# Statistical Downscaling Forecasts for Winter Monsoon Precipitation in Malaysia Using Multimodel Output Variables

LIEW JUNENG AND FREDOLIN T. TANGANG

*Research Centre for Tropical Climate Change System (IKLIM), Faculty of Science and Technology, Universiti Kebangsaan Malaysia, Malaysia*

HONGWEN KANG

*APEC Climate Center, Busan, South Korea, and State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, Beijing, China*

WOO-JIN LEE

*APEC Climate Center, Busan, South Korea*

YAP KOK SENG

*Malaysian Meteorological Department, Petaling Jaya, Selangor, Malaysia*

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ABSTRACT

This paper compares the skills of four different forecasting approaches in predicting the 1-month lead time of the Malaysian winter season precipitation. Two of the approaches are based on statistical downscaling techniques of multimodel ensembles (MME). The third one is the ensemble of raw GCM forecast without any downscaling, whereas the fourth approach, which provides a baseline comparison, is a purely statistical forecast based solely on the preceding sea surface temperature anomaly. The first multimodel statistical downscaling method was developed by the Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) team, whereas the second is based on the canonical correlation analysis (CCA) technique using the same predictor variables. For the multimodel downscaling ensemble, eight variables from seven operational GCMs are used as predictors with the hindcast forecast data spanning a period of 21 yr from 1983/84 to 2003/04. The raw GCM forecast ensemble tends to have higher skills than the baseline skills of the purely statistical forecast that relates the dominant modes of observed sea surface temperature variability to precipitation. However, the downscaled MME forecasts have higher skills than the raw GCM products. In particular, the model developed by APCC showed significant improvement over the peninsular Malaysia region. This is attributed to the model's ability to capture regional and large-scale predictor signatures from which the additional skills originated. Overall, the results showed that the appropriate downscaling technique and ensemble of various GCM forecasts could result in some skill enhancement, particularly over peninsular Malaysia, where other models tend to have lower or no skills.

## 1. Introduction

Short-term climate variability can have negative impact on the socioeconomic well being of the general population of Malaysia. Recurrent flood episodes during the intense winter monsoon period often results in massive evacuation, destruction of public infrastructure, crop yield damage, and loss of lives, particularly in the low-lying areas in the eastern coast of peninsular Malaysia and northern Borneo. For example, the extreme flood event that occurred in southern peninsular Malaysia between December 2006 and January 2007 resulted in the evacuation of more than 200 000 people, 16 deaths, and economic losses of more than 500 million U.S. dollars

*Corresponding author address:* Liew Juneng, Research Centre for Tropical Climate Change System (IKLIM), Faculty of Science and Technology, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor Darul Ehsan, Malaysia.
E-mail: juneng@ukm.my

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(Tangang et al. 2008). In big cities like Kuala Lumpur, frequent flash floods can be a real threat if not properly mitigated. On the other hand, the El Niño–induced prolonged drought often causes severe water shortages; damages rain-fed crops; and exacerbates haze episodes, which in turn can lead to other problems such as poor visibility and unhealthy air quality (Fuller et al. 2004; Gutman et al. 2000; Page et al. 2002). To minimize the damages and associated risks of climate-related disasters, relevant authorities must practice effective climate risk management. Skillful seasonal climate forecasts are relevant to this issue.

Seasonal forecasts are generally provided by a general circulation model (GCM). GCM products such as the European Centre for Medium-Range Weather Forecasts (ECMWF) seasonal forecasts could be useful for large-scale regions such as the greater Southeast Asian region; however, because of their coarse resolution of several hundred kilometers, they may have limited practicality for small-scale local administrative areas within the region. In addition to this, because of the difficulty of simulating rainfall processes, the rainfall forecast of GCMs may not be as skillful as other variables. However, GCMs can provide skillful seasonal forecasts of mean circulation, particularly in the tropics (e.g., Stockdale et al. 1998; Charney and Shukla 1981), and such information may be used to forecast rainfall at a localized area. It has been shown that forecasting skills for rainfall at a local area can be further improved using a statistical downscaling of dynamically forecast atmospheric variables (Feddersen and Andersen 2005; Chu et al. 2008; Landman and Tennant 2000; Pavan et al. 2005). Kang et al. (2007) showed significant skill improvement compared to that of the GCMs when a statistical downscaling of GCM output variables was used to forecast precipitation over some areas in the Philippines and Thailand.

Statistical downscaling aims to specify the empirical relationships between the local-scale rainfall (referred to as the predictand) and the large-scale field (referred to as the predictor). However, if the predictors used are dynamically predicted fields, the scheme is usually referred to as model output statistics (MOS). These relationships are then used to infer local changes by means of projecting the large-scale information onto the variability at local scale (Zorita and von Storch 1999). The technique bridges the scale differences between the coarse resolutions of the GCM output and the local-scale precipitation, and it also possibly corrects the GCM's systematic errors. The major drawback of this approach is the need for a long series of hindcast data of an unaltered model. Every time the GCMs undergo a major update, a long series of hindcast must be recomputed to derive a new empirical relationship between the predictands and predictors.

Another significant advancement in seasonal climate forecasts over the past few decades was the use of compositing multiple GCM forecast techniques to obtain the multimodel ensemble (MME) forecast (Krishnamurti et al. 1999; Palmer and Shukla 2000). The MME technique provides an effective way to handle any uncertainties among the GCMs. Combining the MME and downscaling have proven to have further increased the forecast skills. Kang et al. (2007) showed that the downscaled MME forecasts for some areas in Thailand and the Philippines using six GCMs were more skillful than any individually downscaled GCMs forecast. Chu et al. (2008) also reported a similar conclusion for seasonal precipitation predictions in Taiwan.

Statistical models are less expensive than dynamical models. The skill of the statistical forecast can be used as a baseline comparison for dynamical forecasts (with or without downscaling). In this context, running GCMs cannot be justified if the statistical forecasts are more skillful. However, if the two methods produce comparable skills, the difference between the two types of forecasts can reveal uncertainties. For the Malaysian region, Juneng and Tangang (2008) formulated a purely statistical seasonal prediction system using the canonical correlation analysis method. The model uses dominant modes of observed sea surface temperatures over the Indo-Pacific region for the preceding four seasons. The model generally produced useful skills for areas over northern Borneo for up to 5 months lead time and lower or no skills over peninsular Malaysia. Given the enhancement of skills using MME downscaling over the neighboring countries as highlighted in Kang et al. (2007), the same could be expected for the Malaysian region. In the current study, we examine the seasonal forecast skills of two different MME downscaling techniques: 1) the Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) scheme (Kang et al. 2007) and 2) the canonical correlation analysis (CCA) MME scheme. The skills of these two MME downscaling techniques were compared with the raw MME. A purely statistical CCA model based solely on the observed SST is used as a benchmark (Juneng and Tangang 2008). The next section describes the dataset used in the study. Section 3 elaborates on the results, whereas section 4 provides a summary and conclusions.

## 2. Data and methods

### *a. The datasets*

Hindcast data from seven global models with the target seasons of December–February (DJF) were used as inputs (or predictors) for the statistical downscaling models. These datasets are of the Seasonal Prediction

TABLE 1. Description of the hindcast experiments used in the current study, with the data type being either Seasonal Prediction Model Intercomparison Project/Historical Forecast Project (SMIP/HFP) or CMIP/HFP.

| Acronym | Participating institution | Resolution | Data type |
|---|---|---|---|
| CWB | Central Weather Bureau, Chinese Tapei | T42L18 | SMIP/HFP |
| GCPS | Seoul National University, Korea | T63L21 | SMIP/HFP |
| JMA | Japan Meteorological Agency, Japan | T63L40 | SMIP/HFP |
| GDAPS | Korea Meteorological Agency, Korea | T106L21 | SMIP/HFP |
| METRI | Meteorological Research Institute, Korea | $5° \times 4°$ L17 | SMIP/HFP |
| MGO | Voeikov Main Geophysical Observatory | T42L14 | SMIP/HFP |
| NCEP | National Centers for Environment Prediction | T62L64 | CMIP/HFP |

Model Intercomparison Project (SMIP) type of forecast experiment with 1-month lead time (Kang et al. 2007). The models were developed and operated by seven operational centers (Table 1), and the data were archived at APCC, Busan, Korea. For the Central Weather Bureau (CWB) model, the sea surface temperature (SST) used for lower boundary forcing was the persistence of observation; for the Voeikov Main Geophysical Observatory (MGO), Meteorological Research Institute (METRI), Seoul National University (GCPS), Korea Meteorological Agency (GDAPS), and Japan Meteorological Agency (JMA) models, the SST was the forecasted product. The National Centers for Environment Prediction (NCEP) model was the only coupled model in the group. The variables selected as potential predictor candidates include the sea level pressure (SLP), the 850-hPa air temperature (T850), the surface temperature (T2M), the 500-hPa geopontential height (Z500), the 850-hPa wind velocity fields (U850 and V850), and the 200-hPa wind velocity fields (U200 and V200).

We also compared the GCM's output downscaling approaches with a pure statistical model based on preceding seasonal SST. The SST used was the second version of the optimally interpolated SST (OISST; Reynolds et al. 2002). Four consecutive seasonal anomalies [DJF, March–May (MAM), June–August (JJA), and September–November (SON)] that preceded the targeted season of DJF were stacked to capture the evolution of the SST over a 1-yr period. Further details on the treatment and processing of the SST predictor data are described in Juneng and Tangang (2008). The target rainfall (or the predictand) data were provided by the Malaysian Meteorological Department (MMD). The geographical distribution of the 30 stations used is shown in Fig. 1. These stations are the principle stations from which the collected data were of good quality. The seasonal total was obtained by

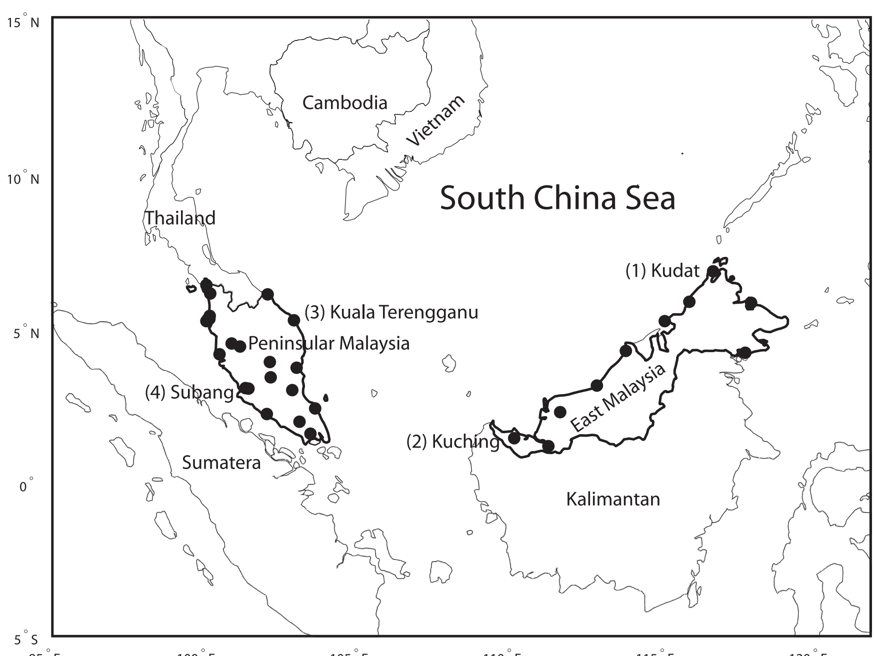



FIG. 1. The geographical distribution of the rainfall stations used in the study. The stations used in Fig. 5 were labeled 1–4.

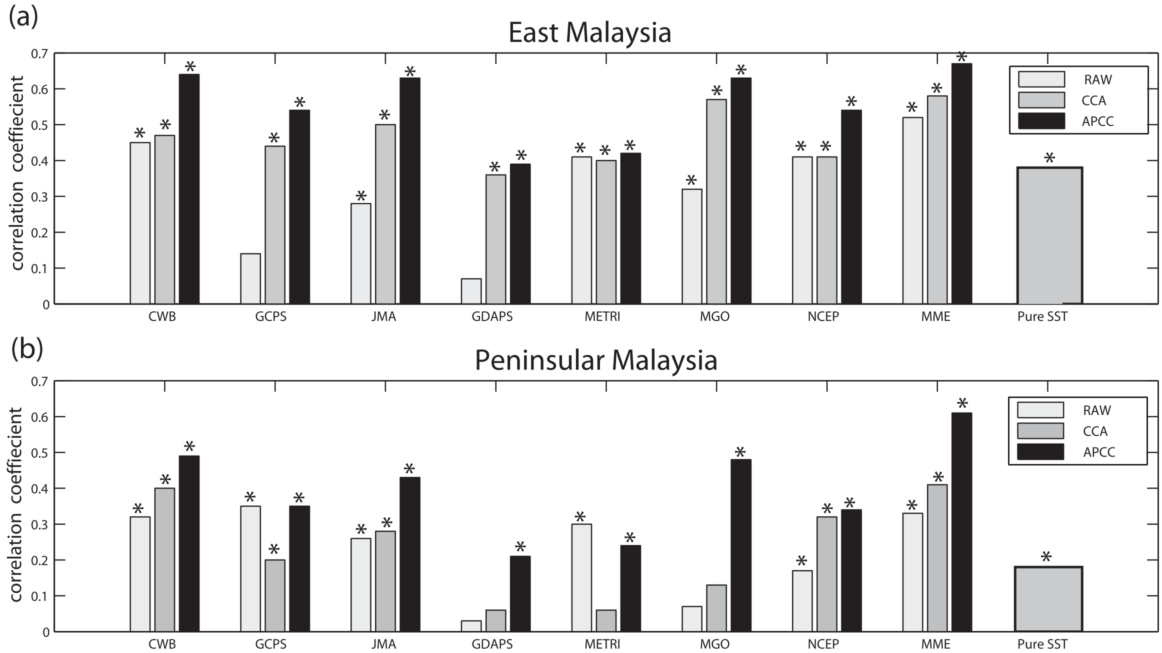



FIG. 2. The correlation skill scores of the raw GCM output (light gray), the CCA downscaling scheme (dark gray), and the APCC downscaling scheme (black) for Malaysian winter monsoon rainfall anomalies averaged over (a) East Malaysia and (b) peninsular Malaysia. The bars with an asterisk indicate averaged skill scores significant at 95% levels.

summation of daily rainfall from each DJF season. Both the predictor field and the precipitation field span a common period of 21 yr from 1983/84 to 2003/04.

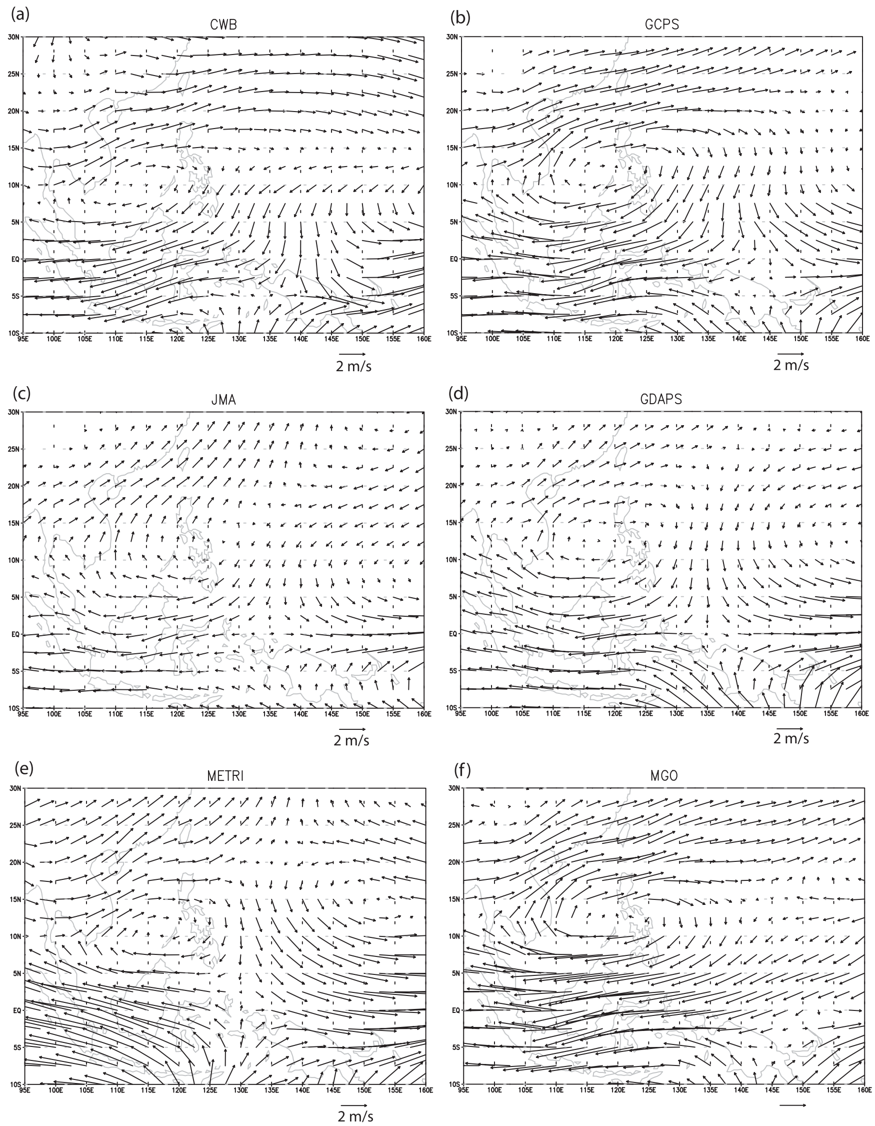
### b. The APCC downscaling scheme

The downscaling scheme developed by the APCC team was based on the multipredictor optimal selection method (Kang et al. 2007). The first step includes the identification of the coupled pattern and transfer function between the station rainfall and the predictor. A movable optimal window scans through the whole globe for an optimal area where the summation of correlation coefficients between predictand and the predictor reaches maximum. The projection of predictors within this optimal window is obtained based on the weighting of the correlation coefficient values. The relationship between the predictor projection and the local rainfall was established using simple linear regression. This method captures the large-scale signals related to the local-scale variability of precipitation and minimizes the impact of climate drift in models (Kang et al. 2007). The process is repeated for each station using each of the eight predictor variables. For each station, the best predictor variables with the highest skill is selected and the established relationship is used for forecast downscaling. This method allows different stations to have different predictors that best describe the variation of the winter precipitation. For each station, the ensemble forecast is represented by a simple composite from each GCM's most skillful prediction. A detailed description of the model is presented in Kang et al. (2007).

### c. Canonical correlation analysis

The CCA technique extracts an optimal linear combination between two multivariate fields to produce maximum correlations (e.g., Barnett and Preisendorfer 1987; Graham et al. 1987; Barnston and Ropelewski 1992; Barnston 1994; He and Barnston 1996; Juneng and Tangang 2008). In this study, the technique was used in downscaling the GCM's output variables and in the pure statistical forecast model in which the observed preceding SST was used as a predictor. In both cases the predictor and target fields were prefiltered separately using the empirical orthogonal function analysis (EOF; e.g., Jackson 1991). The mode selection criterion for both the predictor and predictand fields was based on a minimum of 80% total explained variance. The CCA mode truncation was based on the Guttman–Kaiser criterion where only the modes that have an eigenvalue greater than the average eigenvalue were retained (Jackson 1991; Landman and Tennant 2000).

For the downscaling experiment, the CCA was applied by linking each of the eight predictor variables to the local precipitation field. For a particular GCM model, the best predictor is selected based on the highest average correlation skill over all the stations. The selected CCA relationship between that predictor and the DJF rainfall



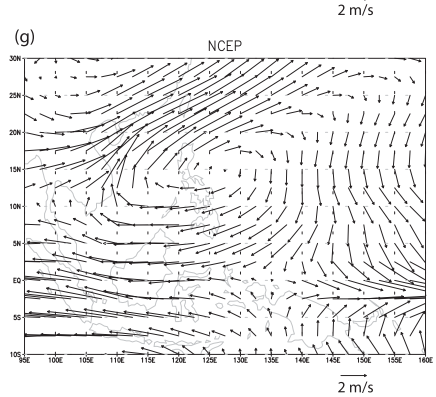




FIG. 3. The El Niño minus La Niña composite of DJF hindcasted 850-hPa winds of (a) CWB, (b) CGPS, (c) JMA, (d) GDAPS, (e) METRI, (f) MGO, and (g) NCEP. The El Niño years (1987/87, 1987/88, 1991/92, 1994/95, 1997/98, and 2002/03) and La Niña years (1984/85, 1988/89, 1995/96, 1998/99, 1999/2000, and 2000/01) were defined by Climate Prediction Center based on the Oceanic Niño Index (ONI).

is used for the downscaling forecast. As in the APCC scheme, a simple average over all downscaling forecasts of all the GCM's candidates was taken as the CCA multimodel ensemble downscaling forecast (CCA-MME).

### *d. Forecast validation*

Artificial skills associated with the overfitting of random noise are a common problem for all empirical

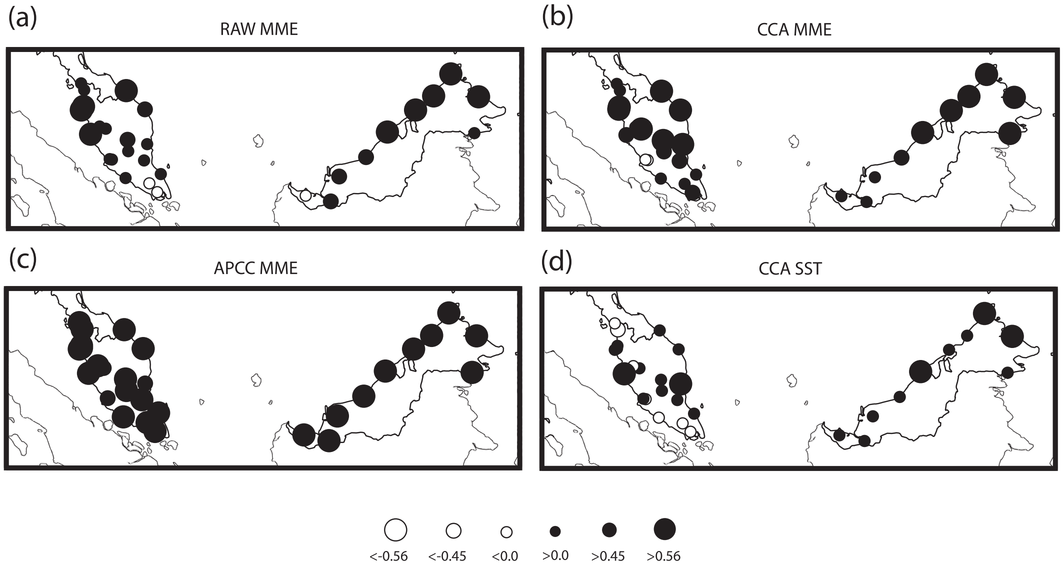



FIG. 4. The spatial distribution of correlation skill scores for the Malaysian winter monsoon rainfall anomalies based on (a) raw GCMs output ensemble, (b) downscaled CCA-MME, (c) downscaled APCC-MME, and (d) pure statistical forecast.

prediction schemes. To minimize such shortcomings, a leave-one-out cross-validation scheme is applied (Barnston and Ropelewski 1992; Barnston 1994; He and Barnston 1996; Yu et al. 1997) for all techniques, including the pure statistical model. This is justified, because the interannual autocorrelation in the data is small and insignificant. The skill score used was the correlation value between the cross-validated time series and the observed precipitation. Given the rather short data period of only 21 yr, the significance of the correlation scores were accessed using a Monte Carlo randomization test (Wilks 1995). For each of the test, 10 000 replicas were used. All the tests were performed at the 95% level.

## 3. Results and discussion

### *a. Cross-validated skill scores*

This section compares the skill scores of four different models: 1) the APCC multimodel ensemble downscaling scheme (APCC-MME); 2) the CCA-MME; 3) raw GCM-simulated rainfall, interpolated to the station coordinates; and 4) a purely statistical model based on observed SST as predictor (CCA-SST). Figure 2 depicts the cross-validated correlation skill scores averaged over two separate regions: East Malaysia and peninsular Malaysia. Anomalous rainfall during the winter season over these two regions appeared to be governed by different mechanisms. The ENSO influence tends to be dominant over East Malaysia (northern Borneo) during the winter season because of anomalous cyclonic/anticyclonic circulation over the western North Pacific during the period (Juneng and Tangang 2005). However, the extent of the circulation does not reach peninsular Malaysia; hence, the ENSO signal is weak over the region. This resulted in much lower seasonal rainfall predictability over peninsular Malaysia than over East Malaysia during this period (Juneng and Tangang 2008).

Consistent with Juneng and Tangang (2008), raw GCM forecasts performed relatively better over East Malaysia than over peninsular Malaysia (Fig. 2). Among the GCMs, the CWB and NCEP models provide high skill scores over East Malaysia, with cross-validated correlation values of 0.45 and 0.50 (significant at 95% level), respectively. The GDAPS model registered the lowest skill score of 0.07 (not significant at 95% level). Averaging the raw GCM simulated precipitation to form the raw GCM ensemble (RAW-MME) provides only a marginal skill improvement, although it is higher overall than any single individual model. This indicates that the multimodel ensemble mean reduces the effect of biases that are specific to individual GCMs. For the peninsular Malaysia region, the GCM's skills appear to be modest with the most skillfull one appearing to be the GCPS, followed by the CWB. Other models such as GDAPS and MGO appear to have very low or no skills over this region. However, the RAW-MME provides only a modest skill improvement compared to both GCPS and CWB models.

The downscaling technique provides skill improvement over the raw GCM forecasts especially for the APCC-MME (Fig. 2). This suggests that the GCMs have less capability in simulating the local precipitation but can simulate the large-scale atmospheric variables

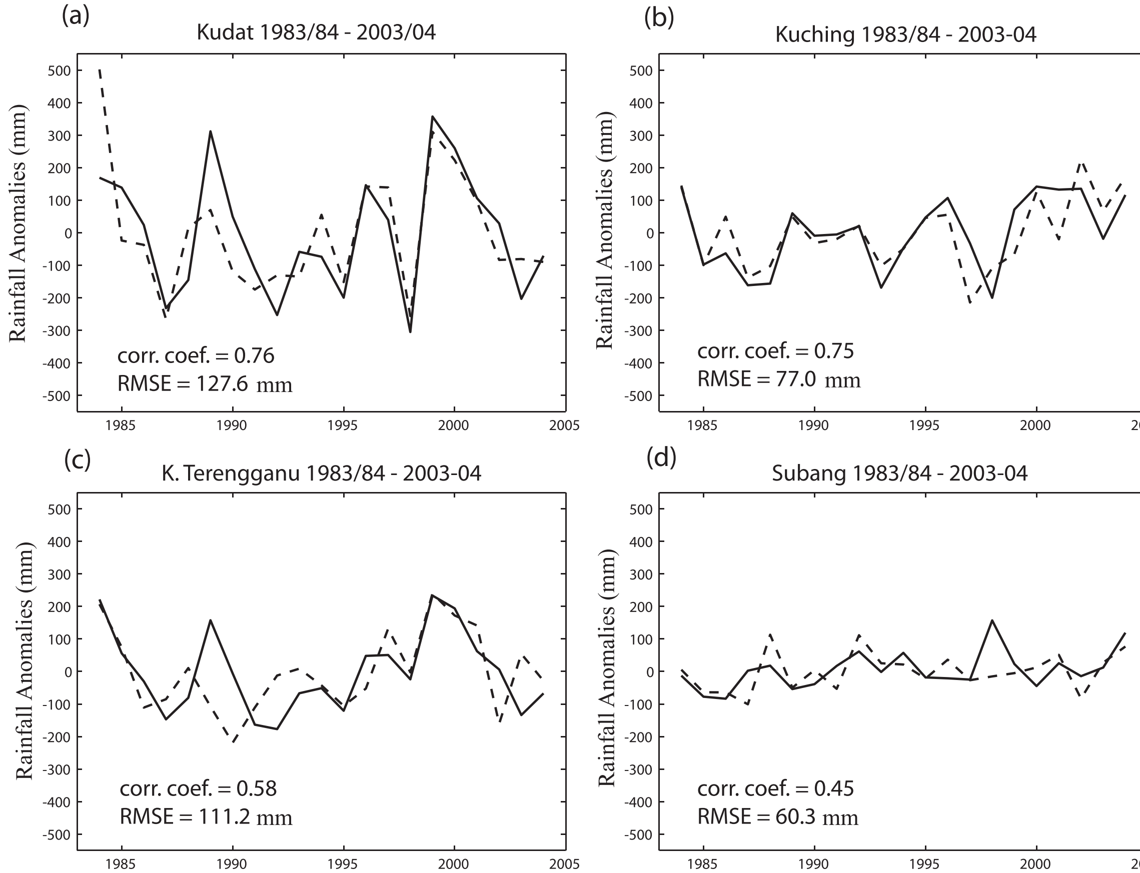



FIG. 5. The observed (dotted) and the APCC downscaled MME (solid) absolute winter monsoon rainfall anomalies at (a) Kudat, (b) Kuching, (c) Kuala Terengganu, and (d) Subang. Both the correlation coefficients and root mean squared errors are shown. The geographical locations of the stations are highlighted in Fig. 1.

relatively well and can be further manipulated to provide a reasonable forecast of seasonal rainfall at local stations. In the Maritime Continent, climate is characterized by strong local convections (Chang et al. 2005). The parameterization of convection in GCMs generally cannot provide information at local or station scale (Neale and Slingo 2003). By downscaling, the large-scale signal in the GCMs can be statistically related to local rainfall, and this can enhance forecast skills. However, the two downscaling techniques tend to perform differently in some models. In the East Malaysian region, the APCC downscaling procedure appears to be superior to that of the CCA technique, except for the GDAPS and METRI models. In peninsular Malaysia, the CCA downscaling technique tends to have much lower skills compared to APCC, especially for the GDAPS, METRI, and MGO models. A general increment of 10%–15% of skill differences can be obtained by using the APCC scheme compared to that of the CCA downscaling method. This could be due to the optimal selection of predictor variables and predictor windows for each of the stations in the APCC scheme, allowing for better extraction of local variability, which may be important at station-scale variation. In the CCA method, prefiltration with EOFs results in a truncation of local variances in both the predictor and the target field. Generally, the APCC downscaling technique performs better over East Malaysia than over peninsular Malaysia. This may suggest that most GCMs capture the large-scale cyclonic/anticyclonic circulation over the western North Pacific during the period of ENSO occurrence in which the skills may originate from. Figure 3 shows the El Niño minus La Niña composites of the hindcasted DJF 850-hPa wind vectors for each of the GCMs used. The Philippine cyclone/anticyclone is generally reproduced in the GCMs, except for slight variations in the intensities and the locations of the center.

The APCC multimodel ensemble forecast performs much better than the CCA multimodel ensemble and the raw GCM multimodel ensemble. In fact, the APCC-MME appears to perform significantly better than the CCA-MME for both regions, with an average skill score exceeding 0.6. In peninsular Malaysia particularly, the

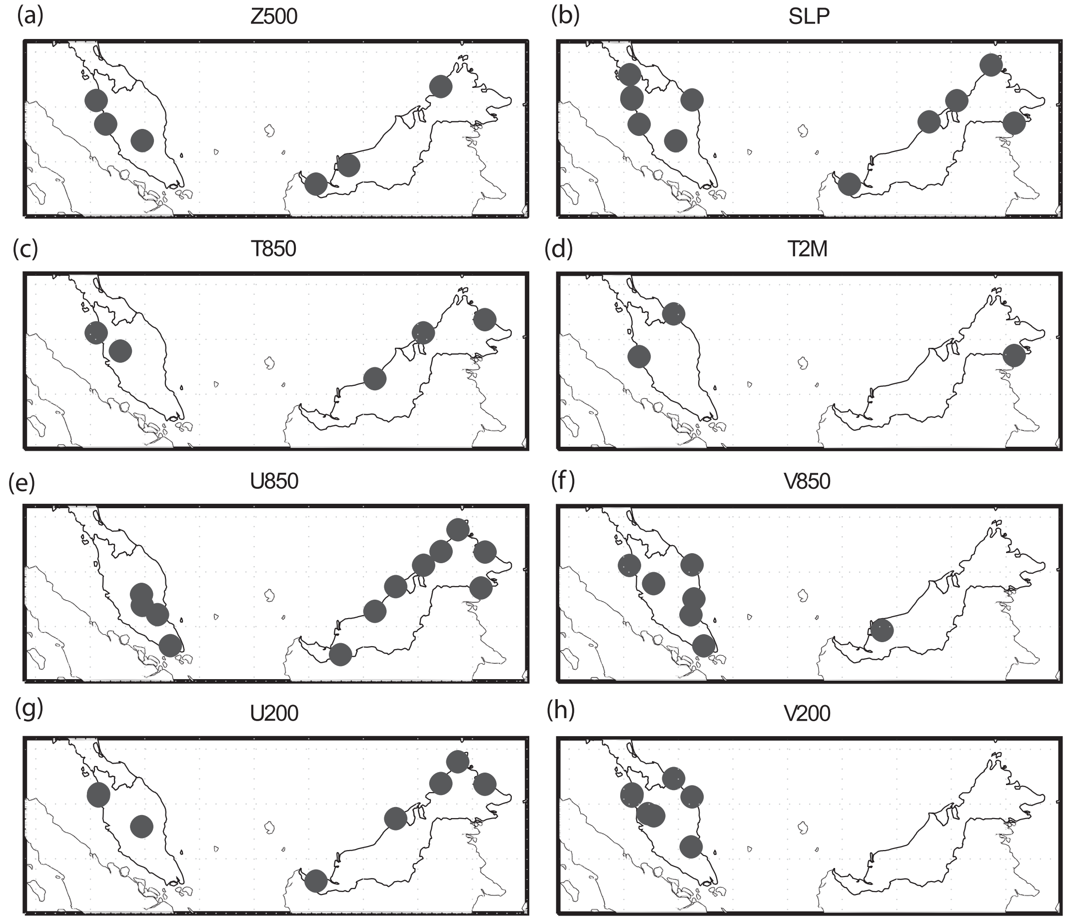



FIG. 6. The stations with significant (95% level) correlation skills of winter monsoon rainfall anomalies using the CWB output fields of (a) Z500, (b) SLP, (c) T850, (d) T2M, (e) U850, (f) V850, (g) U200, and (h) V200.

skills improved twofold compared to the RAW-MME. The improvement of forecast skills by the downscaling and ensemble of the GCM forecast products signifies important progress over previous work. In general, there is essentially no or weak predictability of Malaysian winter monsoon rainfall using purely statistical models over peninsular Malaysia (Juneng and Tangang 2008). As shown in Fig. 2, the skills based on the pure CCA model are much lower than the APCC-MME, especially over peninsular Malaysia. This indicates that the large-scale oceanic information preceding the winter season may not be sufficient to explain the local component of the rainfall variability. In addition to the large-scale signals, the GCMs may also capture regional-scale predictor signals that may have had an influence on the local variability of winter rainfall.

Figure 4 depicts the spatial distribution of skill scores of all MME models, including the pure statistical forecast. Both CCA-SST and RAW-MME show weak or no skills in predicting the rainfall over the southwestern coast of peninsular Malaysia. The CCA-SST in particular forecasted the wrong anomaly signs in several stations over the southwestern coast and northern peninsular Malaysia. The RAW-MME generally produced the correct anomaly signs with modest skills over the northern part of peninsular Malaysia but still failed over the southwestern coast. The downscaled MME seems to increase the skills over the southern region as well as the northeastern coast of peninsular Malaysia. However, the performance of CCA-MME is still weak over western Borneo. The APCC-MME shows superior skill with all the stations registering skill scores over the 95% significant confidence level. The correlation skills range from 0.45 to 0.76 (significant at 95% level). Besides the variance, the scheme also captured most of the high amplitude adequately (Fig. 5). The drought during the 1997/98 El Niño and the subsequent La Niña flood was reasonably captured, especially in northern Borneo (Fig. 5a) and the east coast of peninsular Malaysia (Fig. 5c). However, the skills over central peninsular Malaysia (Fig. 5d)

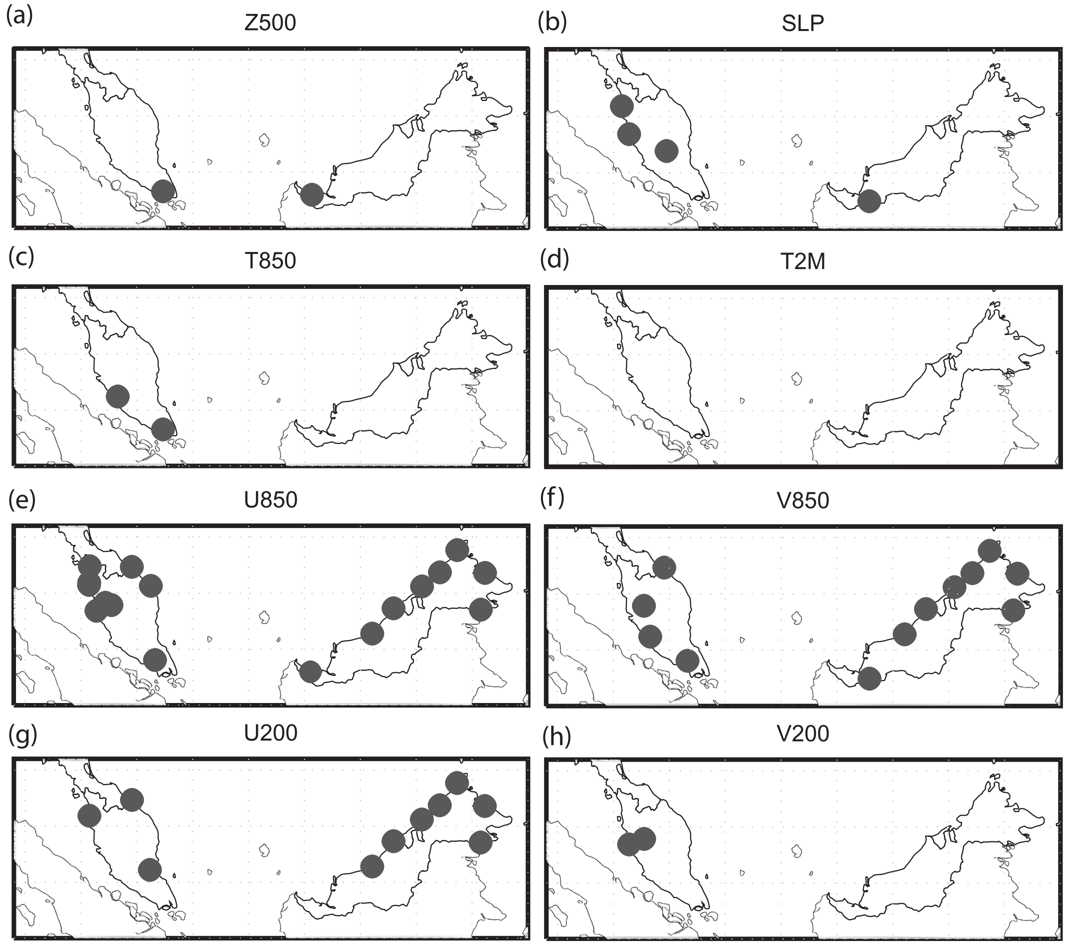



FIG. 7. As in Fig. 6, but for MGO output fields.

remain modest with a correlation value of 0.45 (significant at 95% level).

The APCC downscaling scheme is based on an optimal selection method, which scans through the globe with a moveable window for useful predictors. However, as highlighted by DelSole and Shukla (2009), such a method could artificially inflate the skills because of fortuitous fits. In this case, the source of the skills may not be associated with any physical process that influences the anomalous rainfall. In the following section, we demonstrate that this is unlikely to be the case, because the possible source of the predictability is associated with phenomenon that is known to influence the anomalous rainfall in the region.

### b. *Difference sources of predictability in Peninsular and East Malaysia*

To better interpret the signals of predictability, we carefully examined the skill scores performance of each of the predictor variables for each of the GCMs and selected two GCMs, CWB and MGO, for further examination. Figures 6 and 7 show the stations with significant correlation skills using various model output fields as predictors for CWB and MGO, respectively. Generally, the skills spatial distributions show interpredictor variations. The most skillful predictor for the Malaysian winter monsoon precipitation appears to be U850. With the U850 predictor, both the CWB and MGO attained high skills of correlation, 0.54 and 0.52, respectively, for the East Malaysian region. However, for peninsular Malaysia, the CWB model with U850 as a predictor showed no skill, whereas the MGO skill level was moderate: 0.33. An interesting question to ask is why have the downscaled predictions showed such intermodel variations?

Figure 8 shows the correlation maps of the Malaysian winter monsoon precipitation and the 850-hPa circulations. The precipitation indices are computed as the area average values for Peninsular and East Malaysia separately. The correlation maps for the CWB shows very similar large-scale patterns for both regions, but the magnitude of the correlation was higher for the East Malaysian region. Specifically, the correlations map shows wintertime circulation anomalies during a cold

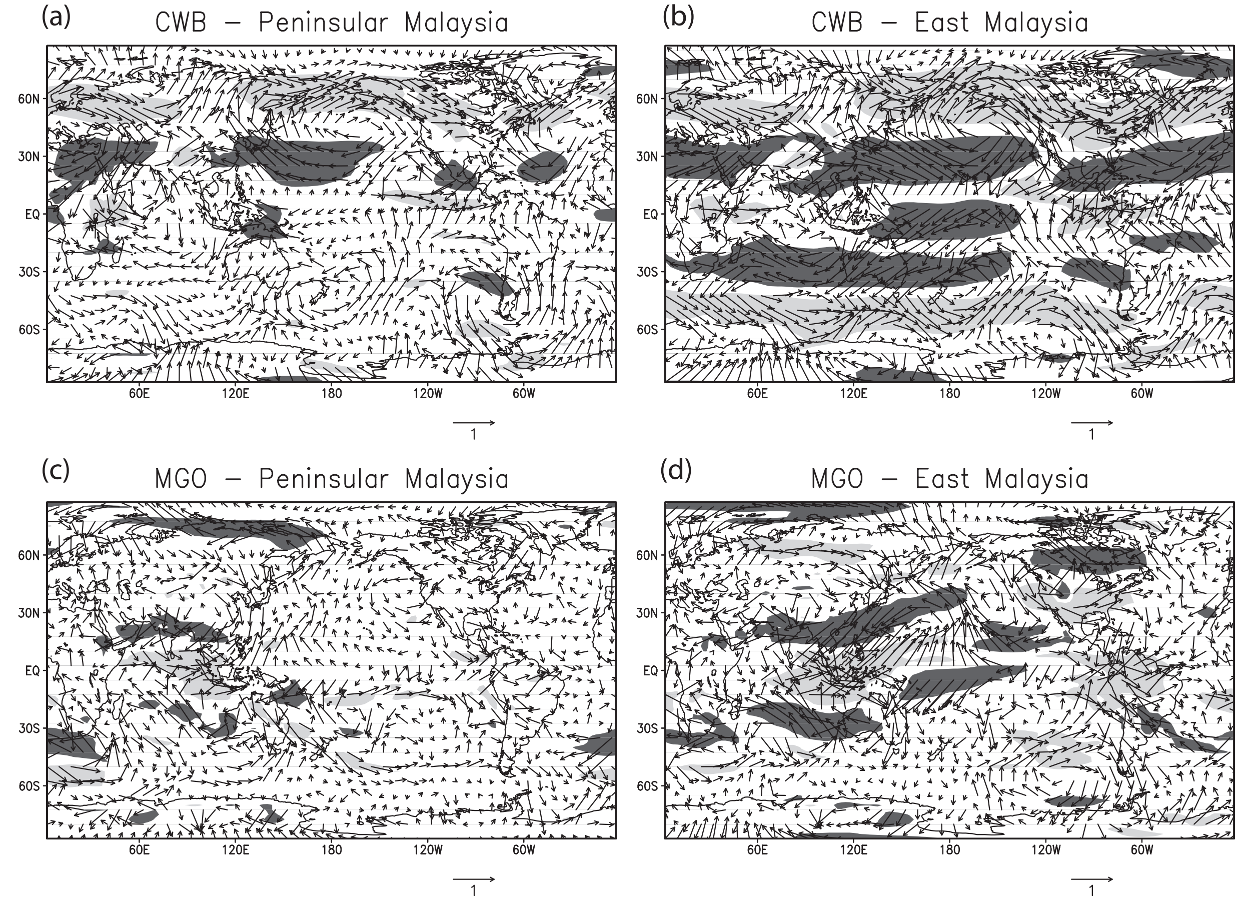



FIG. 8. The correlation coefficients between the CWB 850-hPa horizontal wind and the stations-averaged rainfall anomalies for (a) peninsular Malaysia and (b) East Malaysia regions. (c),(d) As in (a),(b), but for the MGO simulated 850-hPa horizontal wind. The area with correlations between rainfall and the 850-hPa zonal wind above 95% significant level is shaded.

phase of an ENSO event (Juneng and Tangang 2005). This suggests that the large-scale variations simulated by the CWB are important for the prediction of the East Malaysian precipitation but have relatively less influence on peninsular Malaysia precipitation. On the other hand, the correlation maps for the MGO show more regional features. Both the correlation maps for Peninsular and East Malaysia show high regional correlation signals over the Maritime Continent. The correlation map for the peninsular Malaysia suggests that the rainfall anomalies are associated with an anomalous regional-scale cyclonic circulation over the eastern Indian Ocean. The comparable correlation values for both the CWB and MGO over East Malaysia suggest that both regional and large-scale signals are of equal importance to East Malaysian rainfall. However, the relatively diverse regional variations for MGO allowed better downscaling results. Also, the difficulties of most of the GCMs in simulating the regional variations, particularly over the Maritime Continent (Kang et al. 2002; Neale and Slingo 2003), result in a generally poor performance of precipitation prediction in the Peninsular region compared to the East Malaysian region, as indicated in Fig. 2.

## 4. Summary and conclusions

We compare the skill levels of two downscaled multimodel ensemble techniques, the APCC-MME and CCA-MME schemes to the RAW-MME in predicting the Malaysian winter monsoon rainfall. For baseline skills, we also included a purely statistical CCA-based model in the comparison. Generally, the RAW-GCM forecasts are relatively skillful compared to the purely statistical CCA-based model that utilizes the dominant variability signature in the observed SST field as a predictor. This suggests that the GCMs are able to simulate important processes that can be a precursor to the Malaysian winter rainfall anomalies. The GCM prediction is generally better in the East Malaysian stations than those in the peninsular Malaysia region. For peninsular Malaysia, the GCMs tend to have skills over the northwestern region but low or no skills over the southern parts of peninsular Malaysia.

The downscaled forecast products appear to be superior to the RAW-MME GCM forecasts. The CCA-MME appeared to have improved the skills over the northeastern region of peninsular Malaysia. However, it was the APCC-MME that had the most skillful forecasts with the most notable improvement of forecast skills over peninsular Malaysia. Such a skill improvement was attributed to the way the downscaling was formulated. The APCC-MME selects optimal predictors over a moving window by maximizing the correlation between the predictors and the predictands. This technique has the capability of identifying the important local and regional predictors. The CCA-MME, on the other hand, uses dominant features in the predictor fields based on the EOF prefiltering, and that tends to ignore the less dominant but important local and regional features in the predictor fields.

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