

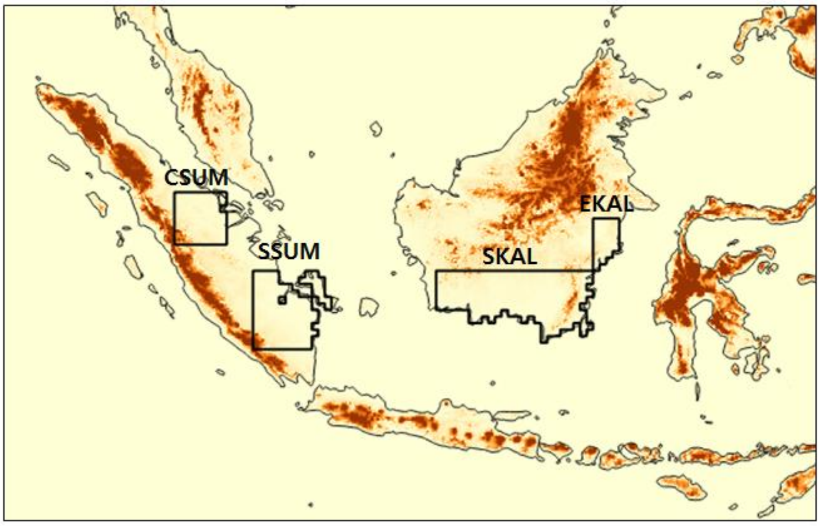


Figure 2. Selected regions for assessing forecast skill

APCC has been collecting monthly dynamic prediction data produced by 16 institutions and has been producing 3-month and 6-month lead Multi-Model Ensemble (MME) climate forecasts every month. In this study, 6-month lead seasonal forecast data which were regrided with 2.5° X 2.5° resolution based on 6 individual Global Climate Models (GCM) were used for the evaluation of forecast skill. Table 1 shows the description of 6 GCMs used in this study.

Grid-to-grid temporal correlation coefficients (TCC) of ASO precipitation for the Indonesian regions are calculated between models (6 individual models and MME data forecasted at July with a 6 month lead-time) and GPCP monthly data. For evaluating the forecast skill for the four selected regions (CSUM, SSUM, EKAL, SKAL), the area-average of forecasted precipitation are compared to the area-average of monthly APHRODITE data. Temporal correlation coefficient (TCC, Spearman's rank correlation coefficient) and normalized objective function (NOF, which is calculated by dividing RMSE by observation mean) were used as measures for trend and error analysis, respectively. The response of performance measures (TCC and NOF) according to the different lead-times are calculated for the regions.

Table 1. Description of dynamical seasonal prediction models used in the study.

Model	Institution	Raw Resolution	Ensemble size
CANCM3	Meteorological Service of Canada (Canada)	T63L31 (AGCM) 1.41° X 0.94° L40 (OGCM)	10
CANCM4	Meteorological Service of Canada (Canada)	T63L35 (AGCM) 1.41° X 0.94° L40 (OGCM)	10
NASA	National Aeronautics and Space Administration (USA)	2°lat X 2.5°lon, L34 (AGCM) 1/3 by 5/8, 27L (OGCM)	10
NCEP	Climate Prediction Center / NCEP/NWS/NOAA (USA)	T62L64	17
PNU	Pusan National University (R. of Korea)	T42L18 (AGCM) 0.7/1.4/2.8°lat X 2.815°lon, L29 (OGCM)	4
POAMA	Centre for Australian Weather and Climate Research/ Bureau of Meteorology (Australia)	T47L17 (AGCM) 0.5~1.5°lat X 2°lon, L25 (OGCM)	30

A TCC called a Pearson's correlation coefficient is used to measure the strength of a linear relationship between two variables. A TCC of 1.0 (-1.0) denotes a perfect (inverse) linear relationship between the forecast and observation and that of zero means the absence of any linear association between them. The TCC between two variables is defined as the covariance of the two variables divided by the product of their standard deviations:

$$TCC = \frac{\Sigma(F-\overline{F})(O-\overline{O})}{\sqrt{\Sigma(F-\overline{F})^2}\sqrt{\Sigma(O-\overline{O})^2}}$$

Where, F and O are the forecast and observed variables. $\bar{F}$ and $\bar{O}$ are the climatological value for forecast and observed variables, respectively.

2.1.2. Comparison of Dynamical and Statistical Downscaling Methods

Dynamical Downscaling

In this study, we employed the Weather Research and Forecasting (WRF) model for regional climate simulations over Southeast Asia at 45-km horizontal resolution with global climate fields used for initial and boundary conditions. The WRF model, developed by the National Center for Atmospheric Research (Skamarock et al., 2008), is an advanced mesoscale numerical weather prediction system designed to serve both operational forecasting and atmospheric research needs. The simulations were performed for five summers (June 1 to August 31) during the period from 2006 to 2010 using the GCM forcing data from CCSM3 to provide initial and lateral boundary conditions for the regional climate model. The physics options used in this study include the WRF Single-Moment 6-Class Microphysics (WSM6) scheme, Kain-Frisch convective parameterization scheme, and the Yonsei University (YSU) planetary boundary layer (PBL) scheme. The WRF regional climate model was run using one-way nesting at 45-km grid spacing and 28 vertical levels covering the Southeast Asia region (Figure 3). To examine the skill of the downscaled simulations, we have compared downscaled results with observed data sets: GPCP satellite estimates for rainfall and NCEP/DOE reanalysis data for surface temperature.

Table 2. Description of WRF model for regional climate simulations.

	Domain 1	**Domain 2**
Horizontal grid	138 × 112	283 × 145
Horizontal resolution	45 km	15 km
Vertical layers	28	
Physical options	Kain-Frisch(new Eta) cumulus scheme, YSU scheme, CAM scheme, WSM 6-class graupel scheme, Noah land-surface model	
Initial data	CCSM3/APCC	
Time Period	2006/5/27 ~ 2010/8/31 (JJA)	

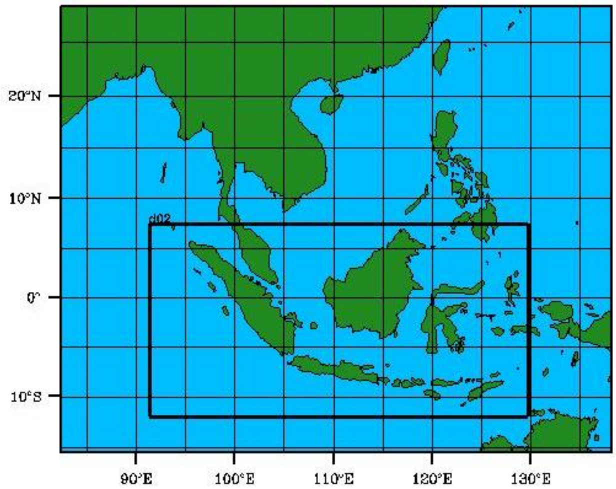


Figure 3. Research domain for both dynamic and statistical downscaling experiments.

Statistical Downscaling

The Moving Window Regression (MWR) downscaling scheme, which was developed by Kang and others (2009) and applied in Korea, was selected as a statistical approach. It is based on a multi-predictor optimal selection method and the overall procedure of the selected scheme includes: 1) selection of best predictor and location using a moving window for each, considering the observation point (predictand), 2) derivation of simple linear regression between the best predictor and predictand, and 3) downscaling for a given forecast based on the regression equations.

This approach requires long-term data measurements. Monthly high-resolution grid (0.5°global) precipitation data (CRU TS3.10) for the period from 1901-2009 period were used as the observed datasets. The CRU data does not include ocean area and contains 3294 grid points on lands for the selected research domain (lon: 80~130, lat: -12 ~30.5). Datasets for June to August and 3-month (JJA) total precipitation during the 27-year period from 1983-2009 were considered.

APCC's MME was used as predictor for comparison with the results of the dynamical downscaling. Variables such as wind at 850hPa (U850 and V850), temperature at 850hPa (T850), geopotential height at 500hPa (Z500), sea surface temperature (SST), mean sea level pressure (PSL) were considered as possible predictors in the process of selecting best predictor. The domain within latitudes from -45 and 45 for all longitude ranges was used in this study in order to decrease computational time.

A movable optimal window finds the best predictor when the maximum temporal correlation coefficient between the predictand and predictors are estimated. As a result, each observation point (predictand) has different location of optimal windows and the best predictors. Finally each point can have a different slope and intercept of the predictor that is the best to describe the variation of the predictand.

2.1.3. Comparison of Statistical Downscaling Methods

Based on the result from comparison between dynamical and statistical downscaling methods, we decided to use statistical downscaling approach for further development of fire danger early warning system. As a result, we also developed and evaluated four different statistical downscaling methods including Simple Bias Correction (SBC), Moving Window Regression (MWR), Climate Index Regression (CIR), and Hidden Markov Chain (HMM) methods.

Simple Bias Correction (SBC) approach

Simple Bias Correction (SBC) is a forecast-based direct downscaling method which uses GCM's prediction data after adjusting the monthly mean of predicted precipitation. For example, if the precipitation prediction data on a specific region is needed, SBC directly uses the grid values of precipitation variables which are produced from GCMs over the given area. The systematic bias is adjusted for precipitation by using the ratio, in order to make the monthly average of prediction same to the average of observation for the same period.

Bias correction between the region-average of forecast data and observation (APHRODITE) was conducted by adding anomaly of forecasted data for each month to the mean of the observation as below equation.

$$\mathrm{P'}_{\mathrm{y,m}} = \left(\mathrm{P}_{\mathrm{y,m}} - \mathrm{P}_{\mathrm{syear-eyear,m}}\right) + \mathrm{APHRO}_{\mathrm{syear-eyear,m}} \text{ for } \mathrm{P}_{\mathrm{y,m}} \geq \mathrm{P}_{\mathrm{syear-eyear,m}}$$

$$\mathrm{P'}_{\mathrm{y,m}} = \left(\mathrm{P}_{\mathrm{y,m}} / \mathrm{P}_{\mathrm{syear-eyear,m}}\right) \mathrm{x}\ \mathrm{APHRO}_{\mathrm{syear-eyear,m}} \text{ for } \mathrm{P}_{\mathrm{y,m}} < \mathrm{P}_{\mathrm{syear-eyear,m}}$$

Where, $P_{y,m}$ and $P'_{y,m}$ are the bias-corrected and forecast precipitation in a specific year(y) and month(m), respectively. $P_{syear-eyear,m}$ and $APHRO_{syear-eyear,m}$ are the climatological value for a specific month (m) derived from forecast and observation(APHRODITE) based on specific periods of start year (syear) to end year (eyear).

Moving Window Regression (MWR) approach

Moving Window Regression (MWR) is a forecast-based indirect statistical downscaling method, which uses the proxy variables produced by GCMs as predictors of regression model when high correlation exists between proxy variables and regional target variables. If there are limitations in directly predicting target variables such as precipitation in the target area, the MWR method uses the oceanic and atmospheric circulation variables as predictors to improve the seasonal prediction predictability in the target region.

The overall procedure of the selected scheme is the same as the method used for the “comparison of dynamical and statistical downscaling methods” part and includes: 1) selecting best predictor and location which shows the highest correlation coefficient within a moving window between the predictand, 2) developing simple linear regression between the best predictor and predictand, and 3) downscaling for a given forecast data based on the regression equations. However, there are differences in predictand used: previous downscaling experiment used June to August (JJA) CRU precipitation on each 0.5°grid within the over the maritime continent while this experiment used August to October (ASO) region-average of APHRODITE precipitation within the four selected regions. In addition, this experiment used the individual models while the previous experiment used MME only.

Climate Index Regression (CIR) approach

Climate Index Regression (CIR) is an observation-based indirect statistical downscaling method that can be used when there is a high correlation between global climate indices and regional target variables with lag time. For real time operation of CIR in predicting monthly precipitation using climate indices, the lag time between the monthly precipitation and indices should be larger than the lead-time. The CIR method is similar to the MWR method in that both methods indirectly utilize the correlation between regional target variables and global scale climate variables related to oceanic and atmospheric circulation. There is a difference between the CIR and MWR methods when selecting predictors to forecast future seasonal target variable values. While the MWR method uses simultaneous proxy predictors that are predicted by GCMs, the CIR method uses the observed climate information from a few months ago by taking into account the lag time.

Predefined 40 climate indices provided by Climate Prediction Center (CPC) for the hindcast period (1983~2005) were used as predictors in this study. The overall procedure of the selected scheme includes: 1) selecting N best predictors (we used 3 in this experiment) and lags which shows the highest correlation coefficient between the predictand (region-average of APHRODITE precipitation), 2) developing multivariate regression using the selected possible N indices (less than N indices can be selected through regression subset selection procedure), and 3) forecasting precipitation based on lagged climate indices. We changed the lag time from 0 to 12 months. The zero lag for an index means that the index should be derived from the forecasted data. Lag greater than the given lead-time means that the index can be derived from the observations.

Hidden Markov Chain Model (HMM) approach

A Hidden Markov Chain Model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved hidden states. In a HMM, the state is not directly visible, but the output, dependent on the state, is visible. The hidden states of data X_t consist of a number of random variables K such as ($X_t = \{x_1, x_2, \cdots, x_k\}$), influence of previous state (X_{t-1}) and the rest of state are independent. The hidden state follows the first Markov model with transition between states only rely on previous state. HMM is simply shown in Figure 4. Using HMM, which was used rainfall simulation (Robertson et al., 2004; Kwon et al., 2013), region-average of ASO precipitation is predicted by the sea level pressure (SLP) anomalies in 6 hindcast models. Before HHM simulation, correlation coefficient between each region and global SLP data was calculated.

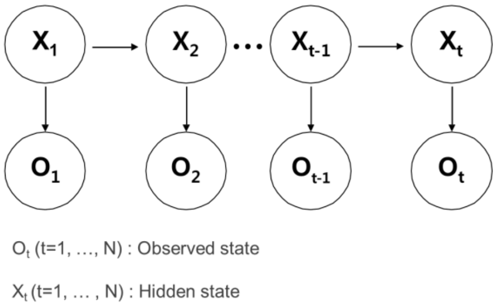


Figure 4. Graphical Representation of HMM.

2.2. Need Assessment and Development of EWS Prototype

2.2.1. Need Assessment

The needs assessment for early warning Information was conducted through the field survey with resource managers. The field survey was comprised of discussions and interviews in land and forest management sector of Indonesia on their information requirements and preferred methods and timing of information delivery.

Three provinces that have frequent occurrences of land and forest fires in Indonesia were selected as study areas: Riau in Sumatra and Central and East Kalimantan. During the fire season Riau in Sumatra and Central Kalimantan produce smoke and haze and may affect the neighbourhood countries such as Malaysia and Singapore. The peak fire season in Riau usually occurs in Feb/March and August/Sept whilst in Central Kalimantan expected during August/Sept. The field survey conducted in May-June 2015 where the stakeholders are at readiness level.

The structured questionnaires, which are provided in the Appendix, were translated into Bahasa Indonesia with two main focuses: existing climate used and fire danger ratings system. The questionnaires were distributed to stakeholders related to land and forest fire in three provinces. As formal written language in the field was a constraints for some stakeholders, we also performed informal discussions to gather all information as needed and converted the results into questionnaire forms.

2.2.2. Training Workshop

The final prototype of the project does not cover overall regions in the maritime continent by focusing hot spot areas selected and the threshold level can be different region by region. It means that training workshop as a part of the capacity building will be important for actual application of the developed prototype EWS in other regions not included in this project. As a result, a two day workshop was held at the Malaysian Meteorological Department (MMD) in Petaling Jaya, Malaysia, June 9-10, 2015.

2.2.3. Development of EWS Prototype

We chose four provinces in Borneo Island as the target area of the EWS prototype as shown in Figure 5.

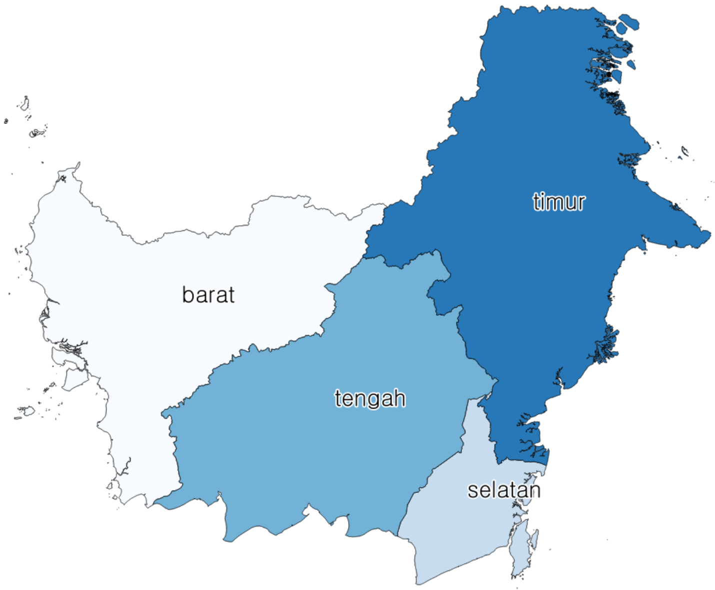


Figure 5. Province boundary within Borneo Island for Early Warning System (EWS) prototype

The overall procedures for development of EWS prototype include 1) construct statistical downscaling model for forecasting monthly area-average precipitation amount for each region, 2) determine number of categories and corresponding ranges of fire danger rating system based on the relationship between total ASO precipitation amount and CO_2 emission, and 3) forecast probabilistic fire danger ratings based on the predicted precipitation amount. Figure 6 shows the overall schematic diagram of the EWS prototype.

First, downscaling packages were programmed using the open-source statistical tool (R) in consideration of further training workshop and free distribution of developed prototype for local stand-alone application. The downscaling package was organized with a large number of functions which can be easily used when forest fire managers want to apply the downscaling methods to regions other than the selected four regions.

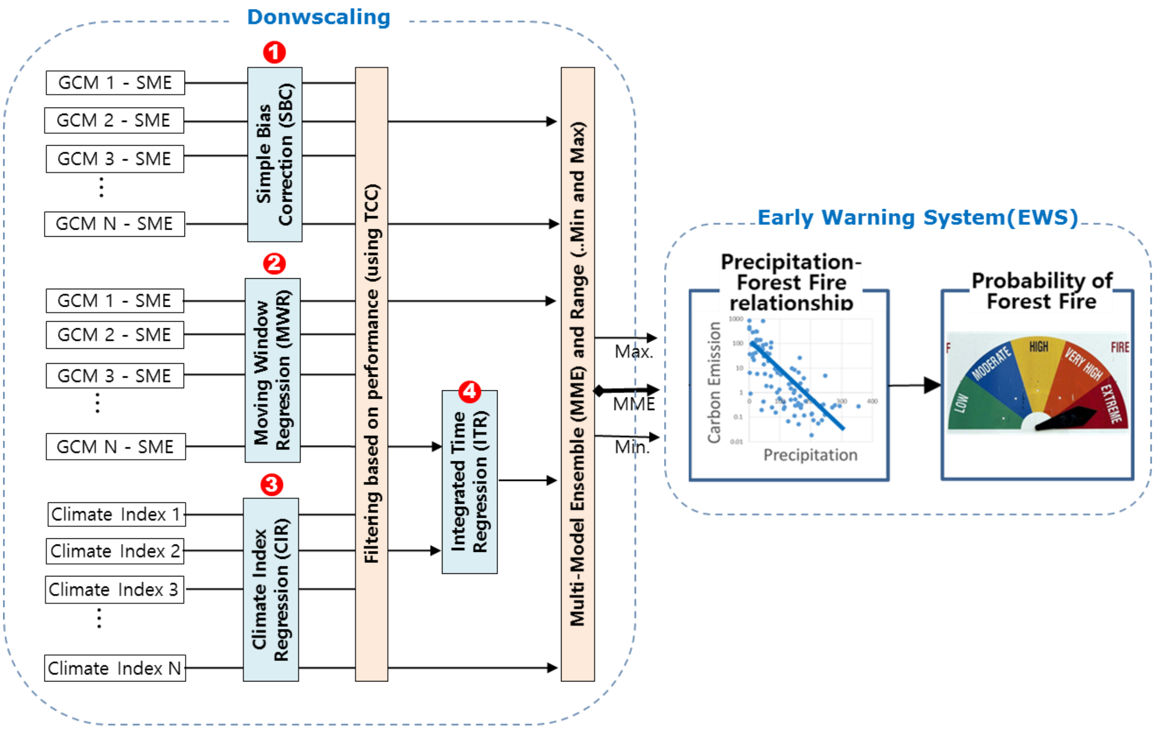


Figure 6. Schematic diagram of Early Warning System (EWS) prototype

We focused on improving the predictability of the downscaling methods with the understanding that accurate long-term seasonal forecast information is the key factor for subsequent successful forest fire prediction. Without a high level of confidence in the quality of the downscaled seasonal climate forecasts, we cannot guarantee the efficacy of the prototype. As a result, the overall seasonal climate forecasting technique for the EWS combines four different downscaling methods according to the degree of using dynamic prediction data produced by global climate models (GCMs). These methods include: 1) the Simple Bias Correction (SBC) method, which directly uses APCC's climate prediction data with 6 month lead time; 2) the Moving Window Regression (MWR) method, which indirectly utilizes the dynamic prediction data; 3) the Climate Index Regression (CIR) method, which predominantly uses the observation-based climate indices without using any prediction data; and 4) the Integrated Time Regression (ITR) method, which uses predictors selected from both CIR and MWR. Since predictability on the Borneo Island may differ depending on the target month and selected method, predictability was evaluated using the simple average of all available forecast information.

In addition, another characteristic of the EWS is to predict real-time monthly precipitation on the target areas. As a result, instead of 40 climate indices which were used in the first year period, we used the 25 real-time climate indices as predictors: 16 climate indices that are updated on a monthly basis by NOAA through the webpage (http://www.esrl.noaa.gov/psd/data/climateindices/list/) and 9 indices that are extracted monthly at APCC using the NCEP/NCAR Reanalysis 1 data (Table 3).

Table 3. Monthly updated climate indices used for seasonal prediction.

Abbreviation	Full name	Source
PNA	Pacific North American Index	NOAA
EP	East Pacific/North Pacific Oscillation	NOAA
WP	Western Pacific Index	NOAA
NAO	North Atlantic Oscillation	NOAA
SOI	Southern Oscillation Index	NOAA
NINO3	Eastern Tropical Pacific SST	NOAA
TNA	Tropical Northern Atlantic Index	NOAA
TSA	Tropical Southern Atlantic Index	NOAA
WHWP	Western Hemisphere warm pool	NOAA
ONI	Oceanic Nino Index	APCC
MEI	Multivariate ENSO Index	NOAA
NINO12	Extreme Eastern Tropical Pacific SST	NOAA
NINO4	Central Tropical Pacific SST	NOAA
NINO34	East Central Tropical Pacific SST	NOAA
NOI	Northern Oscillation Index	APCC
NP	North Pacific pattern	APCC
TNI	Trans-Niño Index	APCC
AO	Antarctic Oscillation	APCC
AAO	Antarctic Oscillation	APCC
PACWARM	Pacific Warm Pool (1st EOF of SST (60e-170E, 15S-15N) SST EOF)	APCC
EOFPAC	Tropical Pacific SST EOF	APCC
ATLTRI	Atlantic Tripole SST EOF	APCC
AMO	Atlantic multidecadal Oscillation	NOAA
QBO	Quasi-Biennial Oscillation	NOAA
ESL	Equatorial Eastern Pacific SLP	NOAA

While the SBC method developed during the first project year was integrated without improvement, the MWR and CIR methods were improved by strengthening predictor selection algorithm in order to avoid overfitting problem in real-time forecast. The concepts of both cross-validation and split-validation were applied in order to prevent overfitting problems, which can occur when constructing statistical forecasting models. The Leave-one-out cross-validation (LOOCV) technique was applied to the observation period (1983-2013). In other words, when predicting target variables for a specific target period (year/month), all predictors for the same target period are removed from the model construction procedure in order to reproduce the same conditions as the real time forecasting. For example, when predicting for January 1983, only predictors from January 1984 to 2013 are utilized in constructing the regression model. Predictions are made in the same way for the rest of simulation period. For each cross-validation process, the split validation approach was applied, and then the best predictors that showed consistent performance for both training and verification periods were finally selected.

In addition, the Integrated Time Regression (ITR) method was added into the prototype of early warning system. ITR is an indirect statistical downscaling method that uses both forecast and observation based predictors from the MWR and CIR methods, respectively. As a result, it can be used only when the MWR and CIR methods simultaneously select predictors for a particular target period. From the best predictors determined by the MWR and CIR methods, a selection of final predictors for the multivariate regression model are finally selected through the Akaike Information Criterion (AIC) analysis.

Second, an analysis of the threshold levels for the study regions was conducted in order to translate the predicted precipitation amount to the fire danger ratings. If the amount of precipitation dips below the threshold level, this predicts an increased risk for severe burning, carbon emissions, and transboundary haze. It is necessary to connect the forecasted precipitation to the possible EWS index based on region-specific threshold level. We used the relationship between region-average ASO precipitation amount and carbon emission amount which was derived from Global Fire Emissions Database (http://www.globalfiredata.org/).

3. Results & Discussion

3.1. Evaluating Forecast Skill of APCC's MME and Downscaling Methods

3.1.1. Evaluation of APCC's Seasonal Forecasts

Figure 7 shows the temporal correlation coefficient (TCC) for ASO average precipitation between models (6 individual models and simple MME) and Observation (GPCP) for the hindcast period (1983~2005). MME and several individual models such as CANCM3, CANCM4, NCEP, and POAMA show TCC near 0.7 around central part of the domain including Kalimantan region.

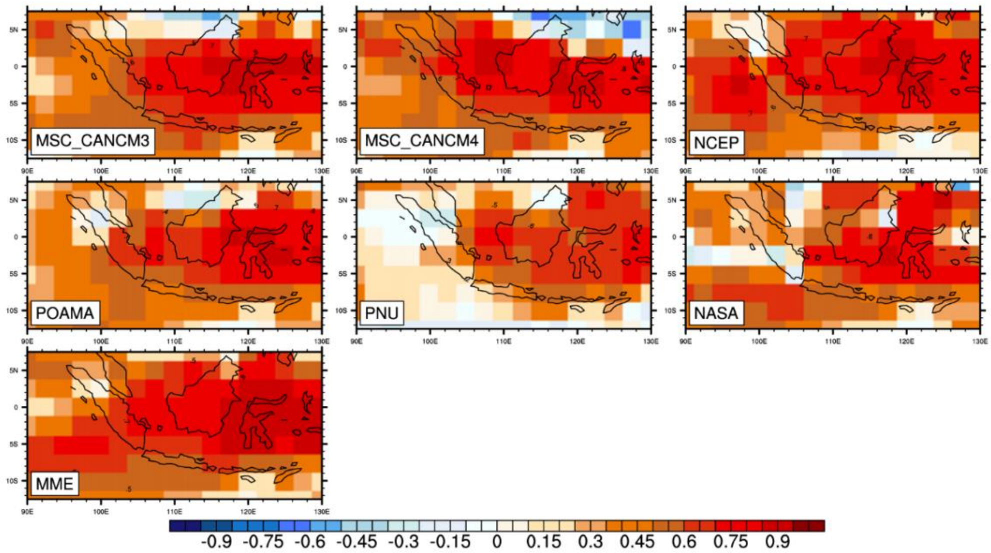


Figure 7. Temporal correlation coefficient between model and OBS(GPCP), period: 1983-2005 ASO, forecasted on July .

We also compared the region-average of ASO precipitation between observation (APHRODITE) and models (including ensemble members of each individual model) without any bias correction. The model performance measures for each region are described in

Figure 8. Individual ensemble members for each model and single model ensemble (SME) scattered with wide ranges in both NOF and TCC, which means the each data set shows the different forecast performance. In particular, model performance was worst within the CSUM region by showing the lowest TCC value. Within the SSUM and EKAL regions, individual model SME showed wide range of NOF even though the TCC values of SME are higher than 0.5 for the most of models. This means that individual models predicted the temporal anomaly trend of ASO precipitation reasonably well but they failed to predict the absolute precipitation amount for a specific month. Most individual models, except for NASA model, showed a similar forecast performance within the SKAL region by showing narrow ranges of NOF and TCC values around 0.6. Among the four regions, the SKAL region showed the most reasonable forecast performance by showing rower NOF and higher TCC values. SKAL, for example, which was basically the area analysed in Spessa et al. looks to have the best skill of any of the regions.

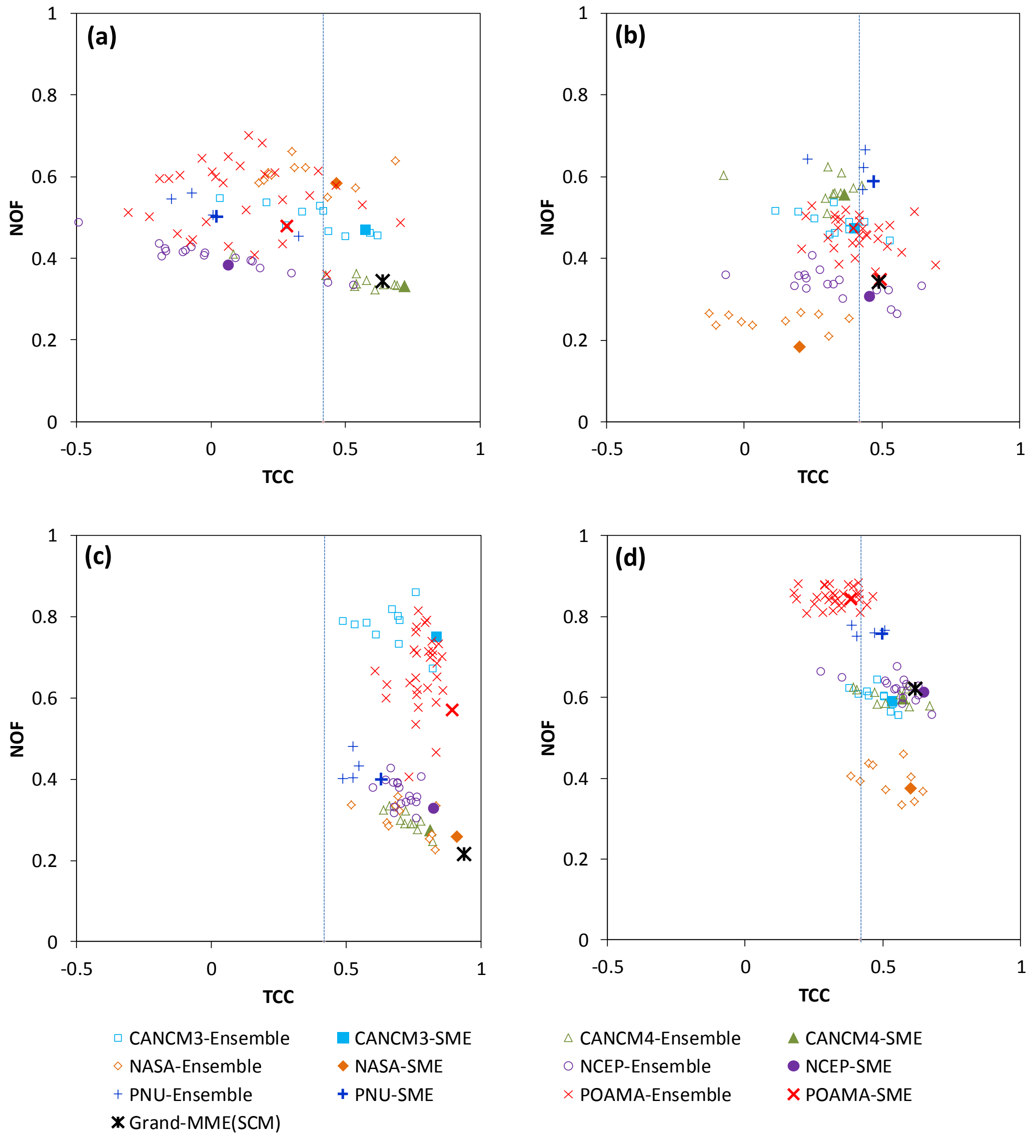


Figure 8. Performance measures (TCC and NOF) of forecasted ASO total precipitation forecasted on July without bias correction within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions. Blue vertical line means the critical TCC value at 0.05 of significant level.

A comparison of time-series of forecasted ASO total precipitation and performance measures, which derived based on MME are shown in Figure 9. It also should be noticed that absolute ASO precipitation amount for the driest year (1997) were closely predicted by all four downscaling methods within the EKAL and SKAL regions.

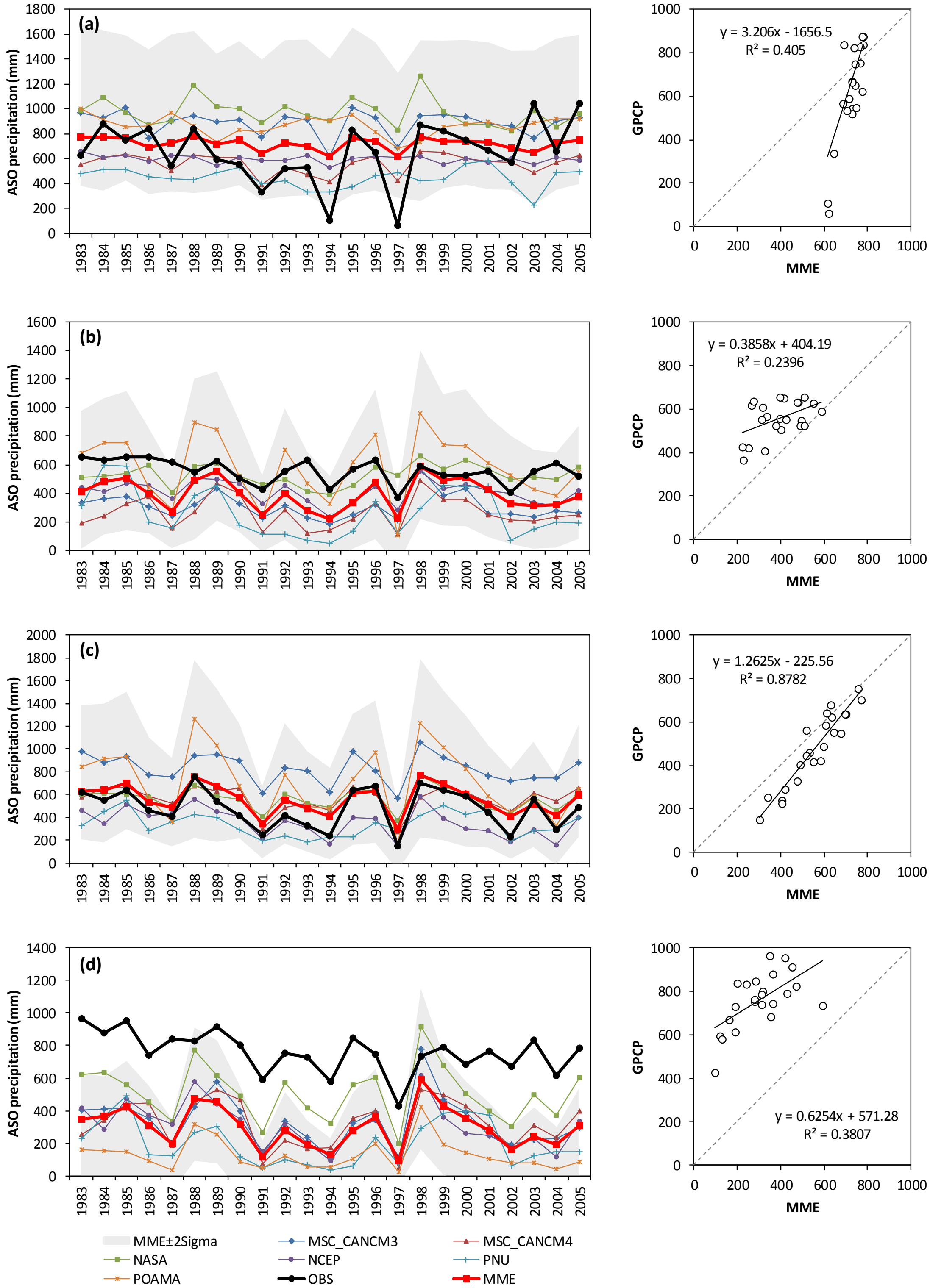


Figure 9. Comparison of time-series of forecasted ASO total precipitation forecasted on July (left) and performance measures (right) within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions. Shaded area represents the uncertainty range between MME ± 2Sigma based on every ensemble members of individual models.

Figure 10 shows the response of performance measures (TCC and NOF) according to the different lead-time. It shows the decrease in forecast performance caused by a decrease in TCC and an increase in NOF as lead-time increases within all the regions.

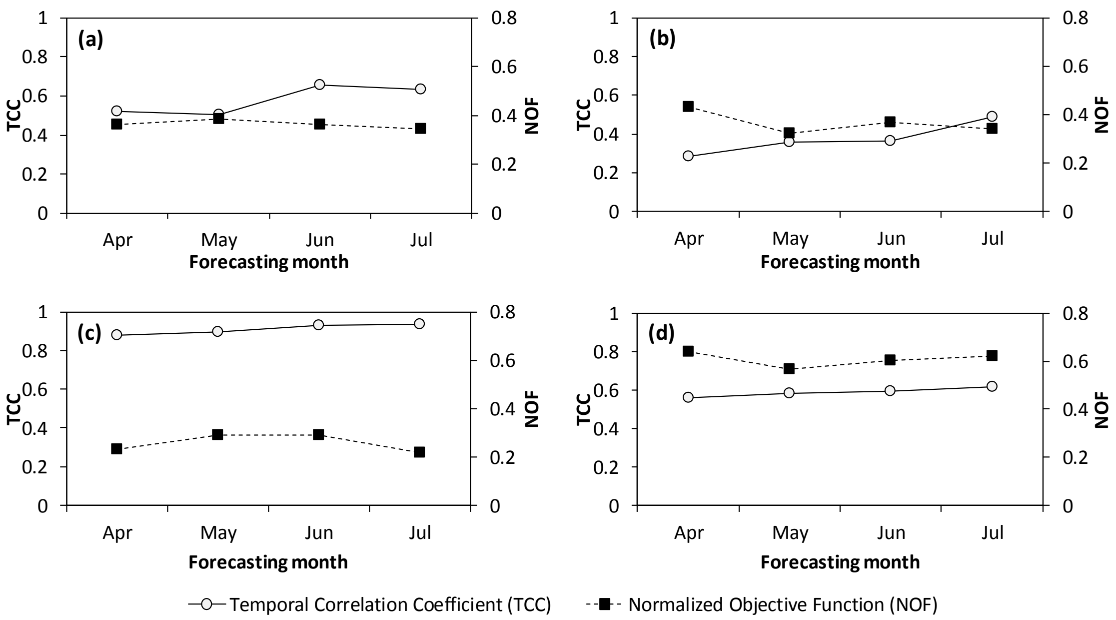


Figure 10. Response of performance measures (TCC and NOF) of simple bias correction (SBC) downscaling method according to the different lead-time within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions.

3.1.2. Comparison of Dynamical and Statistical Downscaling Methods

An assessment of forecast skill over fire-prone regions in Southeast Asia was performed and both dynamic and statistical downscaling experiments were conducted for JJA precipitation using the WRF model and a Moving Window Regression (MWR) method, respectively.

First, Figure 11 shows the 5-year average precipitation from the Global Precipitation Climatology Project (GPCP; Huffman et al., 2001) data, CCSM3, and WRF. GPCP showed local maxima over the coast of Myanmar and west of the Philippines for both individual months from June to August and the JJA average. The APCC/CCSM3 also shows maximum precipitation over the coast of Myanmar. However, the WRF simulates the precipitation center further southward than observation. In addition, the WRF simulated excessive precipitation over a large area of equatorial Indian Ocean. The GPCP analysis by Xie et al. (2003) with 1°x 1°resolution is much smoother than the simulation data and tends to produce higher estimates of precipitation over the oceans. The GPCP datasets also contain errors that can cause uncertainties in describing the local maximum. In addition, a typical WRF simulation is conducted in a series of well-defined steps including: domain definitions, geographic data preparations and preprocessing of data that forms the lateral, initial and lower boundary conditions. As a result, errors in any steps of the process may result in the spatial differences in the results.

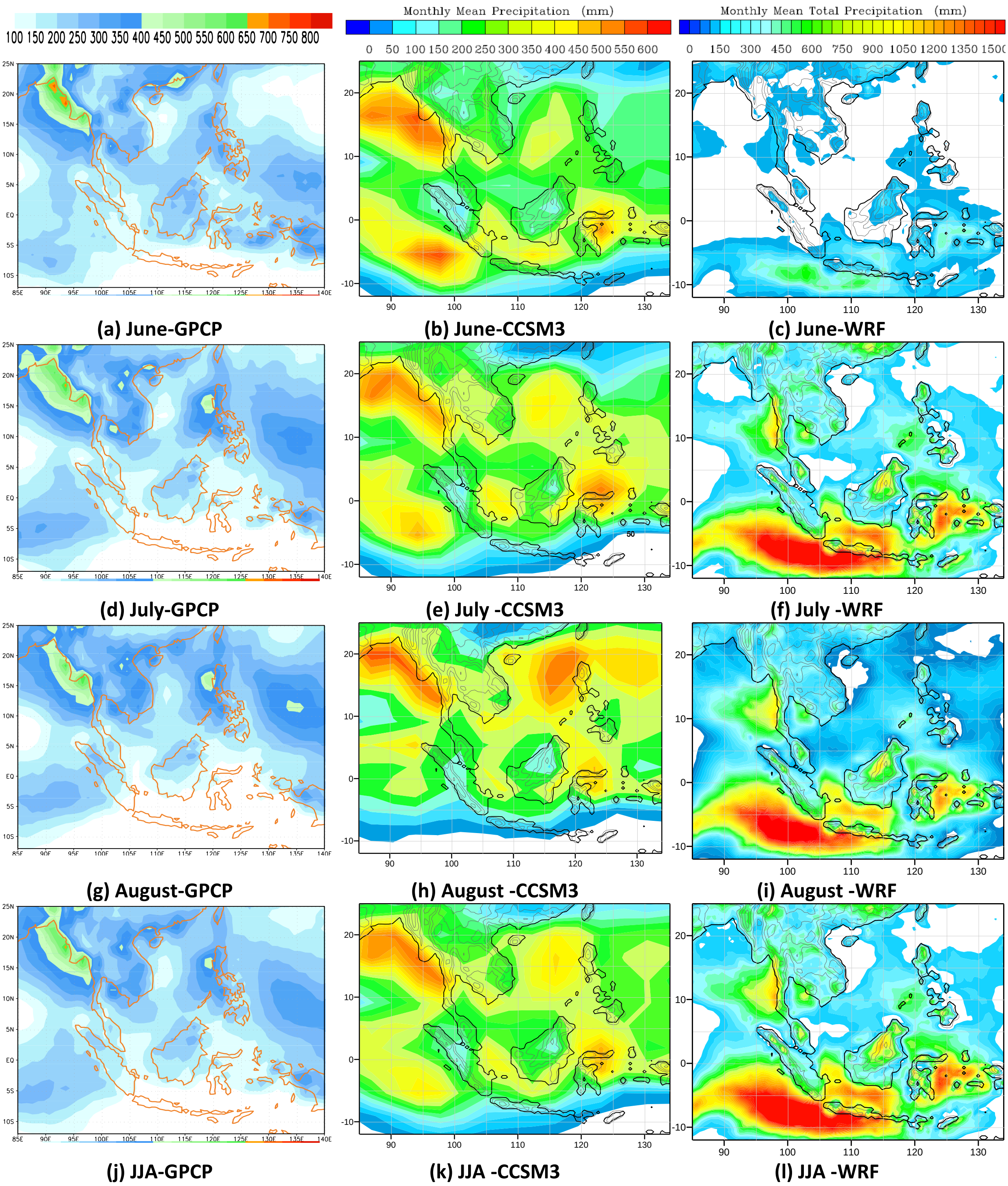


Figure 11. Mean precipitation (mm) from the GPCP observation (first column), CCSM3 (second column), and WRF (third column) for June (first row), July (second row), August (third row), and JJA average (fourth row).

Second, Figure 12 shows the temporal correlation coefficient between the CRU precipitation data and forecasts by MME. Only areas with TCC value greater than 0.352 are displayed (0.352 is the critical value of TCC at the 10% significance level). It shows that the areas with

TCC greater than 0.352 (significant areas) was larger when only 1-month lead time forecasts are used, compared to the TCC using different lead times. Significant areas also decreased during August by showing decreasing trends as lead time increased. The forecast skill of precipitation showed the highest value over Borneo Island, Indonesia while Sulawesi Island had the lowest predictability. Figure 13 shows the spatial distribution of the selected best predictors for precipitation. Spatial distribution of the best predictors show similar pattern among years when a downscaling experiment is decided based on variable and model.

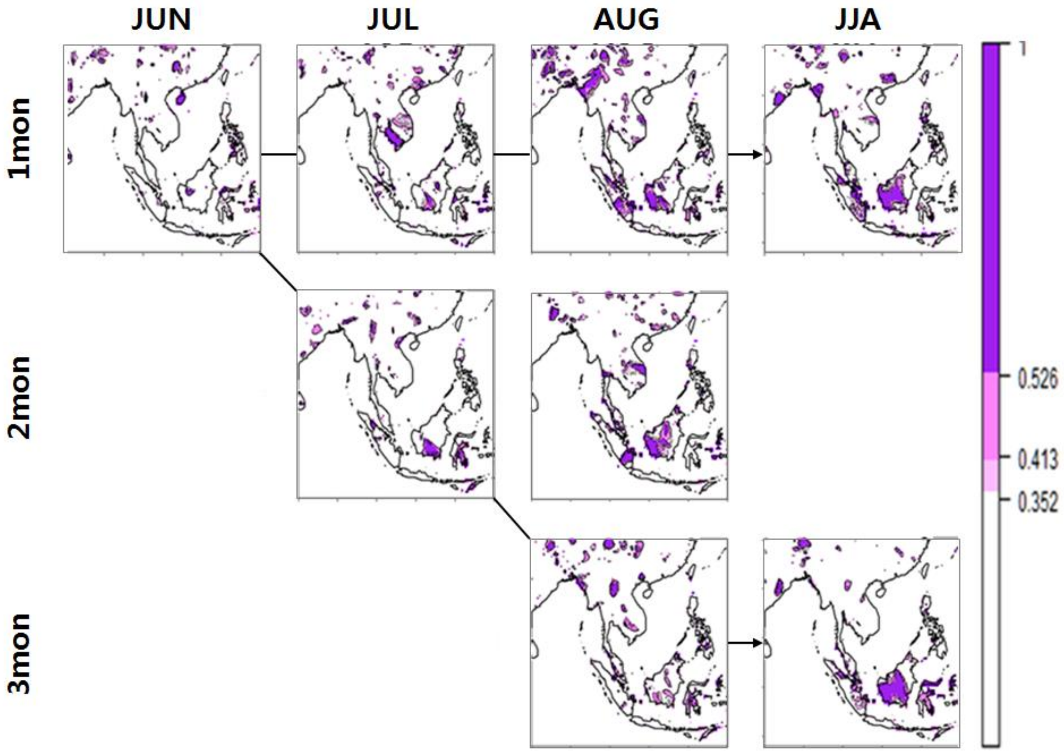


Figure 12. Temporal correlation coefficient for precipitation from the MME forecast.

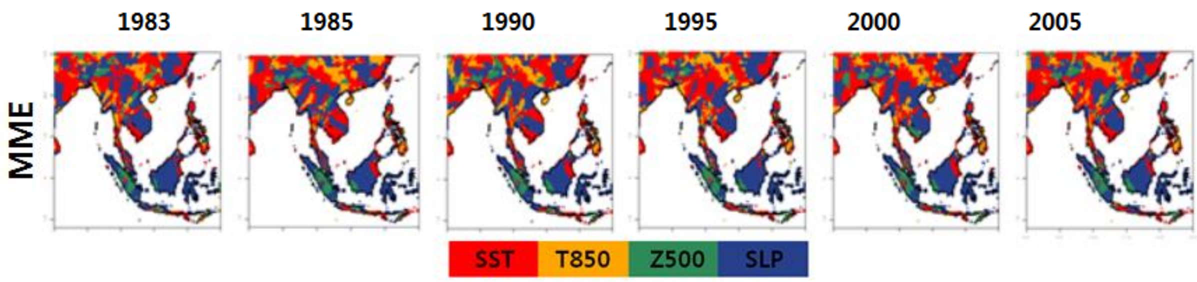


Figure 13. The spatial distribution of best predictors from CCSM3 (top) and MME (bottom) for precipitation forecast in specific years.

We then focused on a preliminary analysis connecting the downscaled seasonal forecasts and drought conditions triggering forest fires. Previous research on biomass burning in Indonesia area was reviewed. Field and Shen (2008) reported that the 3-month total precipitation was determined to be the best predictor for predicting the severe biomass burning carbon emissions in equatorial Southeast Asia. We compared the predicted 3-month (June to August) total precipitation, using both dynamical and statistical downscaling approaches, to the threshold values (below which extreme burning/C emissions become more likely) presented by Field and Shen for SSUM region.

The following Figure 14 show the comparisons of the predicted 3-month total precipitation to the Global Precipitation Climatology Project (GPCP) data for Southern Sumatra. The GPCP data is a gridded dataset that interpolates global monthly rainfall based on observation data from rain gauge stations and remotely sensed data. The statistical downscaling method (SDM) underestimated the 3-month total precipitation and generated values close to the threshold value for the SSUM region. It also showed that SDM has limitations in representing yearly variations of 3-month total precipitation. For the dynamical downscaling method (DDM), the method mimics the yearly variations in 3-month total precipitation and it succeeds in predicting the several drought conditions in 1997 for the SSUM regions. However, it made incorrect predictions in generating values below the threshold value for the years 1999, 2001, and 2005.

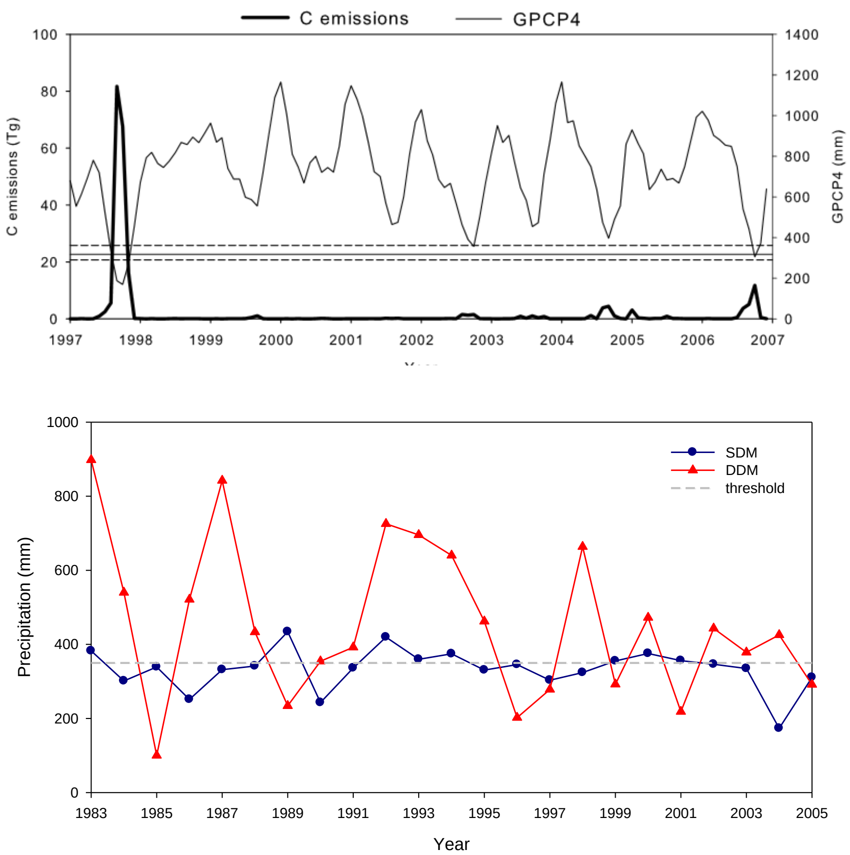


Figure 14. Comparison of monthly carbon emissions and 3-month observed total precipitation for SSUM (up) and predicted 3-month total precipitation for SSUM using different downscaling methods (bottom).

3.1.3. Comparison of Statistical Downscaling Methods

Simple Bias Correction (SBC) approach

We also compared the region-average of ASO precipitation between observation and models using simple bias correction (SBC) downscaling method and the model performance measures are described in Figure 15 for each region. In comparison to the results in Figure 8 which does not have bias correction, the SBC method decreases the NOF by removing the difference in monthly mean precipitation between observed and forecasted data (Figure 15). However, the SBC method does not have impacts on TCC because the SBC keeps the anomaly for each month. As a result, maximum NOF ranges decreased from 1.7 to 0.6, 2.2 to 1.0, 2.9 to 1.4, and 1.3 to 0.8 for CSUM, SSUM, EKAL, and SKAL, respectively. The SBC method can be used for the cases when the absolute precipitation amount is important for the management purpose. Among the four regions, SKAL region showed the most reasonable forecast performance by showing rower NOF and higher TCC values, while CSUM region shows the lowest values in both NOF and TCC. In the case of SSUM and EKAL regions, scattering of NOF and TCC values for single model ensemble (SME) in wider ranges shows that each model has significantly different forecast skill in these regions. It should be noted that NCEP-SME shows better forecast performance within SSUM, EKAL, and SKAL regions than the overall Grand-MME by showing lower NOF and higher TCC. Within the CSUM region, CANCM3-SME shows the higher performance compared to the Grand-MME. It agrees with the results in Figure 7 which shows the spatial distribution of TCC over the maritime continent. Figure 16 shows the response of performance measures (TCC and NOF) on the SBC method according to the different lead-time. It shows the decrease in forecast performance caused by a decrease in TCC and an increase in NOF as lead-time increases within all the regions.

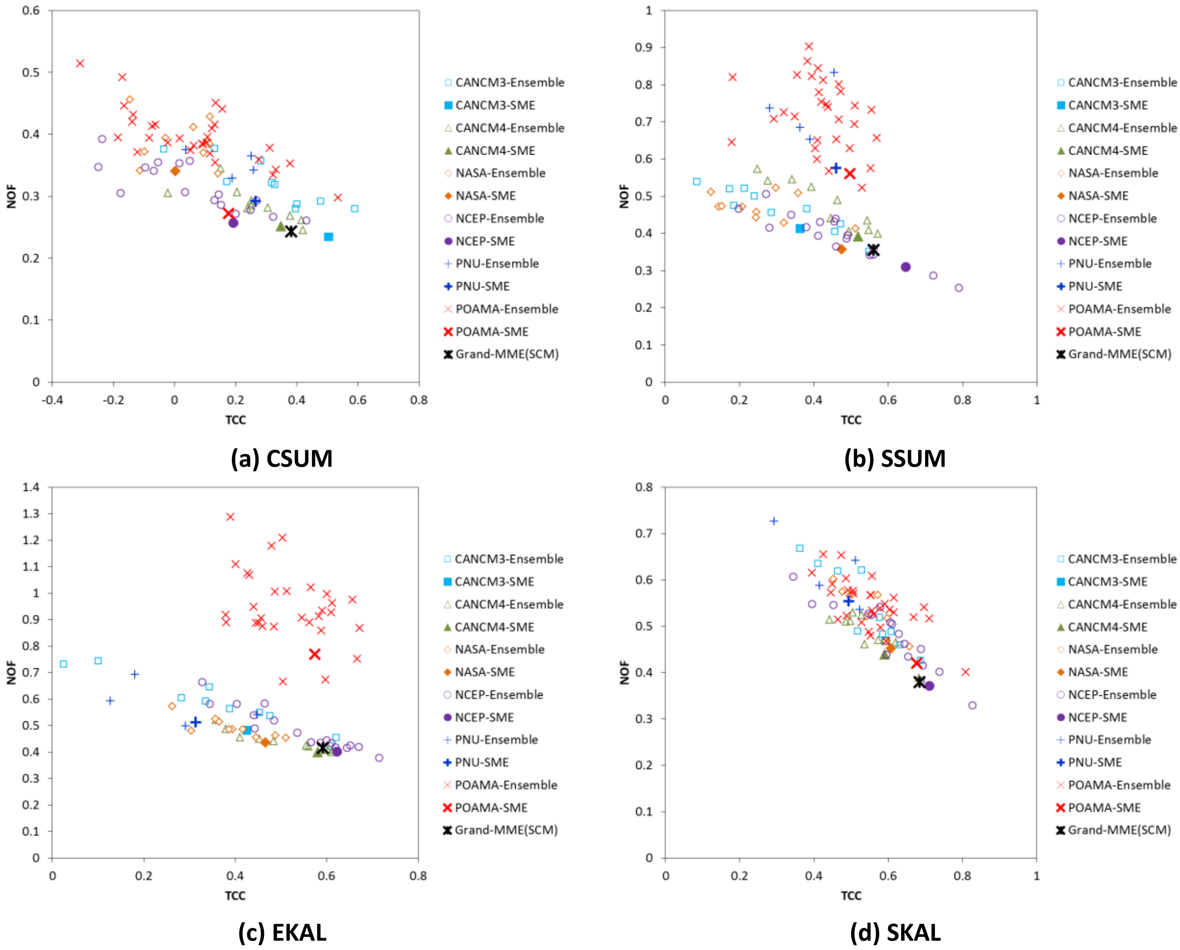


Figure 15. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the simple bias correction (SBC) downscaling method.

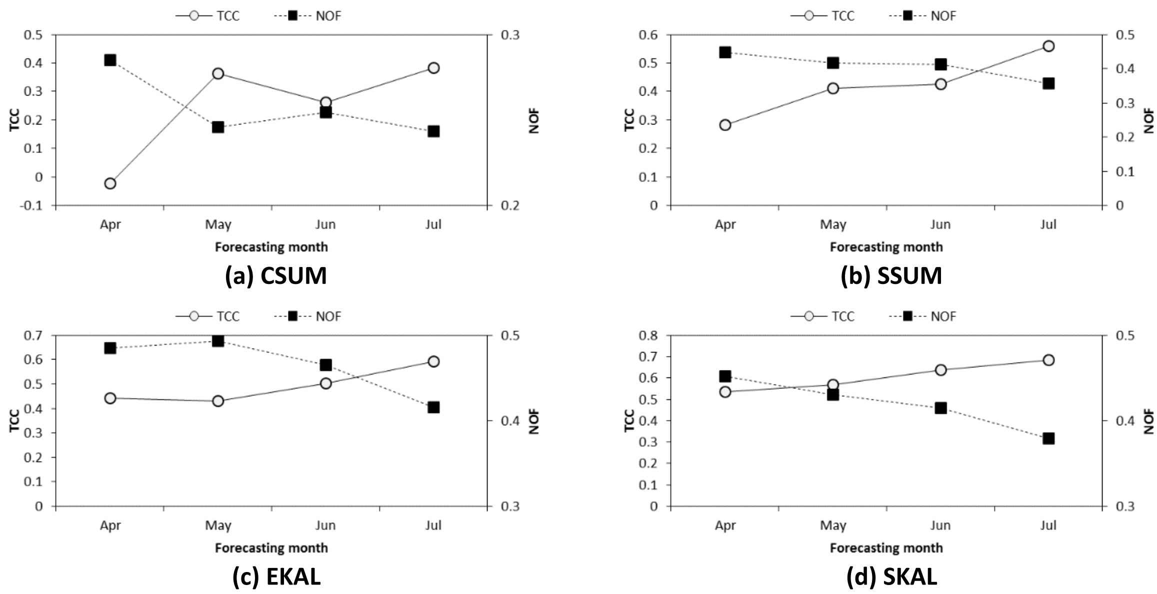


Figure 16. Response of performance measures (TCC and NOF) of simple bias correction (SBC) downscaling method according to the different lead-time within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions.

Moving Window Regression (MWR) approach

The selected best predictors for each month and region are presented in Table 4. The most frequently selected predictor was SLP and followed by SST and T850. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the Moving Window Regression (MWR) method are shown in Figure 17. In general, TCC and NOF values of individual model SME shows that increase in TCC leads to decrease in NOF. Compared to the results by SBC method in Figure 15, CSUM region showed the greatest increase in forecast performance through an increase in TCC of Grand-MME from 0.46 to 0.79 and a decrease of NOF from 0.76 to 0.19, while the other regions showed the similar ranges of TCC and NOF values. Grand-MME showed the best performance in both CSUM and SKAL regions, while NASA-SME and NCEP-SME showed the best performance within SSUM and EKAL regions, respectively. The response of performance measures (TCC and NOF) of forecasted ASO total precipitation according to the different lead-time are shown in Figure 18. It is usually expected that forecast skill decreases as the lead-time increases. However, only CSUM region showed the expected trend with an increase in TCC as lead-time decreased.

Table 4. Selected best predictors for each Single Model Ensemble (SME) and month within the selected regions.

Model		CSUM	SSUM	EKAL	SKAL
CANCM3	Aug	SST	SLP	SLP	SLP
	Sep	SLP	T850	T850	T850
	Oct	T850	SLP	T2m	T850
CANCM4	Aug	SST	SLP	SLP	SLP
	Sep	T2m	SPT	T850	V850
	Oct	T850	T850	SLP	V850
NASA	Aug	Z500	T850	SLP	U200
	Sep	T20	U200	SLP	SLP
	Oct	V850	U200	SLP	SLP
NCEP	Aug	SST	SLP	SLP	SLP
	Sep	SST	SST	SST	SST
	Oct	SLP	V850	SST	SLP
PNU	Aug	SST	SST	SLP	SLP
	Sep	T2m	SLP	SLP	SLP
	Oct	SST	SST	SST	SST
POAMA	Aug	SLP	Z500	SLP	T850
	Sep	SLP	Z500	Z500	Z500
	Oct	V850	V850	Z500	T2m

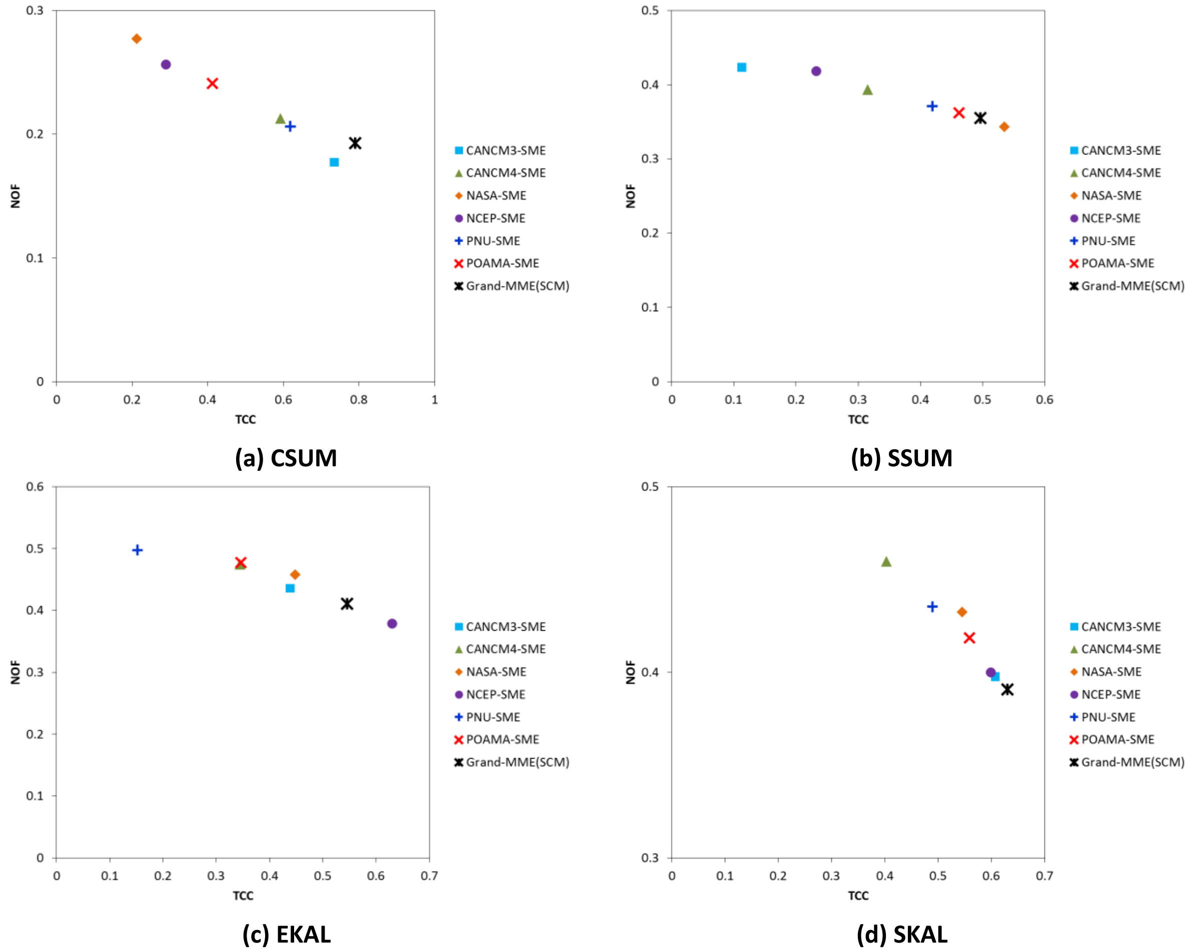


Figure 17. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the Moving Window Regression (MWR) downscaling method.

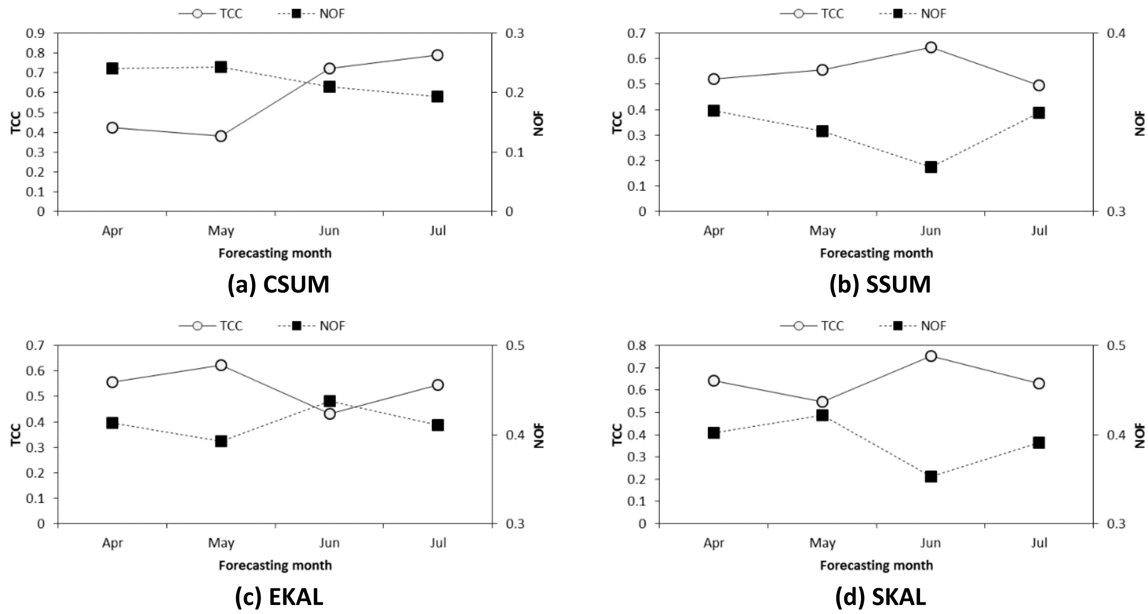


Figure 18. Response of performance measures (TCC and NOF) of Moving Window Regression (MWR) downscaling method according to the different lead-time within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions.

Climate Index Regression (CIR) approach

The selected best predictors for each month and region are presented in Table 5. The most frequently selected predictor was SOI and followed by CENSO, AO, NINA34, NOI, EA, and WPO. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the Climate Index Regression (CIR) method are shown in Figure 19. First, it should be noted that the forecast-based approach showed better performance within all regions except for SSUM region by showing higher TCC and lower NOF values. Even though the forecast-based approach showed better forecast skill, it is not always guaranteed because selected climate index with zero lag-time, which is provided by CPC, is based on observation data. As a result, higher forecast skill can be guaranteed only if dynamic forecast models accurately predict the selected index. Performance measures of the forecast-based approach showed the similar ranges within all the regions by showing TCC and NOF values around 0.8 and 0.3, respectively. Response of performance measures (TCC and NOF) of forecasted ASO total precipitation according to the different lead-time are shown in Figure 20. Only CSUM and SSUM regions showed the expected trend by an increase in TCC as lead-time decrease.

Table 5. Selected best predictors lag-time for the observed-based and forecast-based climate index regression (CIR) approaches within the selected regions.

Model		CSUM	SSUM	EKAL	SKAL
Observed	Aug	TNA(1)	CENSO(1), WPO(7)	NINA34(1), ONI(1)	NINA34(1), ONI(1)
	Sep	AO(12), EA(12)	AO(12), GML(3), AAO(6)	SOI(4), NINA3(2)	SOI(4), NINA3(2)
	Oct	EA(7), AAO(12), PNA(8)	WPO(7), TSA(8), NOI(3)	SOI(5), WPO(11)	NOI(3), NINA4(3)
Forecast	Aug	PACWARM(0), NTA(0)	CENSO(0)	NINA34(1), ONI(1)	SOI(0), NINA34(1), CENSO(0)
	Sep	AO(12), EA(12)	NOI(0), AO(12), GML(3)	SOI(0), WHW(0), CENSO(0)	WHW(0), SOI(0), CENSO(0)
	Oct	NP(0), EA(7)	AO(0), WPO(7), TSA(8)	NINA1(0), CENSO(5)	NOI(3), AO(0), SOI(0)

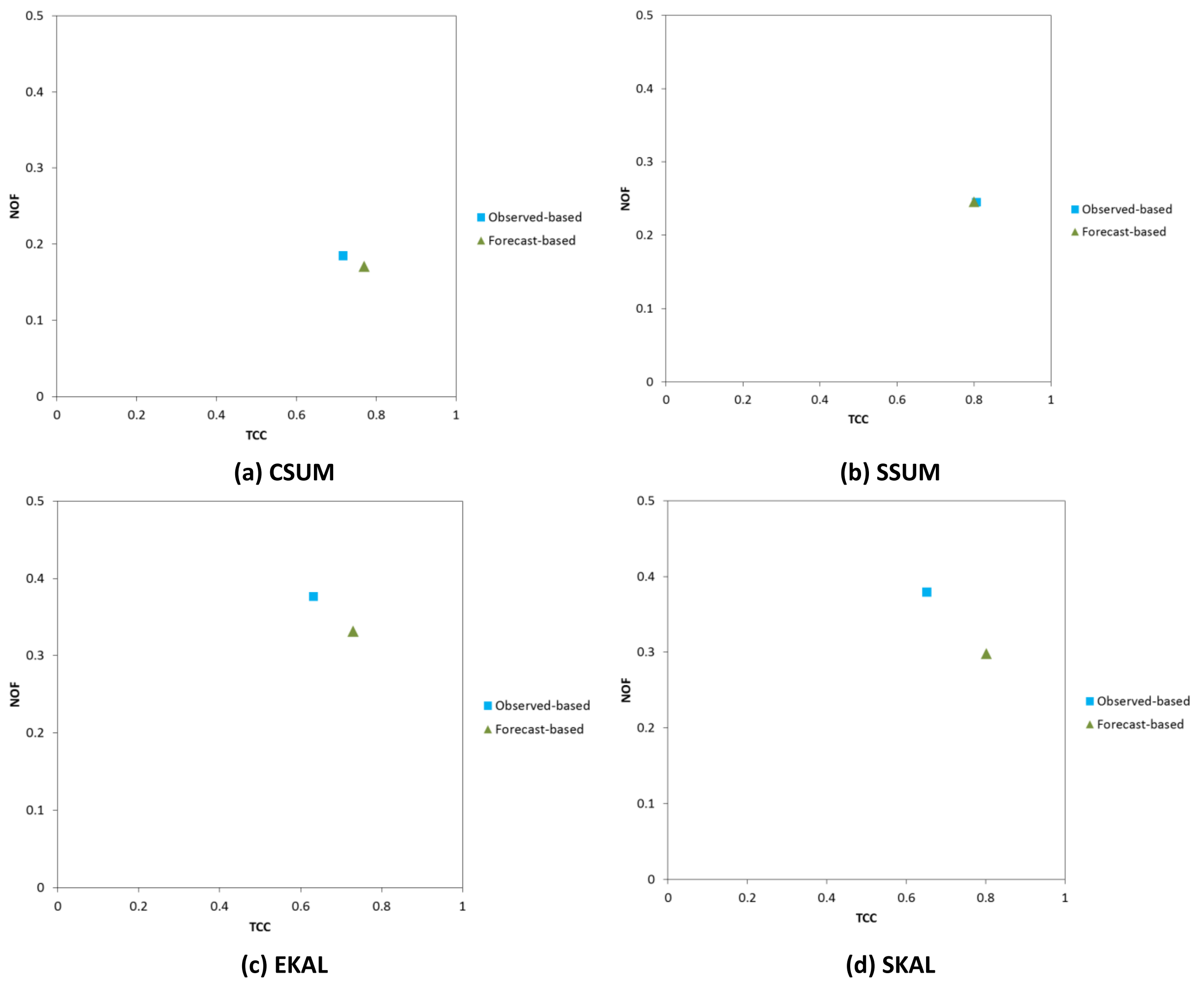


Figure 19. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the Climate Index Regression (CIR) downscaling method.

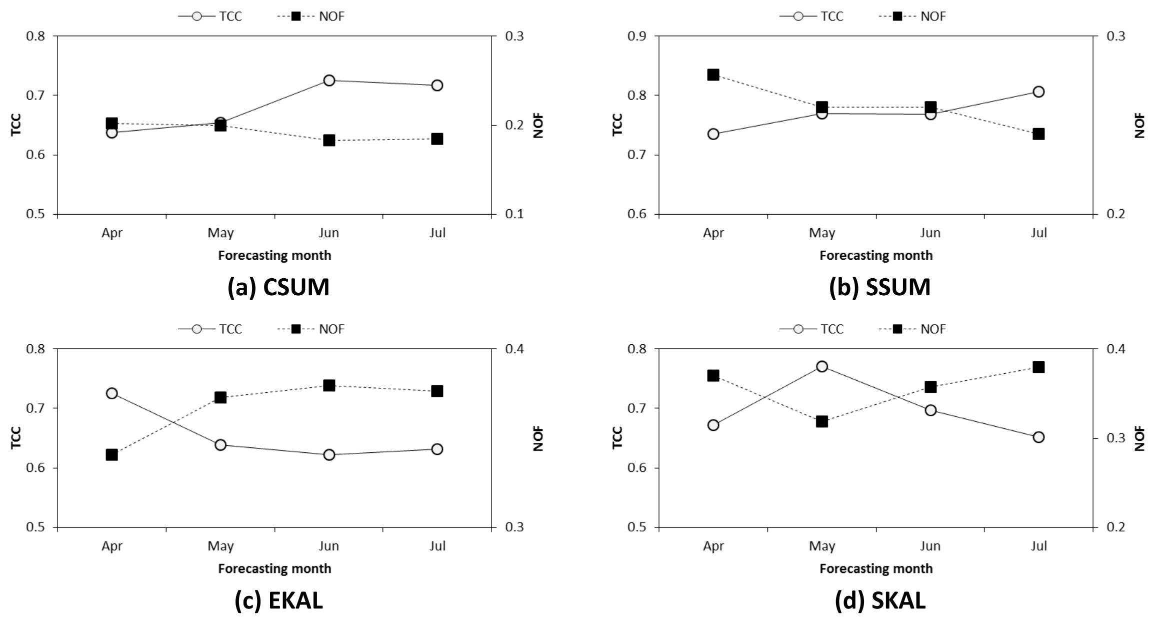


Figure 20. Response of performance measures (TCC and NOF) of Climate Index Regression (CIR) downscaling method according to the different lead-time within (a) CSUM, (b) SSUM, (c) EKAL, and (d) SKAL regions.

Hidden Markov Chain Model

The model performance measures (NOF and TCC) of predicted ASO precipitation using HMM are shown in Figure 21 for each region. Among the four regions, TCC of MME was greater than 0.5 over SSUM, EKAL, and SKAL regions, while TCC value was low over SSUM region. In terms of NOF, NOF decreased as TCC increased within each region. Within the EKAL and SKAL regions, MME showed the best performance in both TCC and EOF, while NASA-SME and PNU-SME individual models showed the better performance than MME within the CSUM and SSUM regions, respectively.

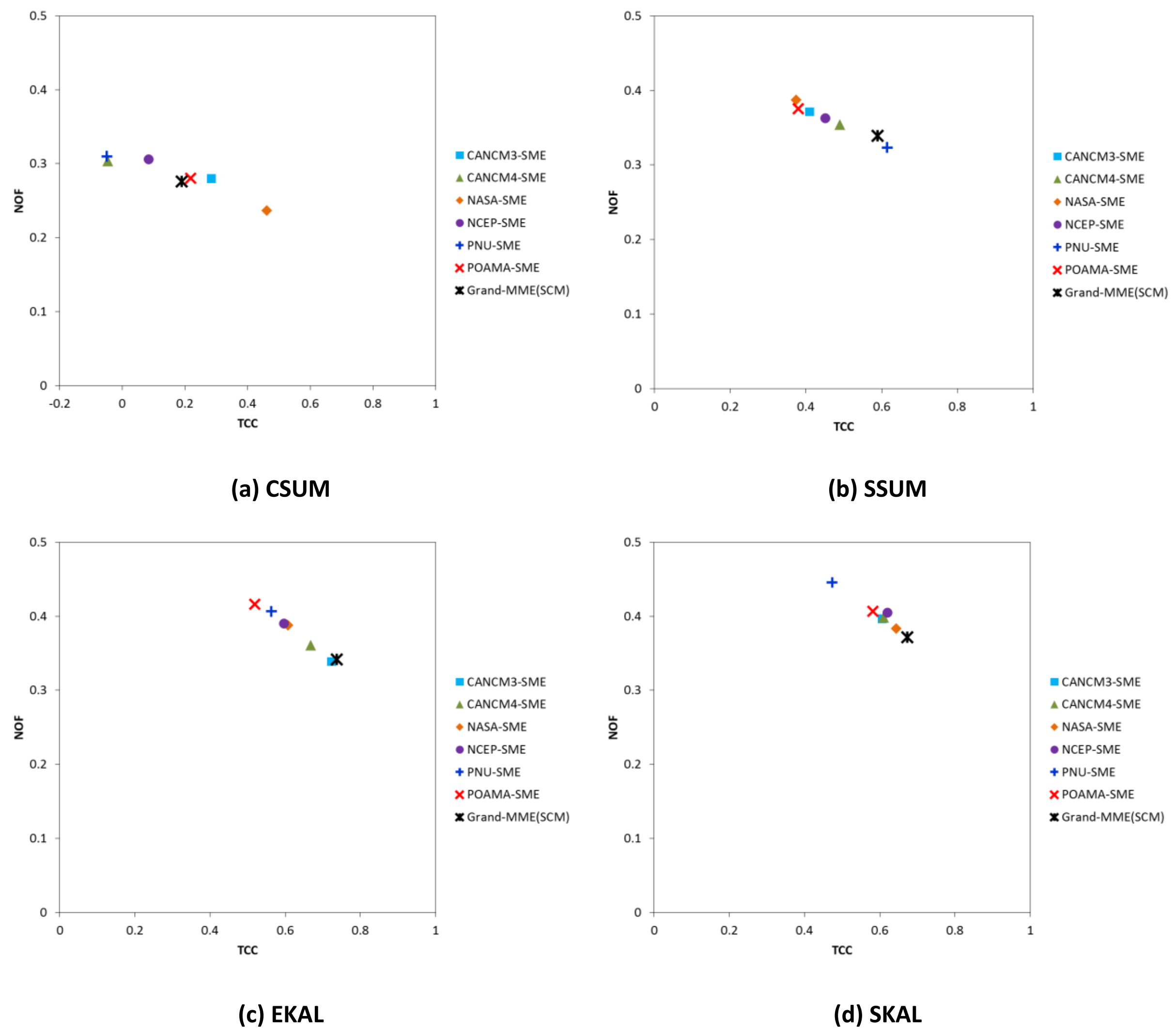


Figure 21. Performance measures (TCC and NOF) of forecasted ASO total precipitation using the Hidden Markov Chain Model (HMM) downscaling method.

Comparison of statistical downscaling methods

A comparison of time-series of forecasted ASO total precipitation and performance measures, derived based on Grand-MME using four SDMs including SBC, MWR, CIR-Observation-based, and HMM, is shown in Figure 22. The EKAL and SKAL regions showed similar forecast skill regardless of statistical downscaling methods. However, MWR and CIR showed higher performance within the CSUM region compared to SBC, while only CIR showed the higher model performance within the SSUM region. As a result, CIR downscaling approach showed the most stable forecast skill within all selected regions. It should also be noted that the absolute ASO precipitation amount for the driest year (1997) was closely predicted by all four downscaling methods within the EKAL and SKAL regions.

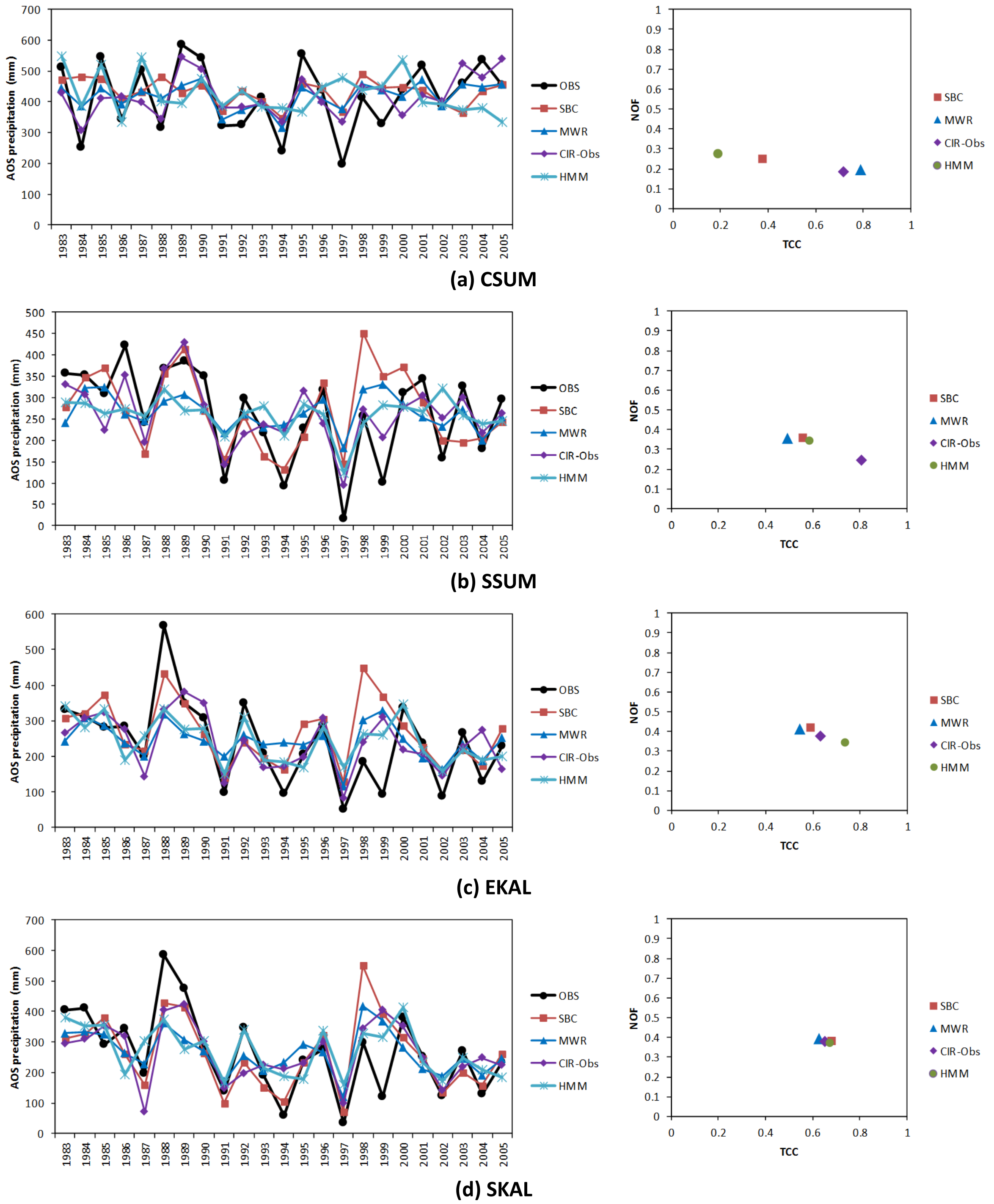


Figure 22. Comparison of time-series of forecasted ASO total precipitation (left) and performance measures (right) within the selected regions.

3.2. Needs Assessment and Development of EWS Prototype

3.2.1. Needs Assessment

All three study areas use a weather/climate forecasting and fire danger rating system with 4 criteria (low, moderate, high, and extreme) as an early warning system tool. The fire hotspot is the main indicator for fire occurrence that is used widely on district, provincial, and national levels. All stakeholders need more reliable information related to weather conditions so they can have improved anticipation for their prevention program. Detailed information for each study area is provided below.

Riau: The main agency at Riau province that handles land and forest fire is Regional Office for Nature Conservation, an agency under Ministry of Environment and Forestry which has four Fire Brigade Offices at Pekanbaru city, Siak Regency, Rengat Regency and Dumai city. Two offices, Pekanbaru city and Siak Regency, were visited. At Siak Regency we discussed with the Head of Office the climate information used and fire danger rating system. Another agency is Forestry Provincial Office, located at Riau University and Lancang Kuning University. We also sent the questionnaire to Siak Regency Disaster Agency. With 10 questionnaire completed, input from a range of land and forest fire management stakeholders has been considered. Almost all stakeholders interviewed used hotspots as the indicator of fire occurrences. The Meteorology Agency issues weather information on quarterly basis as well as daily basis. However the coverage of the weather stations for the whole province still needs improvements.

Central Kalimantan: This province has the highest hotspot almost every year. The soil is primarily peat, which may burn for several hours, days or weeks. Peatland fire is a ground fire type which spreads slowly underground and dominated by the smoldering process. Different from flaming combustion, which results in complete combustion, the smoldering process produces much higher carbon emissions. The fire brigades use climate information issued by BMKG as well as FDRS. Furthermore, the fire brigade office is also equipped with AWS and could generate more local FDRS. The total questionnaires completed is 8 forms where half of them came from head of fire brigades. Almost all fire managers need more accurate information for 6 and 3 months ahead, to increase preparedness.

East Kalimantan: This province has a long story of land and forest fire. The 1982/83 fire in East Kalimantan destroyed about 3.5 million ha of forest. Forest fires occur almost every year, however each event is specific in intensity and extent. The 1997/98 fire was declared a national disaster, since it affected more than 5 million ha of forest in East Kalimantan alone. There are some agencies involved in fire management such as Provincial Forestry Office (Dinas Kehutanan), Provincial Nature Conservation, Provincial Agency for Disaster Management (Badan Daerah Penanggulangan Bencana/BPBD). Previously, the Forestry Office had a Technical Implementation Unit known as the Land and Forest Fire Control Agency and 11 Local Fire Centers, which were established by joint cooperation through the Integrated Forest Fire Mangement (IFFM) Project funded by GTZ Germany during 1994-2000. This project developed the early warning systems based on several methods including Keytch Byram Drought Index (KBDI), hotspot monitoring, as well as the Fire Danger Rating Systems. A discussion with the Director of Provincial Disaster Management Authority, illuminated the fact that they use all information available on weather, climate, hot spot and fire danger rating systems from various sources. This information is then reported to National HQ on daily basis as well as delivered to all agencies to inform them as early as possible. However, they still need more reliable and accurate data related to weather for 3 and 6 months forward to predict the fire season at early stage.

3.2.2. Training Workshop

The APEC Climate Center (APCC) led a two day workshop at the Malaysian Meteorological Department (MMD) in Petaling Jaya, Malaysia, June 9-10, 2015 (Table 6). The workshop was done with financial and logistical support from MMD for APCC's APN grant project regarding the development of a fire and haze early warning system in Southeast Asia. The workshop had 32 participants including 12 participants from Indonesia (predominantly from the Ministry Of Environment And Forestry and forest fire control officials from the provinces most impacted by forest fires) and 17 participants from Malaysia (predominantly from MMD and the Forestry Department). Dr. Jaepil Cho led hands-on training sessions on the Early Warning System computer program developed as a part of this project. Details are described in the Appendix.

Table 6. Program of the workshop

Day/Session	Morning	Afternoon
Tue, Jun 9	- Opening - Lecture on "Introduction to APCC" and "Seasonal Climate Forecasting" *by Dr. JH Yoo, APCC*	Lectures and hands-on on "Statistical Downscaling Techniques" *by Dr. JP Cho, APCC*
Wed, Jun 10	- Lecture on "Bringing fire early warning system science to public policy management" *by Dr. Raffles B Panjaitan* *Director of Forest Fire Control, Indonesia* - Project Reports: Fieldwork Report & Project Results and Outcomes *by Dr. Israr Albar, Indonesia DF*	Demonstration on "The Prototype Early Warning System (EWS)" *by Dr. JP Cho, APCC*

3.2.3. Development of EWS Prototype

Table 7 shows the results of prediction models that have been selected for each case (month and lead-time) in Selatan region. When using the Simple Bias Correction (SBC) method, a total of 115 models were selected for precipitation. The number of selected models decreased as the lead time increased by showing 26, 27, and 23 models for 1 to 3-month lead-time while 14, 10, and 15 models for 4 to 6-month lead-time. The MWR method selected 24 models for precipitation forecasting. When utilizing the Climate Index Regression (CIR) method, only 3 indices were selected for July and August. About the ITR method, 12 models were selected to forecast precipitation for Selatan region. Overall, the SBC method, which is based on dynamic prediction data, shows the highest model selection and is followed by statistical downscaling methods such as MWR, and CIR/ITR. Figure 23 shows an example of spatial distribution of the predictors that have been selected by the MWR method for 4 to 6-month lead precipitation prediction for August.

Table 7. Selected downscaling method and models for each month according to different lead time in Selatan region.

month	1 month lead	2 month lead	3 month lead	4 month lead	5 month lead	6 month lead
Jan		B_NASA M_CANCM3 M_PNU	M_PNU	M_PNU		
Feb	B_CANCM3 B_NASA	B_CANCM4	B_CANCM3		M_CANCM4	
Mar		B_CANCM3 M_NASA	B_NCEP M_CANCM4 M_NCEP		M_NASA	M_CANCM4
Apr		M_CANCM3				
May	B_POAMA M_CANCM4	B_PNU	M_NCEP M_POAMA	B_CANCM4		B_CANCM4
Jun		M_PNU	B_PNU			
Jul	B_NASA B_POAMA B_CANCM4 B_NCEP I_NASA	B_NASA B_CANCM4 B_NCEP C_Lag	B_NCEP B_NASA C_Lag	B_CANCM4 B_POAMA M_POAMA		B_NCEP B_POAMA
Aug	B_CANCM3 B_NASA B_POAMA B_CANCM4 B_NCEP I_CANCM4	B_NASA B_CANCM4 B_CANCM3 B_PNU B_NCEP B_POAMA I_CANCM4 I_NCEP	B_CANCM3 B_NCEP B_NASA B_CANCM4 B_POAMA C_Lag	B_CANCM4 B_POAMA B_NASA B_NCEP I_POAMA I_NCEP	B_CANCM4 B_NASA B_NCEP B_PNU B_POAMA I_CANCM3 I_NCEP I_POAMA	B_NCEP B_POAMA B_CANCM3 B_NASA I_CANCM4 I_CANCM3 I_NASA I_POAMA
Sep	B_CANCM3 B_NASA B_POAMA B_CANCM4 B_NCEP B_PNU M_PNU M_POAMA	B_NASA B_CANCM3 B_NCEP B_POAMA	B_CANCM3 B_NCEP B_NASA B_CANCM4	B_NASA	B_NASA B_NCEP	B_NCEP B_POAMA B_CANCM3
Oct	B_CANCM3 B_NASA B_POAMA B_CANCM4 B_NCEP B_PNU M_PNU	B_NASA B_CANCM4 B_CANCM3 B_PNU B_NCEP B_POAMA	B_CANCM3 B_NCEP B_NASA B_CANCM4 B_POAMA M_NCEP	B_CANCM4 B_NASA B_NCEP B_CANCM3 B_PNU	B_CANCM4 B_NCEP B_PNU	B_CANCM4 B_NCEP B_NASA
Nov	B_POAMA B_NCEP	B_NASA B_CANCM4 B_NCEP B_POAMA	B_CANCM3 B_NCEP B_CANCM4 B_POAMA M_NCEP	B_NCEP		B_CANCM3 B_PNU M_CANCM3
Dec	M_NASA				M_PNU	

B_, M_, C_, I_ indicate SBC, MWR, CIR, ITR downscaling method, respectively.

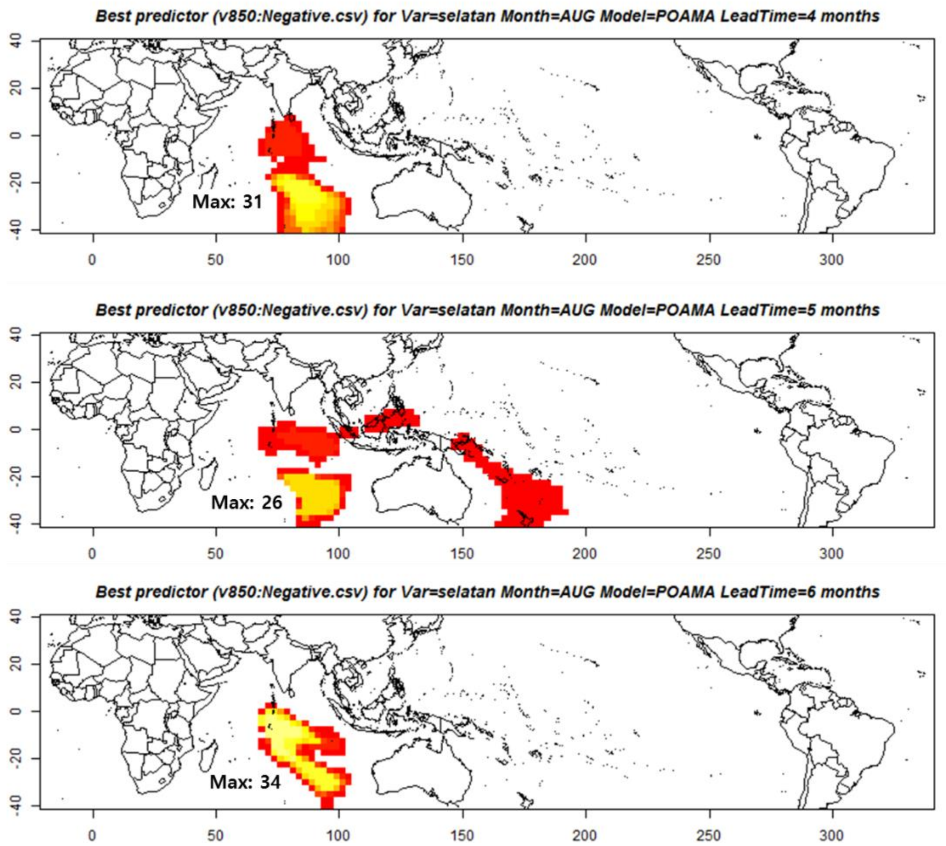


Figure 23. Spatial distribution of selected variables by the POAMA models for 4 to 6-month lead precipitation predictions in August (yellow indicates most frequent selection through the cross-validation procedures from 1983 to 2015).

Figure 24 and Table 8 show the temporal correlation coefficient for each month according to changes in lead time. The TCC values were calculated using MME within the condition that forecasts are issued every month. As a result, more forecast information were used for calculating MME when the lead-time is getting shorter. For example, when we predict precipitation levels in August during the month of July based on 3-month lead-time data, all three prediction results (including 1-month lead prediction issued in July, 2-month lead prediction issued in June, and 3-month lead prediction issued in May) can be used for estimating MME. The months of August shows Temporal Correlation Coefficient (TCC) values that are greater than 0.6 for all lead times. In most of the months, when the selected models are based on dynamic model predictions, there is a decreasing trend in TCC values as the lead times increase.

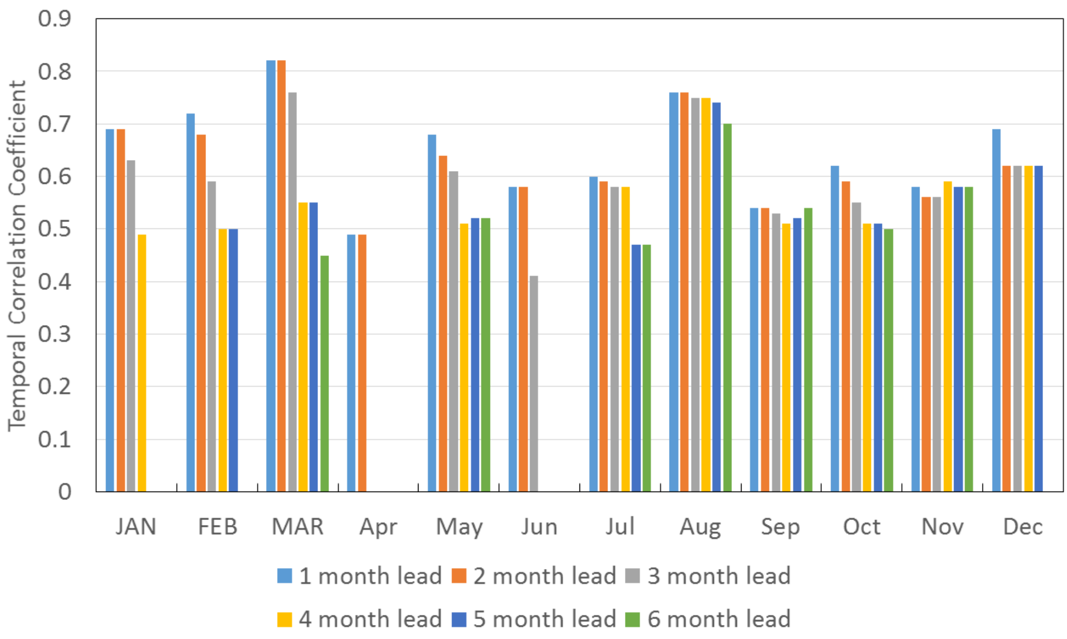


Figure 24. Temporal correlation coefficients (TCC) according to changes in lead time for predicting precipitation in Selatan region using multi-model ensemble (MME) average.

Table 8. Temporal correlation coefficients (TCC) according to changes in lead time for predicting precipitation in Selatan region using multi-model ensemble (MME) average.

Month	1 month	2 month	3 month	4 month	5 month	6 month
JAN	0.69	0.69	0.63	0.49		
FEB	0.72	0.68	0.59	0.5	0.5	
MAR	0.82	0.82	0.76	0.55	0.55	0.45
APR	0.49	0.49				
MAY	0.68	0.64	0.61	0.51	0.52	0.52
JUN	0.58	0.58	0.41			
JUL	0.6	0.59	0.58	0.58	0.47	0.47
AUG	0.76	0.76	0.75	0.75	0.74	0.7
SEP	0.54	0.54	0.53	0.51	0.52	0.54
OCT	0.62	0.59	0.55	0.51	0.51	0.5
NOV	0.58	0.56	0.56	0.59	0.58	0.58
DEC	0.69	0.62	0.62	0.62	0.62	

When we consider ASO precipitation amount as a trigger for forest fire, we can issue an ASO precipitation forecast from April to July because we are using 6-month lead forecast data in developing prototype EWS. Figure 25 shows the comparison of forecasted and observed monthly precipitation amount for August to October. The forecasted values in the graph are MME, which was estimated using multiple model output which is issued on April.

August precipitation predictions (4-month lead forecast) demonstrated the best predictability by showing 0.56 of R2 while predictability for September (5-month lead forecast) and October (6-month lead forecast) was lower at 0.25 and 0.24 of R2, respectively. As we mentioned previously, the number of available models decreased as lead-time increased by showing 22, 5, and 3 of individual forecast models for August, September, and October, respectively. The result also showed that lower precipitations were overestimated and higher precipitations were underestimated for all the cases.

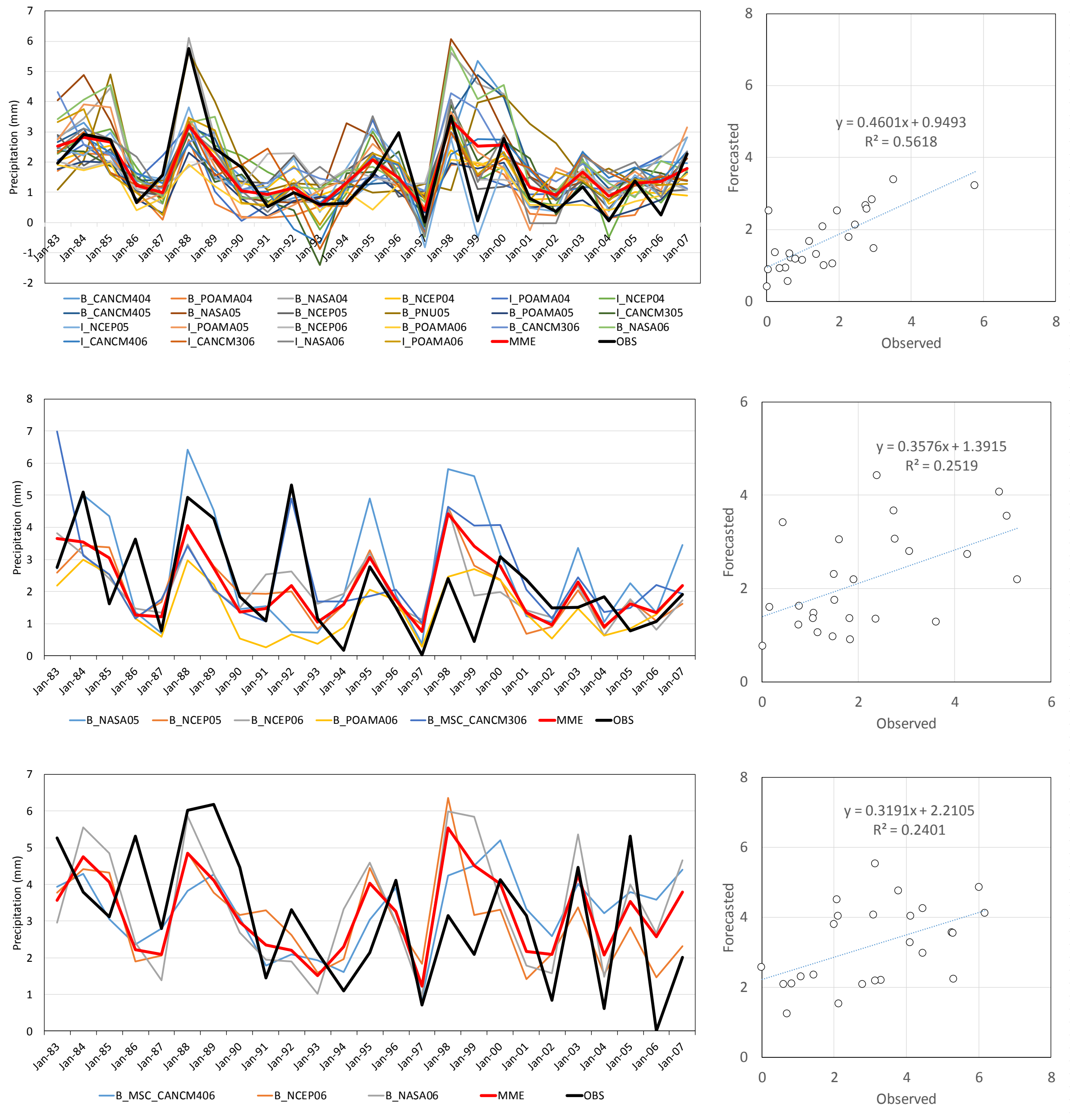


Figure 25. Timeseries (left) and scatter plot (right) of monthly precipitation for August (top), September (middle), and October (bottom) issued on April.

In order to translate forecasted precipitation into fire danger ratings, 4 categories (Extreme, High, Moderate, and Low) were established based on the results from the field survey. At first, we attempted to determine the ranges for each category using a segmented regression method. However, the resulting threshold precipitation was too low, which increased the likelihood of extreme carbon emissions being predicted due to scattered data. As a result, we set the threshold value manually based on Figure 26. The figure shows the time series of 3-month accumulated monthly precipitation and carbon emission in Selatan region with the determined ranges for 4 fire danger ratings.

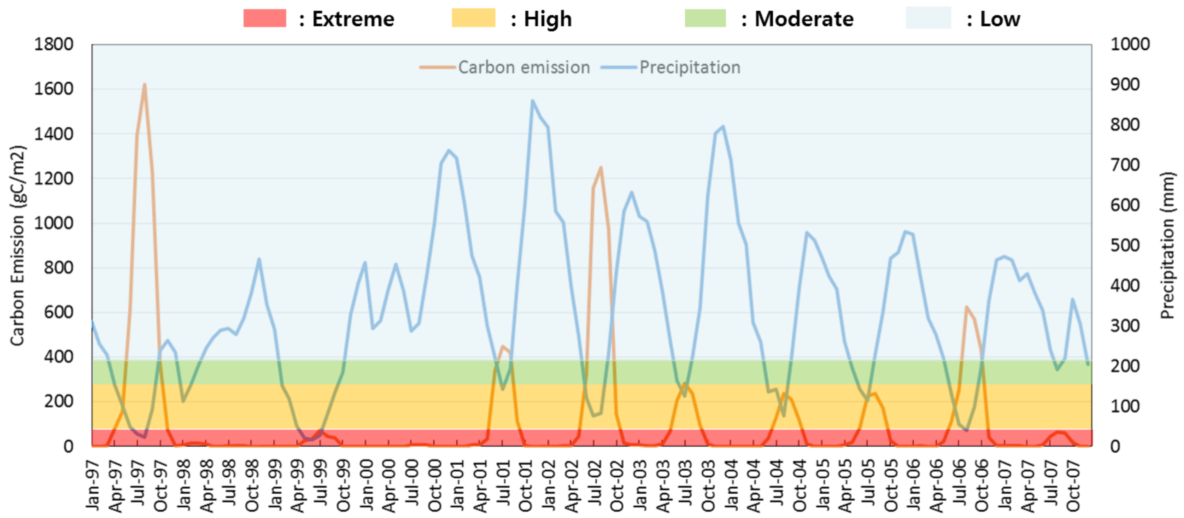
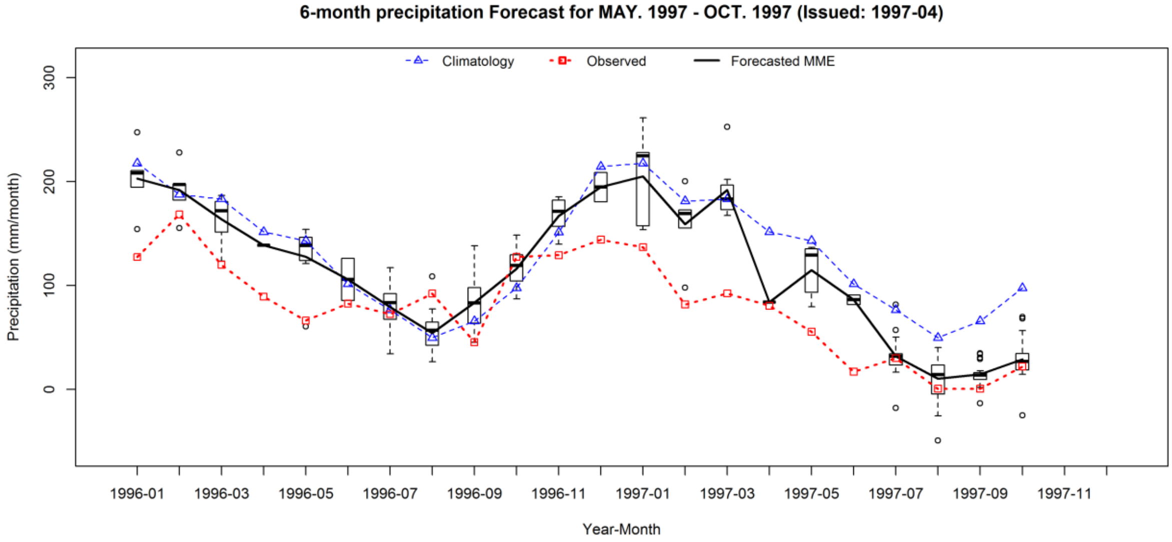


Figure 26. Time series of 3-month accumulated monthly precipitation and carbon emission in Selatan region with the determined ranges for fire danger ratings.

We designed a template for delivering forecast information on both precipitation and probability of forest fire for ASO period. Figure 27 shows the forecast summary for monthly precipitation and probability of forest fire in Selatan region for August to October in 1997 which was issued on April, 1997. The graph shows the graphical information for previous and current years by providing climatology (blue), observed (red), and forecasted precipitaion (black). The boxplot in the figure shows the variations of predicted values by individual models. The figure shows that severe dought during August to October, 1997 was closely predicted in Selatan region. The bottom-left table shows the overall summay of 1-month lead forecast skill scores based on the long-term period with monitoring data. The used performance measures include TCC and NRMSE, which can be used for continous variables and Accuracy and Heidke Skill Score (HSS), which in turn can be used for category forecasts. For calculating Accuracy and HSS, we equally divided the observed monthly precipitation into 4 categories (25% for each). HSS measures the fraction of correct forecasts after eliminating those forecasts which would be correct due purely to random chance (http://www.cawcr.gov.au/projects/verification). In Selatan region, August and April showed the highest (0.54) and lowest (-0.09) HSS values, respectively. Right-bottom table shows the information on probability of forest fire for each danger rating. During ASO in 1997, probability fire danger was predicted high by showing 95% of forecasted precipitation belongs to High Range and 5% belongs to Extreme Range.



Monthly skil score for JAN. 1983 - DEC. 2007

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
TCC	0.69	0.73	0.82	0.49	0.7	0.6	0.59	0.76	0.53	0.63	0.58	0.69
NRMSE	0.75	0.8	0.74	0.86	0.76	0.8	0.79	0.66	0.86	0.76	0.8	0.71
Accuracy	0.68	0.48	0.56	0.33	0.76	0.84	0.72	0.76	0.64	0.64	0.44	0.72
HSS	0.35	0.26	0.35	-0.085	0.53	0.44	0.17	0.54	0.26	0.2	0.079	0.52

Probability of Forest Fire for

	1997: Sep~Oct
Extreme	5
High	95
Moderate	0
Low	0

Figure 27. Forecast summary for monthly precipitation and probability of forest fire in Selatan region for August to October, in 1997 (issued on April, 1997)

Finally, the forecast summary will be provided through the web hosting server in APC (http://www.apcc21.org/eng/html/apn.jsp). The forecast information will be issued on April to July and the forecast summary will be posted on the webpage shown in Figure 28.

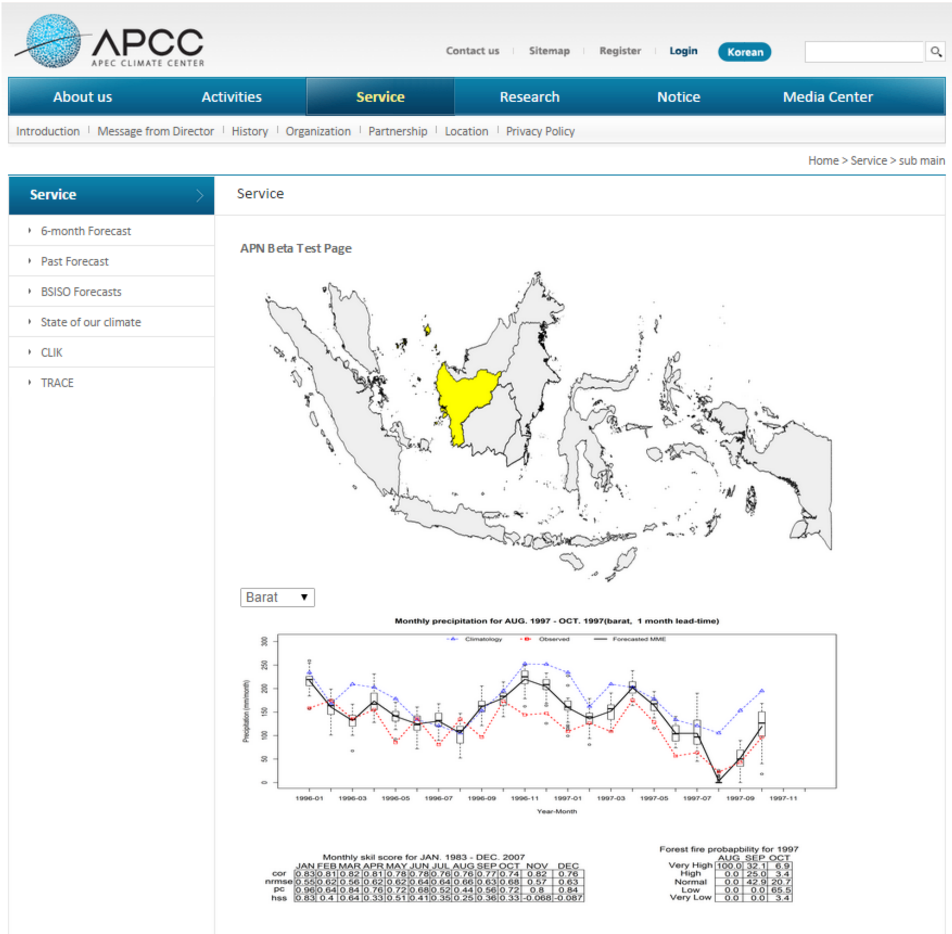


Figure 28. Webpage of prototype early warning system for delivering forecast information.

4. Conclusions

The APEC Climate Center (APCC) produces climate prediction information utilizing a multi-climate model ensemble (MME) technique. First, we focused on skill assessment of the different forecasting approaches. We compared the region-average of ASO precipitation between observation (APHRODITE) and models (including ensemble members of each individual model) without any bias correction. Individual models predicted reasonably the temporal anomaly trend of ASO precipitation but they failed to predict the absolute precipitation amount for a specific month. We applied both dynamical and statistical downscaling approaches over the maritime continent for June to August. Even though both dynamic and statistical downscaling approaches did not add further prediction skill during JJA on Southeast Asia region, it can be said that statistical downscaling using the MME forecast will be more appropriate for a real-world application toward Southeast Asian haze problems compared to dynamic approaches. As a result, we applied four different statistical downscaling methods over four regions in Southeast Asia for August to October (ASO) period. Statistical downscaling methods including Simple Bias Correction (SBC), Moving Window Regression (MWR), Climate Index Regression (CIR), and Hidden Markov Chain (HMM) were compared. Comparison results showed the higher forecast skills within the Sumatra regions compared to the Kalimantan regions.

Based on the downscaling experiments, four different downscaling methods, in accordance with the degree of utilizing the seasonal climate prediction information, were developed and integrated into the prototype of Early Warning System (EWS) in order to improve predictability. These methods include: 1) the Simple Bias Correction (SBC) method, which directly uses APCC's dynamic prediction data with a 3 to 6 month lead time; 2) the Moving Window Regression (MWR) method, which indirectly utilizes dynamic prediction data; 3) the Climate Index Regression (CIR) method, which predominantly uses observation-based climate indices; and 4) the Integrated Time Regression (ITR) method, which uses predictors selected from both CIR and MWR. The downscaling package is based on the open source license for further training workshop and free distribution of developed prototype. Long-term predictability of monthly precipitation for the 4 regions within Borneo Island was evaluated. Based on earlier version of the prototype, APCC led a two day workshop in Petaling Jaya, Malaysia, including hands on training sessions on statistical downscaling and prototype. Needs assessment for early warning Information was also conducted through the field survey with resource managers. Finally, EWS prototype was improved based on feedback from both field survey and training workshop participants. The forest fire early warning information on Southeast Asia created using the EWS will be provided though the hosting server in APCC.

5. Future Directions

The current South East Asia Fire Danger Rating System (FDRS) was developed and implemented in 1998 by ASEAN, in cooperation with the Canadian Forest Service. The FDRS is a system that monitors (as opposed to predicting) numerous meteorological variables, such as temperature, relative humidity, rainfall, and wind speed to comprehensively assess the current risk of forest fires. Seasonal FDRS forecasting would entail predicting all of these variables at a 3-month lead time in order to estimate the future risk of forest fires. This, however, would constitute a major research effort, and ultimately the suggestion was rejected with the thought that staying within the bounds of the originally planned proposal and predicting only seasonal precipitation would be a more realistic and achievable goal. In the future, the project team may consider creating a more comprehensive fire and haze EWS that incorporates all the variables included in the current Fire Danger Rating System.

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Appendix

A.1. Kick-off Meeting

- **Period**: August 15th, 2012
- **Place**: Singapore
- **Participants:** 9 in total (Indonesia: 3, Malaysia: 1, Japan: 1, USA: 1, APCC: 3 participants)
- **Program details**

Name	Presentation Title
Jaepil Cho	Toward a fire and Haze Early Warning System for Southeast Asia
Saji Hameed	Downscaling strategies and skill assessment
Robert Field	Overview of the Fire Danger Rating System at the Malaysian Meteorological Department
Orbita Roswintiarti	Development and Operation of the Southeast Asia and Indonesian Fire Danger Rating System
Antoyo Setyadipratikto	The Operation of FDRS Development for Land and Forest Fire Prevention and Mitigation
Jaepil Cho	Overview of the Fire Danger Rating System at the Korea Forest Research Institute
Israr Albar	Forest Fire Management in Indonesia & Plan for Developing Needs from Managers

- **Participants' list**

1. Jaepil Cho, APEC Climate Center, Busan, Korea
2. Jin Ho You, APEC Climate Center, Busan, Korea
3. Su-Chul Kang, APEC Climate Center, Busan, Korea
4. Saji Hameed, The University of Aizu, Aizu, Japan
5. Robert Field, NASA GISS & Columbia University, New York, USA
6. Kwan Kok Foo, Malaysia Meteorological Department, Kuala Lumpur, Malaysia
7. Orbita Roswintiarti, Indonesian National Institute of Aeronautics and Space, Jakarta, Indonesia
8. Israr Albar, Indonesian Ministry of Forestry, Jakarta, Indonesia
9. Antoyo Setyadipratikto, Indonesian Agency for Meteorology, Climatology and Geophysics, Jakarta, Indonesia

- **Issues Discussed**
    1. Activities during the first year will be focused almost exclusively on skill assessment of the different forecasting approaches. Outreach activities will be minimized during the first year. There was agreement that improved understanding of forecasting skill will translate into more useful operational products during the second year.
    2. The dynamical downscaled model will be run at APCC through the guidance of Saji. We will consider comparing downscaled WRF forecasts to those from RegCM and statistical downscaling.
    3. The APCC will be responsible for developing a specific work plan over the coming weeks (horizontal resolution, domain).
    4. Hindcast periods should include a mix of normal, moderate and severe fire seasons.
    5. The scope of the project will remain focused on seasonal precipitation forecasting. We discussed expanding activities to include seasonal FDRS forecasting, to capitalize on the adoption of the system in Indonesia and Malaysia. This was seen as too far beyond the scope of the current proposal, however, and constitutes a major research effort. We will consider seeking additional funds for such a project as the current project progresses.
    6. Seasonal precipitation forecasts will be interpreted in terms of historical precipitation-fire relationships.

A.2. Project Meeting for Needs Assessment

- **Period**: August 1st, 2014 (14:00~17:00)
- **Place**: Sapporo (Gracery Hotel)
- **Participants:** 5 in total (Indonesia: 2, Malaysia: 1, Japan: 1, APCC: 1)
- **Program details:** Presentation by Jaepil Cho (
- **Participants' list**
    1. Jaepil Cho, APEC Climate Center, Busan, Korea
    2. Saji Hameed, The University of Aizu, Aizu, Japan
    3. Kwan Kok Foo, Malaysia Meteorological Department, Kuala Lumpur, Malaysia
    4. Israr Albar, Indonesian Ministry of Forestry, Jakarta, Indonesia
    5. Ardhasena Sopaheluwakan, Indonesian Agency for Meteorology, Jakarta, Indonesia
- **Issues Discussed**
    7. There is a need to provide probability-based information.
    8. The possibility of selecting one downscaling method instead of using multiple.
    9. The appropriate warning level will be 3 or 5.

10. Providing a regional graph without a map is desirable for increasing the understanding of local managers. These issues will be considered through needs assessment surveys and interviews by resource managers.
11. Distribution of the final results via an email to the administrator of the region is desirable.
12. Indonesian Ministry of Forestry will play a role as a focal point for the survey and interview of local administrators.
13. The survey can be separately conducted for 2 or 3 different groups such as local government, fire manager, and public.
14. Malaysia Meteorological Department will play a role as a focal point for the training workshop of local resource manager which is currently planned around March 2015 in Malaysia.

A.3. APEC Climate Center (APCC) Workshop on "Toward a Fire and Haze Early Warning System for Southeast Asia"

- **Period**: June 9-10, 2015
- **Venue**: Malaysian Meteorological Department, Petaling Jaya, Malaysia
- **Participants:** 32 in total (Indonesia: 12 participants, Malaysia: 17 participants, APCC: 3 participants)
- **Local Host**: Mr. Kwan Kok Foo, Malaysian Meteorological Department
- **Program details**

Day 1: Tuesday, 9 June 2015	
0830 – 0900	Registration at Crystal Crown Hotel
0900 – 1100	- Opening Ceremony at Crystal Crown Hotel - Welcoming Remarks *By Dato' Che Gayah Ismail, Director General, Malaysian Meteorological Department* *By Dr. Jinho Yoo, APCC* - Opening Address *By H. E. Dato' Sri Dr. Noorul Ainur Mohd. Nur., The Ministry of Science, Technology and Innovation of Malaysia, Secretary-General,* - Press Conference - *Tea/Coffee Break*
1100 – 1130	Lecture on "Introduction to APCC" *Dr. JH Yoo, APCC*
1130 – 1300	Lecture on "Seasonal Climate Forecasting" *Dr. JH Yoo, APCC*
1300 – 1410	*Lunch Break*
1410 – 1540	Lectures and hands-on on "Statistical Downscaling Techniques" *Dr. JP Cho, APCC*

1540 – 1600	*Tea/Coffee Break*
1600 – 1730	Lectures and hands-on on "Statistical Downscaling Techniques" *Dr. JP Cho, APCC*
2000 – 2200	Reception Dinner Hosted by the Minister of Science, Technology and Innovation, Malaysia at Kuala Lumpur Tower
Day 2: Wednesday, 10 June 2015	
0900 – 0930	Lecture on "Bringing fire early warning system science to public policy management" *Dr. Raffles B Panjaitan, Director of Forest Fire Control, Indonesia*
0930 – 1100	Project Reports: - Fieldwork Report - Project Results and Outcomes *Dr. Israr Albar, Indonesia DF*
1100 – 1120	*Tea/Coffee Break*
1120 – 1250	Demonstrate on "The Prototype Early Warning System (EWS)" *Dr. JP Cho, APCC*
1250 – 1400	*Lunch Break*
1400 – 1530	Demonstration on "The Prototype Early Warning System (EWS)" *Dr. JP Cho, APCC*
1530 – 1550	*Tea/Coffee Break*
1550 – 1700	Demonstration on "The Prototype Early Warning System (EWS)" *Dr. JP Cho, APCC*
1700 – 1730	1.1. Wrap up and Closing Session
2000 – 2200	1.2. Farewell Dinner Hosted by APCC at Saloma Theatre Restaurant

- **Participants' list**

1. Dr. Jaepil Cho, APEC Climate Center, Climate Change Research Team.
2. Dr. Jin Ho Yoo, APEC Climate Center, Climate Prediction Team Leader
3. Mr. Joseph Patrick Larsen Climate Prediction Team Leader, Staff
4. Mr. Binsar Oktavianus Togatorop, Forest Fire Extinction Operation, Ministry Of Environment and Forestry, Indonesia
5. Mr. Deny Haryanto, Fire Hotspot Monitoring Data Analysis Officer, Directorate of Forest Fire Control, Ministry Of Environment and Forestry, Indonesia
6. Ms. Eny Haryati, Forest Fire Data Analysis Officer, Directorate of Forest Fire Control, Ministry Of Environment and Forestry, Indonesia
7. Ms. Eva Famurianty, Forest Fire Prevention Data Analysis Officer, Directorate of Forest Fire Control, Ministry Of Environment and Forestry, Indonesia

8. Mr. Heru Budianto, Secretary of Forest Fire Brigade East Kalimantan, Natural Resources Conservation Agency, Ministry of Environment and Forestry, Indonesia
9. Dr. Israr Albar, Directorate of Forest Fire Control, Ministry of Environment and Forestry, Indonesia
10. Mr. Jaya Dharwiniar Cipta, Staff-Suppression Analyst, Dir. Forest Fire Control, Ministry of Environment and Forestry, Indonesia
11. Dr. Raffles Brotestes Panjaitan, Director, Directorate of Forest Fire Control, Ministry Of Environment and Forestry, Indonesia
12. Mr. Rollanda Utama, Head of Forest Fire Brigade Sarolangun, Forest Fire Brigade of Sarolangun, Jambi Nature Resource Conservation Agency, Indonesia
13. Mr. Sahat Irawan Manik, Secretary of Forest Fire Brigade, Forest Fire Control, Natural Resource Conservation Agency of West Kalimantan, Indonesia
14. Mr. Syailendra Djawar, Regional Head of Operations Mangala Agni Pekanbaru, Ministry Of Environment and Forestry, Indonesia
15. Mr. Taufikurohman Eli Karliman, Head of Forest Fire Brigade Pontianak, Forest Fire Control, Natural Resource Conservation Agency of West Kalimantan, Indonesia
16. Ms. Aminah Ismail, Meteorological Officer, Atmospheric Science and Cloud Seeding Division, Malaysian Meteorological Department
17. Mr. Jeffri Bin Abd. Rasid, Director, International Affairs Division, Forestry Department Peninsular Malaysia
18. Mr. Mohd Khairi Deraman, Meteorological Officer, Atmospheric Science and Cloud Seeding Division, Malaysian Meteorological Department
19. Mr. Mohd Rizuan Bin Razali, Fire Authority, Water Resources Management Branch, Fire and Rescue Operation
20. Mr. Mohd Ridzuwan Endot, Forest Management Division, Forestry Department Peninsular, Malaysia
21. Mr. Muhamad Azren Bin Abd. Aziz, Assistant Secretary, Disaster Management, National Security Council
22. Mr. Muhamad Sofian Muhamad Yusof, Meteorological Officer, Weather and Climate Model Development Division, Malaysian Meteorological Department
23. Ms. Noor Azura Ismail, Meteorological Officer, Climate and Hydrology Section, Malaysian Meteorological Department
24. Ms. Norizan Binti Abdul Patah, Director, Geospatial Data Development and Analysis Division, Malaysian Remote Sensing Agency
25. Ms. Nur Adira Mahmud, Meteorological Officer, National Weather Center, Malaysian Meteorological Department
26. Ms. Nurul Athirah Ahmad Ezani, Meteorological Officer, Atmospheric Science and Cloud Seeding Division, Malaysian Meteorological Department

27. Mr. Pauzan Bin Ahmad, Chief Operations Management, Fire and Rescue Operation
28. Mr. Ramli Mat, Senior Assistant Director, Forest Plantation & Protection, Forestry Department Peninsular Malaysia
29. Ms. Siti Fariza Mat Tahir, Meteorological Officer, Climate and Hydrology Section, Malaysian Meteorological Department
30. Mr. Zamzul Rizal Bin Zulkifli, Environmental Control Officer, Air Division/Air Quality Data Management Section, Department Of Environment
31. Ms. Zureen Norhaizatul Che Hassan, Meteorological Officer, Weather and Climate Model Development Section, Malaysian Meteorological Department
32. Mr. Kwan Kok Foo, Atmospheric Science & Cloud Seeding Division, Malaysian Meteorological Department

B.1. Field Survey

- **List of resources manager/stake holders interviewed**

Survey areas	Stake holders
Riau Province	1. Nature Conservation Agency 2. Secretary Fire Brigades 3. Fire Brigade Minas 4. Fire Brigade Siak 5. Fire Community Siak 6. BMKG Agency 7. Siak Regency Disaster Management Authority
Central Kalimantan	1. Nature Conservation Agency 2. Sebangau National Park 3. Secretary Fire Brigades 4. Fire Brigade Palangkaraya 5. Fire Brigade Muara Teweh 6. Fire Brigade Kapuas 7. Local Disaster Management Authority
East Kalimantan	1. Nature Conservation Agency 2. Kutai National Park 3. Secretary Fire Brigades 4. Fire Brigade Paser 5. Provincial Land and Fire Control Office 6. Provincial Disaster Management Authority

- **Structured questionnaire form**

1. Are you using weather/climate forecast information?

   ☐ Yes ☐ No

2. If you selected 'yes' in question No 1, what is the source of the forecast information?

   ----

3. If you selected 'yes' in question No 1, How often do you use the 3-6 Month Forecast?

   ① Monthly or less ② Monthly ③ Two to three times a month ④ More than four times a month

4. If you selected 'yes' in question No 1, what is the lead-time of the forecast information?

   ① Short-range forecast (less than 1week) ② Mid-range forecast (1 week ~ 3 month) ③ Long-range forecast (3 month ~ 6 month)

5. If you selected 'yes' in question No 1, what is the time-scale of the forecast information?
   ① Hourly ② Daily ③ Weekly ④ Monthly

6. If you selected 'yes' in question No 1, what is the spatial scale of the forecast information?
   ① Station ② ~50km(grid)
   ③ 50~100km(grid) ④ 100~200km(grid) ⑤ 200km ~ (grid)

7. If you selected 'yes' in question No 1, what is the weather variable of the forecast information?
   □ Precipitation □ Temperature
   □ Relative humidity □ Wind speed □ Solar radiation

8. If you selected 'yes' in question No 1, what is the delivery methods of the forecast information?
   ① Webpage ② Email ③ FTP ④ Mobile App ⑤ Others (_________)

9. If you selected 'yes' in question No 1, how do you think about the accuracy of the forecast information for your fire management work?
   ① Very high ② High ③ Medium ④ Low ⑤ Very low

10. If you selected 'yes' in question No 1, how useful is the forecast information for your fire management work? (How much are you satisfied with the forecast information?)
   ① Very high ② High ③ Medium ④ Low ⑤ Very low

11. If you selected 'Low' or 'Very low' in question No 10, what is the expected lead-time of weather information for improving future forest fire management?
   ① Short-range forecast (less than 1week) ② Mid-range forecast (1 week ~ 3 month)
   ③ Long-range forecast (3 month ~ 6 month)

12. If you selected 'Low' or 'Very low' in question No 10, what is the expected the time-scale of weather information for improving future forest fire management?
   ① Hourly ② Daily ③ Weekly ④ Monthly

13. If you selected 'Low' or 'Very low' in question No 10, what is the expected the spatial scale of forecast information for improving future forest fire management?
   ① Station ② ~50km(grid)
   ③ 50~100km(grid) ④ 100~200km(grid) ⑤ 200km ~ (grid)

14. If you selected 'Low' or 'Very low' in question No 10, what is the expected weather variable of the forecast information for improving future forest fire management (select all)?

□ Precipitation □ Temperature □ Relative humidity □ Wind speed □ Solar radiation

15. If you selected 'Low' or 'Very low' in question No 10, what is the expected delivery method of the forecast information for improving future forest fire management (select all)?

① Webpage ② Email ③ FTP ④ Mobile App ⑤ Etc (_________)

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16. Are you using fire danger early warning information?

□ Yes □ No

17. If you selected 'yes' in question No 16, what is the source of the fire danger information?

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18. If you selected 'yes' in question No 16, How often do you use the fire danger information?

① Monthly or less ② Monthly ③ Two to three times a month ④ More than four times a month

19. If you selected 'yes' in question No 16, what is the lead-time of the fire danger information?

① Short-range forecast (less than 1week) ② Mid-range forecast (1 week ~ 3 month) ③ Long-range forecast (3 month ~ 6 month)

20. If you selected 'yes' in question No 16, what is the time-scale of the fire danger information?

① Hourly ② Daily ③ Weekly ④ Monthly

21. If you selected 'yes' in question No 16, what is the spatial scale of the fire danger information?

22. If you selected 'yes' in question No 16, how many fire danger ranges are provided?

① 2 ② 3 ③ 4 ④ 5 ⑤ greater than 5

23. If you selected 'yes' in question No 16, what is the delivery methods of the fire danger

information?

① Webpage ② Email ③ FTP ④ Mobile App ⑤ Others (_________)

24. If you selected 'yes' in question No 16, how do you think about the accuracy of the fire danger information?

① Very high ② High ③ Medium ④ Low ⑤ Very low

25. If you selected 'yes' in question No 16, how useful is the fire danger information for your work? (How much are you satisfied with the information?)

① Very high ② High ③ Medium ④ Low ⑤ Very low

26. If you selected 'Low' or 'Very low' in question No 25, what is the expected lead-time of the fire danger information?

① Short-range forecast (less than 1week) ② Mid-range forecast (1 week ~ 3 month)
③ Long-range forecast (3 month ~ 6 month)

27. If you selected 'Low' or 'Very low' in question No 25, what is the expected the time-scale of the fire danger information?

① Hourly ② Daily ③ Weekly ④ Monthly

28. If you selected 'Low' or 'Very low' in question No 25, what is the expected the spatial scale of the fire danger information?

29. If you selected 'Low' or 'Very low' in question No 25, what is the expected appropriate number of danger ranges of the information?

① 2 ② 3 ③ 4 ④ 5 ⑤ greater than 5

30. If you selected 'Low' or 'Very low' in question No 25, what is the expected delivery method of the fire danger information for improving future forest fire management (select all)?

① Webpage ② Email ③ FTP ④ Mobile App ⑤ Etc (_________)