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RESEARCH REPORT

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PREFACE

It is our pleasure to present this report on the APEC Climate Center (APCC)'s research activities in 2013, which has been a very productive year for our Center.

APCC has expanded its research scope, in response to regional societal and scientific needs. While building expertise in climate prediction remains a priority, we are extending our reach to include policy-relevant climate applications and value-added climate information products.

APCC has accelerated efforts to better our service to the region. As one of the main services provided by APCC, the MME 3-month prediction information has been productively applied by scientists in developing countries that are unable to produce their own prediction information. Furthermore, in order to better prepare for climate-related hazards in a timely manner, APCC launched its 6-month MME prediction service in September 2013. We also began to release forecasts of the Boreal Summer Intraseasonal Oscillation (BSISO), starting from July 2013, as the world's first operational BSISO forecast service. Our researchers also achieved great success in publishing their papers in noted academic journals. Dr. Ok-Yeon Kim, for example, published a paper in *Climate Dynamics* and her research was later selected as one of the Research Highlights by another distinguished journal, *Nature Climate Change*. The following research report provides more information about our research outcomes from 2013.

We will continue to promote the best use of our research outcomes in various scientific and application areas. Our successes and achievements would not have been possible without the support of our valued partners. In this regard, I extend my thanks to you and I hope you enjoy this 2013 Research Report.

Chin-Seung Chung
Director, APEC Climate Center

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Dr. Ok-Yeon Kim | Climate Change Research Team

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Prediction of the Seasonal Tropical Cyclone Activity in the Western North Pacific using an APCC MME-based Statistical Approach

Dr. Ok-Yeon Kim | Climate Change Research Team

ABSTRACT

This paper describes the development of the APCC multi-model ensemble (MME)-based dynamical- statistical model for predicting tropical cyclone (TC) activity during the western North Pacific (WNP) TC season. The model is based on the statistical relationship between the interannual variability of the number of the WNP TCs during the active TCs season (July-October; JASO) and the APCC MME predicted variability of the key predictors for this season. Note that one or two key predictors are selected for each predictand (i.e., tropical storms, typhoons, and intense typhoons) by forward selection. This model provides a combination of statistical and dynamical methodologies, thus realizing better skill than the statistical as well as dynamical method. Further, MME prediction, which is used to derive the predictors for the statistical model, is more skillful in the seasonal forecasts than other individual models considered.

The leave-one-out cross validation results of the APCC MME-based retrospective dynamical-statistical model demonstrate its high skill in predicting TC number when using APCC MME-based predictors; the correlation coefficients range from 0.51 to 0.68. A comparison between the observed number of TCs and the APCC MME real-time TC forecasts also demonstrates that the APCC MME seasonal prediction has high skill in forecasting the seasonal TCs in the WNP during JASO. The information derived from the APCC MME-based model for predicting the TC number may be valuable, in particular to the people residing in the tropical cyclone-prone areas in the Asia-Pacific region.

1. INTRODUCTION

With the increase in tropical cyclone (TCs) activity in the western North Pacific (WNP) in the recent decades (Kim et al. 2011; Zhou et al. 2011) and the increase in the severity of the damage caused by TCs in many coastal regions (Kim et al. 2012), there has been a growing demand for seasonal TC forecasts over an extended range with several months' lead times. With the improvement in seasonal climate prediction and seasonal TC forecasts, more attention has been given to the details of seasonal TC activities (e.g., frequency and intensity). Forecast centers in various countries have issued and shared information about seasonal TC forecasts; a list of some of the agencies that issue TC seasonal forecasts for the WNP is presented in Table 1 (Klotzback et al. 2012).

Table 1 Agencies that issue forecasts for various tropical cyclone basins; S stands for a statistical approach and D represents a dynamical approach

	North Atlantic	Eastern North Pacific	Central North Pacific	Western North Pacific	Australia Region	North Indian Ocean	South Indian Ocean	South Pacific Ocean
City University of Hong Kong, China				S				
Colorado State University, USA	S							
Cuban Meteorological Institute, Cuba	S							
European Centre for Medium-Range Weather Forecasts, UK	D	D		D	D	D	D	D
International Research Institute for Climate and Society, USA	D	D		D	D			D
Macquarie University, Australia					S			S
National Meteorological Service, Mexico		S						
National Climate Centre, China				S				
NOAA Climate Prediction Center, USA	S	S	S					
Tropical Storm Risk, England	S			S	S			

Source: Seasonal Forecasting of Tropical Cyclones, in Global Guide to Tropical Cyclone Forecasting (WMO report; Klotzbach et al. 2012)

Seasonal TC forecasts are made mainly by adopting a dynamical approach or a statistical approach (Zhan et al. 2012). In the first approach, dynamical information obtained directly from coupled atmospheric-ocean climate models are used for seasonal TC prediction (e.g., Camargo and Zebiak 2002; Vitart 2006; Camargo and Barnston 2009; Alessandri et al. 2011; Park et al. 2011). TCs are identified and tracked on the basis of the definition of the criteria, i.e., the thresholds and the domain over which they are computed. Fully coupled high-resolution GCMs are essential to this approach. In the second approach, empirical predictand-predictor relations based on lagged relationships from previous seasons are employed for TC prediction (e.g., Chan et al. 2001; Goh and Chan 2010, 2012; Kim et al. 2010). Here, the predictand, i.e., TCs activities are predicted on the basis of empirically determined relationships by using predictors based on large-scale atmospheric-ocean dynamics (e.g., the recent evolution of sea surface temperature (SST) anomalies as an example of a predictor). Several works have focused on the second approach on the basis of the consideration that model-based predictions of seasonal mean large-scale fields can be used as a set of predictors for the statistical prediction of TC activity. Wang et al. (2009) made the first attempt to build an empirical relationship between the observed interannual variability of hurricanes in the Atlantic and the variability of SST and vertical wind shear (VWS) in 26-yr (1981-2006) hindcasts from the National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS). Kim and Webster (2010) furthered this study and developed a hybrid forecast model of the seasonal hurricane activity in the North Atlantic. Their model combined the European Centre for Medium-range Weather Forecast (ECMWF) hindcasts (29 years; 1981-2009) and an empirical model to forecast extended-range seasonal hurricane numbers for the North Atlantic. Kim et al. (2012) also employed the hybrid statistical-dynamical technique to develop a track-pattern-based model for the prediction of seasonal TC activity in the WNP. They used seasonal large-scale information from the NCEP CFS retrospective forecasts to develop the hybrid statistical-dynamical model. These studies showed that the forecast skill of the hybrid forecast model was better than or at least comparable to that of other publically available models. This research focuses on the development of such an approach for predicting the seasonal TC activity in WNP.

The Asia-Pacific Economic Cooperation (APEC) Climate Center (APCC) has employed the multi-model ensemble (MME) seasonal forecast system for several years now. From the viewpoint of seasonal forecasts, the skill of the MME system is higher than that of the single-model component (Palmer et al. 2004; Hagedorn et al. 2005; Weigel et al. 2008; Wang et al. 2009). This is so because the MME may reduce the model errors in individual models by combining ensembles from different agencies, i.e., combining different analyses and forecast models. Therefore, the APCC MME seasonal forecasts were used to develop a seasonal TC forecast model in this work.

The objective of this study is to establish a seasonal TC activity prediction system for the WNP by combining the APCC MME dynamical prediction system with a statistical model. Dynamical model-based predictions of large-scale variables are used as a set of predictors in the statistical forecasts of TC activity over an extended range (July-August-September-October, JASO) with lead times of several months. To accomplish our purpose, we first examine (1) the predictive skill of the APCC MME seasonal hindcast datasets for the WNP; (2) the relation between the variables (predictors) from the APCC MME and the variability of the WNP TCs; i.e., which fields can be selected as potential predictors; (3) the performance of the APCC MME hindcasts-based statistical prediction system in reproducing historical seasonal TC activity; and (4) the comparison of the skills of the seasonal TCs activity forecasts based on the APCC MME real-time forecasts with those of the forecasts issued by other operational centers.

2. DATA AND METHODS

2.1 Observation and Reanalysis

The observational TC location data used in this study are archived from Joint Typhoon Warning Center (JTWC) Western North Pacific best track data. The dataset includes information on latitude and longitude, the maximum sustained wind speed, and the minimum sea level pressure. Although this dataset provides TC information over the whole year, this study focuses on TCs formed during JASO, which covers about 80% of the annual number of TCs in the WNP. We define tropical storms as systems whose maximum sustained wind speed is greater than or equal to 34 knots (this definition includes typhoons and intense typhoons whose maximum sustained wind speeds exceed 64 and 85 knots, respectively) on the basis of the tropical cyclone intensity scale prescribed by the Regional Specialized Meteorological Centers (RSMC), Tokyo. The observational SST and wind data covering the 27-yr (N) period 1982-2008 are from National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation (OI) SST v2 (Reynolds et al. 2002; hereinafter, NOAA OISST) and National Centers for Environmental Prediction (NCEP)-National Center for Atmospheric Research (NCAR) Reanalysis II (Kanamitsu et al. 2002; hereinafter, NCEP-R2) on a 1° (longitude) by 1° (latitude) grid and a 2.5° (longitude) by 2.5° (latitude) grid, respectively. The other parameters used are zonal wind at 850 (U850) and 200 hPa (U200), relative vorticity at 850 hPa (VOR), and vertical wind shear (VWS), which is defined as the difference in zonal wind between 200 hPa and 850 hPa (U200-U850). JASO seasonal mean of these variables are obtained by averaging the four monthly mean values.

2.2 Hybrid dynamical-statistical prediction method

As mentioned above, we employ a climate model-based statistical approach to develop a seasonal TC activity prediction system. We utilize the empirical relationship between coupled atmosphere-ocean dynamical climate model forecasts of key atmospheric and oceanic anomalies and the observed seasonal tropical cyclone activity (Wang et al. 2009). A brief description of the APCC coupled climate model forecasts and the introduction of a statistical method used in this study is given in this sub-section.

1) The APCC coupled MME system

Seasonal climate hindcasts and real-time forecasts from five coupled models from the Meteorological Service of Canada (MSC), National Aeronautics and Space Administration (NASA) of USA, National Centers for Environmental Prediction (NCEP) of USA, and Pusan National University (PNU) of Korea are used in this study. A brief description of these one-tier prediction models is provided in Table 2.

Table 2 Description of the APCC one-tier prediction models

Country	Institute	Model name	AGCM/resolution	OGCM/resolution	Ensemble No.
Canada	MSC	MSC_CANCM3	AGCM3/T63L31	OGCM4/CanOM4 (1.41°lon × 0.94°lat L40)	10
Canada	MSC	MSC_CANCM4	AGCM4/T63L31	OGCM4/CanOM4 (1.41°lon × 0.94°lat L40)	10
USA	NASA	NASA	GEOS-5/288x181 L72	MOM4/720 × 410 L40	9
USA	NCEP	NCEP	GFS/T62L64	MOM3/ $\frac{1}{3}$°lat × 1°lon L40	15
Korea	PNU	PNU	CCM3/T42L18	MOM3/0.7-2.8lat L29	10

In this study, we construct the MME using the simple composite method (SCM). In the SCM, equal weights are assigned to the ensemble mean prediction of each model under the assumption that each model is relatively independent and that each has the capability to accurately forecast the climate to some extent. The mean bias from each model is removed by calculating anomalies with respect to the each model's own seasonal climatology. We use the hindcasts and real-time forecasts of the five selected coupled models for the JASO season with the initial conditions (ICs) of 1 June (one-month lead seasonal prediction), 1 May (two-month lead seasonal prediction), and 1 April (three-month lead seasonal prediction).

2) Statistical prediction

The statistical prediction method adopted for the development of dynamical-statistical model is based on least absolute deviation (LAD) regression, which minimizes the sum of absolute errors (SAE; Wilks 2006). LAD regression differs from ordinary least squares (OLS) regression in that the SAE is used instead of the sum of squared errors; the SAE of the fit from the observation values is minimized to obtain the regression coefficients and constant in the multivariate linear regression. Therefore, LAD regression is less influenced by outliers than is OLS regression. In addition, LAD regression is more appropriate for small sample sizes because it does not involve the assumption that the residuals follow a Gaussian distribution (Kim et al. 2010). Hence, LAD regression has been widely used for the statistical models to predict the seasonal TC activities in various ocean basins (e.g., Gray et al. 1992, 1993, 1994; Chu et al. 2007; Kim et al. 2010). Kim et al. (2010) mentioned that LAD regression exhibits good predictive skill for summertime TC frequency over the East China Sea.

3. RESULTS AND VALIDATION

3.1 APCC MME predictive skill

Since the simultaneous large-scale environmental fields from the APCC MME hindcasts are used as the potential predictors for the dynamical-statistical TC activity forecasts, we first analyze the predictive skills of APCC MME hindcasts for the large-scale variables, including SST, VWS, VOR, and zonal wind at 850 and 200 hPa. The APCC MME hindcasts predictive skill for the variables during JASO season is cross validated by correlating APCC MME hindcasts anomalies with the observations. The forecast anomaly of the JASO season is defined as the deviation from the 26-yr (N-1) seasonal mean climatology that does not include the target season.

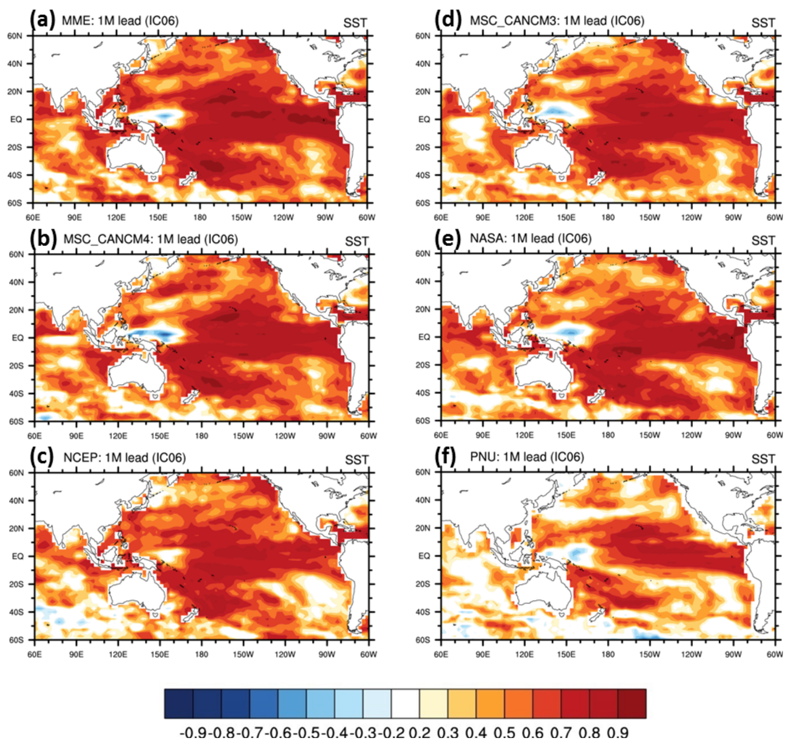

Figure 1 Anomaly correlations between the observed JASO SSTs and (a) APCC MME and (b)-(f) individual model hindcasts of JASO SSTs at 1-month lead time (IC06) over the period 1982-2008 (27 years). Correlations (shaded) between -0.2 and 0.2 are omitted.

Figure 1 shows the spatial distribution of anomaly correlations between the observed and the APCC models' hindcasts for JASO SST at 1-month leads (IC06). APCC MME and individual models exhibit high predictive skill for JASO SST over the central and eastern equatorial Pacific. The models MSC_CANCM3, CM4, and NCEP (Figure 1(b)-(d)) exhibit higher predictive skills than the other models. APCC MME (Figure 1(a)) exhibits the highest predictive skill among the individual models; thus, APCC MME, with an anomaly correlation skill reaching 0.8, is capable of predicting the interannual variation in SSTs over the central and eastern equatorial Pacific in JASO season.

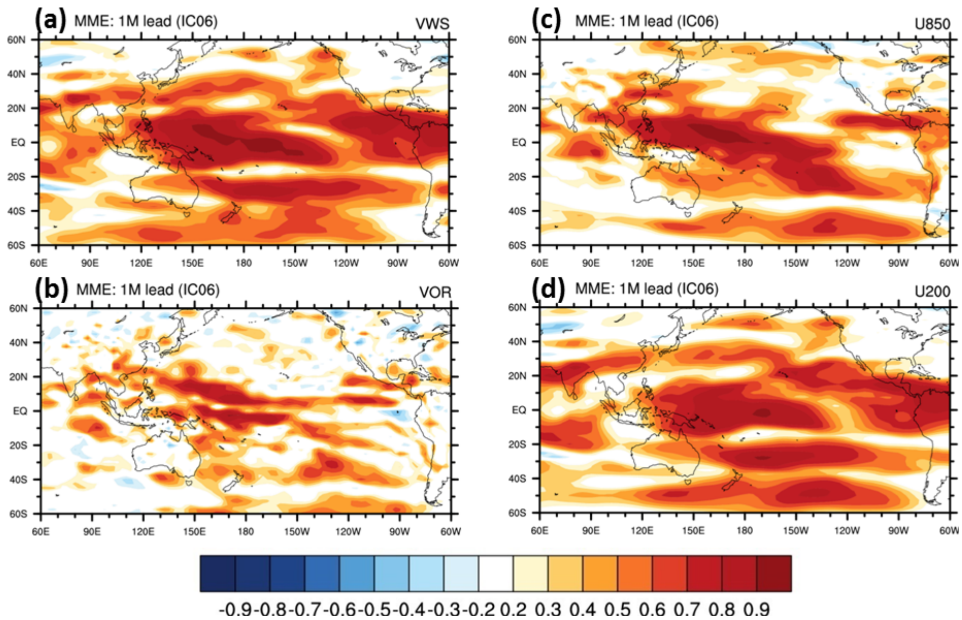

Figure 2 Anomaly correlations between the observed and APCC MME hindcast JASO (a) VWS, (b) VOR, (c) U850 and (d) U200 at 1-month lead time (IC06) over the 27-yr period 1982-2008. Correlations (shaded) between -0.2 and 0.2 are omitted.

Figure 2a shows the anomaly correlation distribution between the observed and APCC MME hindcasts JASO VWS at 1-month lead (IC06). APCC MME demonstrates high predictive skills in simulating the seasonal VWS over the tropical western and central Pacific, where the horizontal distribution of zonal VWS is closely related to TC development and activity (Chan and Liu 2004; Aiyyer and Thorncroft 2011). As in the case of SST, APCC MME exhibits the highest predictive skill among the individual models in reproducing the interannual variation in JASO VWS in the western and central equatorial Pacific.

The map of anomaly correlation between the observed and APCC MME hindcast JASO VOR at 1-month lead (IC06) revealed high skill in simulating seasonal JASO VOR over the western and central equatorial Pacific (Figure 2b). Relative vorticity in these regions is one of the vital factors for the genesis of TCs in the WNP (Chan and Liu 2004; Goh and Chan 2012; Kim et al. 2012). In addition, the relative vorticity associated with the monsoon trough in the WNP is an important factor for the formation of TCs in the western and central equatorial Pacific (Holland 1995; Stowasser et al. 2007). As in the case of SST and VWS, APCC MME exhibits the highest skill among the other models in simulating JASO VOR.

The spatial maps of anomaly correlation between the observations and APCC MME hindcast JASO U850 and U200 are also shown in Figures 2c and 2d. The model exhibits significant predictive skill for the equatorial western and central Pacific. The anomaly correlation is as high as 0.8 at the 1-month lead in this region. The correlations for U200 are significant over a wider extent than those for U850 (Figure 2c).

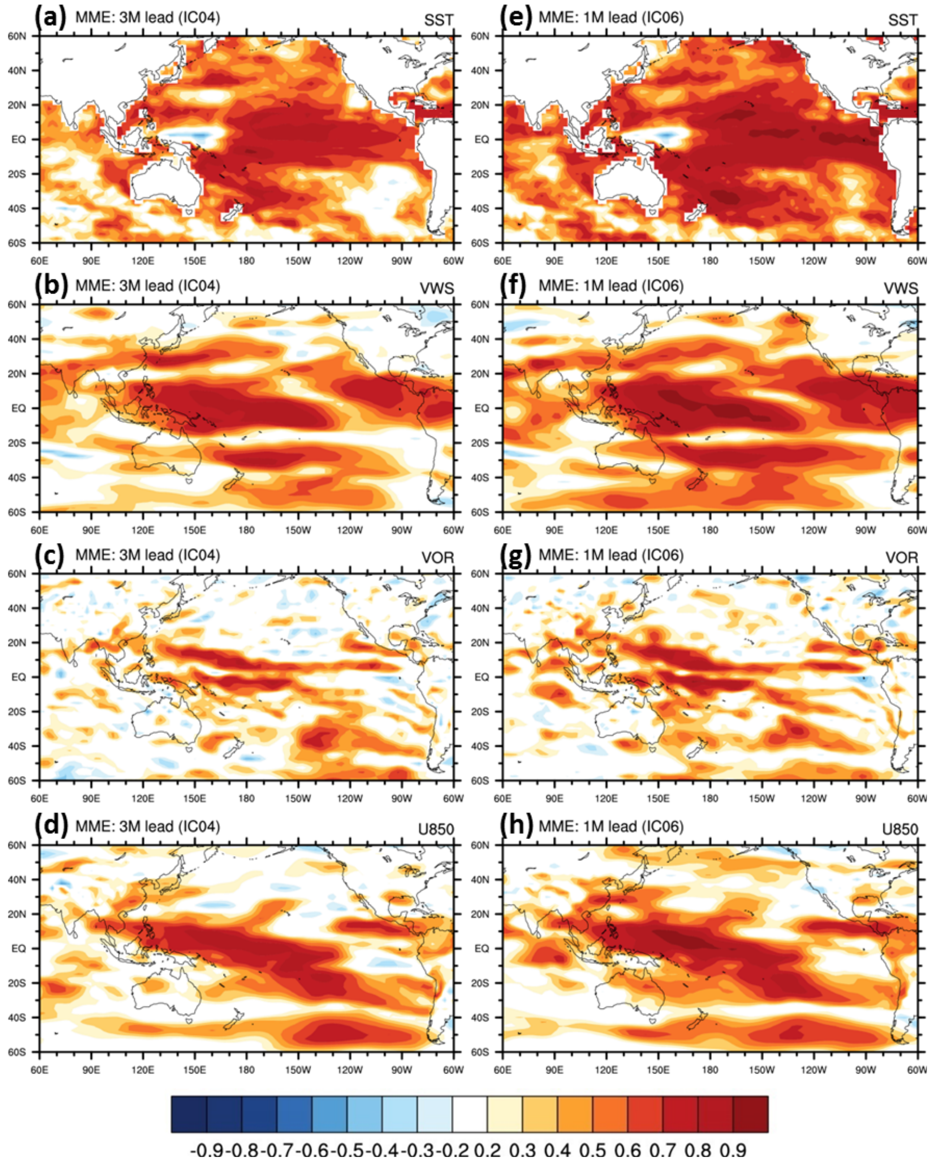

Figure 3 Anomaly correlation between the observed and APCC MME hindcast JASO (a), (e) SST; (b), (f) VWS; (c), (g) VOR; and (d), (h) U850 with different lead times (left column: 3-month lead, i.e., IC04; right column: 1-month lead, i.e., IC06) over the 27-yr period 1982-2008. Correlations (shaded) between -0.2 and 0.2 are omitted.

Figure 3 shows the spatial distribution of the anomaly correlation between the observed and APCC MME hindcast JASO large-scale fields at different lead times (2-month (IC05) and 3-month (IC04)). The skill slightly increases over the eastern/central (for SST, Figure 3a and 3e) and western/central Pacific (for VWS, VOR and U850, Figure 3b-d and 3f-h) with the decreases in forecast lead time. Compared to the predictive skill for VOR and U850 (Figure 3c, g and 3d, h), the predictive skill for SST and VWS (Figure 3a, e and 3b, f) is less sensitive to the length of the forecast lead time. In general, APCC MME hindcasts reasonably represent the observed large-scale anomaly fields that are potentially related to the WNP TC activity, regardless of the forecast lead time.

3.2 Variability of WNP TCs and its relation to potential predictors

1) Variability of WNP TCs

An analysis of the time series of the number of observed seasonal TCs from 1982 to 2008 together with its linear trends and the corresponding detrended time series (Figure 4), revealed a slightly decreasing trend of tropical storms (TS, Figure 4(a)) and typhoons (TY, Figure 4(b)), but no trend in the case of intense typhoons (ITY, Figure 4(c)). The averaged total number of the seasonal WNP TS, TY, and ITY over the entire 27-yr year period are 18.7, 12.3, and 8.6, respectively, and these are considered the long-term climatology of the seasonal TC activity. The standard deviations of the total number of TCs and the detrended interannual component are very similar (3.5, 3.0, and 2.7 for TS, TY, and ITY, respectively), indicating that the interannual change dominates the WNP TC variability. Therefore, the detrended interannual fluctuations are considered as the base time series in the following analysis.

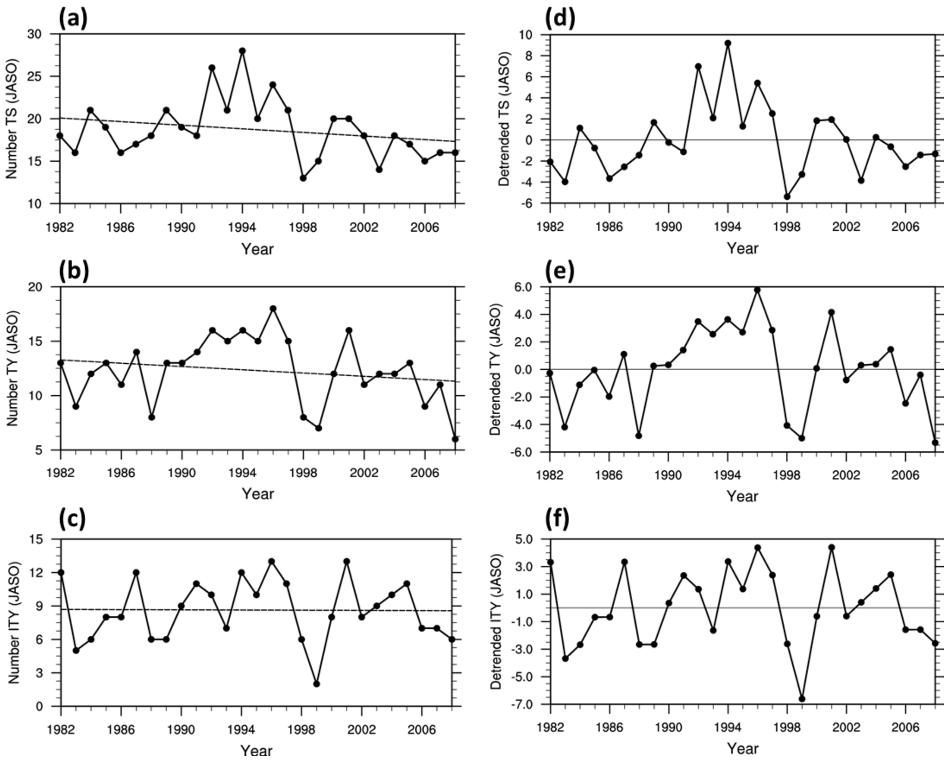

Figure 4 Time series of the number of (a) tropical storms, (b) typhoons, and (c) intense typhoons during the TC season (JASO) from 1982 to 2008; (d)-(f) show the same time series after detrending.

2) Relation to potential predictors

We next examine how the interannual variabilities of TCs are related to the observed and APCC MME hindcast JASO SST, which is one of the potential predictors in the dynamical-statistical model. Figure 5 shows the correlations between the detrended interannual variations in TY (Figure 5(a)-(c)) and ITY (Figure 5(d)-(f)) and JASO SST from observations (Figure 5(a) and (d)) and the APCC MME hindcasts with 3-month (Figure 5(b) and (e)) and 1-month (Figure 5(c) and (f)) lead time. Note that the distributions of correlations for TS are very similar to those for TY and ITY (not shown). On the interannual timescale, the correlations of APCC MME hindcast SST with TCs are similar to those for the observed SST. This is the El Niño pattern with significant positive correlations in the tropical eastern and central Pacific.

The interannual variations in TCs activity in the WNP is mostly controlled by the El Niño-Southern Oscillation (ENSO) phenomenon (Chan 2000; Chan and Liu 2004). That is, in El Niño years, the TC activity appears to be more intensified than that in the La Niña years (Camargo and Sobel 2005; Chan and Liu 2004). Recently, Zhan et al. (2011) also demonstrated that ENSO modulates the conversion of barotropic energy from a large-scale flow to a synoptic disturbance over the WNP, which contributes to changes in the frequency of intense TCs. This influence of the El Niño on the TC activity in the WNP is well represented in the APCC MME hindcast SST because the APCC coupled MME prediction can simulate the ENSO SST anomalies (Jeong et al. 2012).

The magnitude of correlation with the APCC MME hindcasts SST depends on the forecast lead time. The correlations with 1-month lead time (IC06, Figure 5(c) and (f)) are relatively higher in the tropical eastern and central Pacific than those with 3-month lead time (IC04, Figure 5(b) and (e)). In addition, the difference in the strength of correlations with different lead times is more obvious in the case of ITY (Figure 5(e) and (f)) than TY (Figure 5(b) and (c)). On the basis of the correlation distribution between the APCC MME hindcast SST and the observed interannual variations in the WNP TCs, we decided to use SST averaged over the tropical Pacific (0°-20°N, 160°E-120°W) as one of the potential predictors for the interannual variation in the WNP TC activity. Since the APCC MME predictive skill for SST (Figure 1) is high in this region, this result validates the use of SST in that region as the potential predictors for the interannual variation in the WNP TC activity.

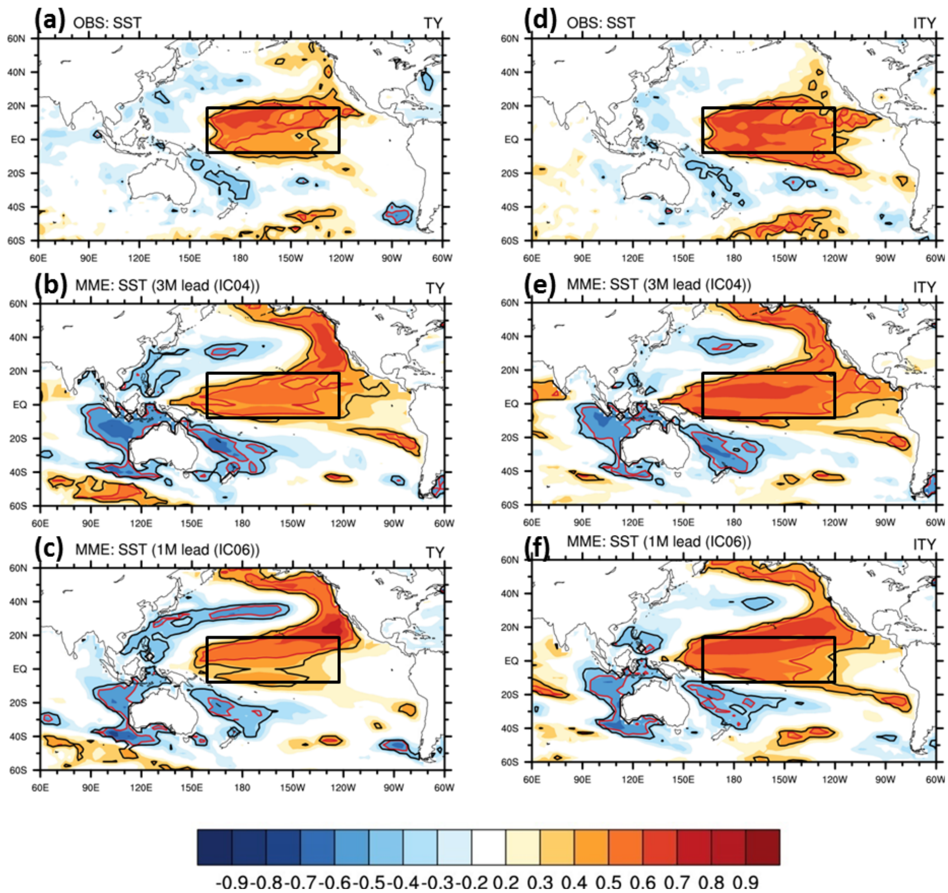

Figure 5 Correlations of (a), (d) observed and (b), (c), (e), and (f) APCC MME hindcast JASO SST with the 27-yr (1982-2008) time series of detrended interannual variation in (a)-(c) TY and (d) - (f) ITY. The APCC MME hindcast SST are from (b), (e) April ICs (3-month lead, IC04) and (c), (f) June ICs (1-month lead, IC06). Correlations (shaded) between -0.2 and 0.2 are omitted. Black (red) solid lines indicate correlations above the 5% (1%) significance level. Boxes indicate the region where SSTs are averaged and used as predictors for the dynamical-statistical forecasts of TC activity in the WNP.

As shown in the correlation distribution between the observed interannual variation in TCs and the observed JASO VWS (Figure 6(a) and (d)), the interannual variability of TCs is associated with a significant negative wind shear in the tropical central Pacific. Clark and Chu (2002) reported a substantial reduction in vertical wind shear equatorward of 18°N over the eastern portion of the WNP during El Niño events when intense TCs exhibit a long life span. This pattern is well represented in the correlation map with the APCC MME hindcasts (Figure 6(b)-(c) and 6(e)-(f)).

Note that the observed interannual changes in TCs are related to the increased APCC MME hindcast VWS in the northern and southern parts of the central Pacific, which is not clearly observed from Figure 6(a) and (d).

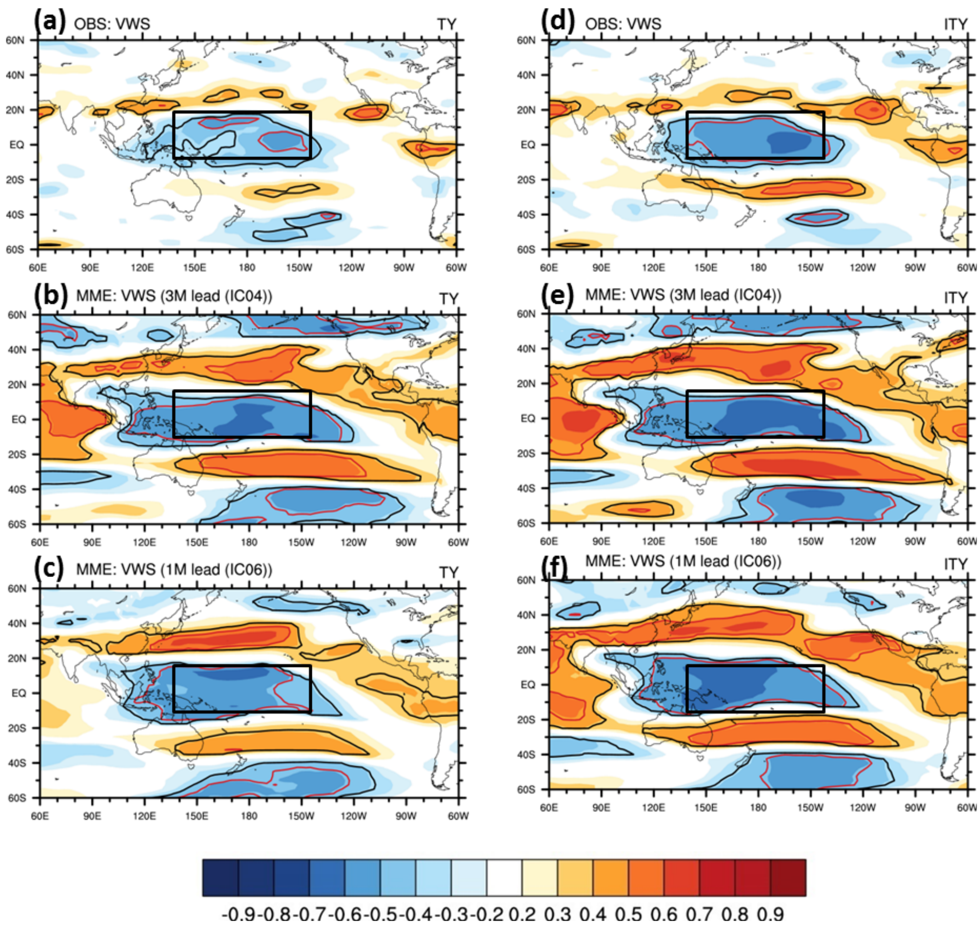

Figure 6 Same as in Figure 5, but for WS.

As in the case of SST (Figure 5), the magnitude of correlations with the APCC MME hindcast VWS is slightly higher in the forecast with the 1-month lead time (Figure 6(c) and (f)) than in that with the 3-month lead time (Figure 6(b) and (e)). Further, the strength of correlations is higher in the case of ITY (Figure 6(e)-(f)) than in the case of TY (Figure 6(b)-(c)). Taking into consideration the close relationship between VWS and the development and intensification of TCs in the WNP (Gray

1977; Chan and Liu 2004) and the significant correlation between the APCC MME hindcast VWS and the interannual variability of the WNP TCs, we used VWS averaged over the tropical central Pacific (10°S-20N°, 130°E-150°W) as a potential predictor for the TC activity forecasts.

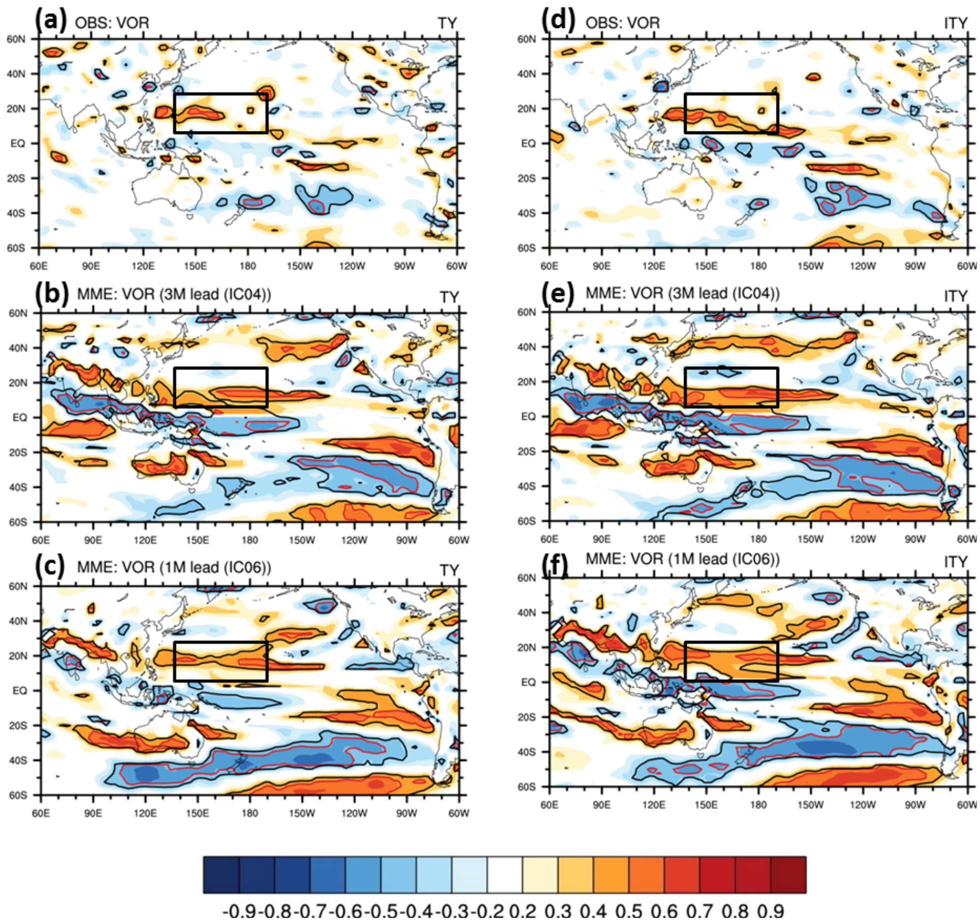

Figure 7 Same as in Figure 5, but for VOR.

Relative vorticity at 850 hPa is also regarded as one of the potential predictors in the dynamical-statistical TCs prediction system (e.g., Kim et al. 2010; Goh and Chan 2012; Kim et al. 2012; Chan and Liu 2004). Molinari and Vollaro (2013) recently found that over 70% of all July-November tropical cyclones in the WNP form in the monsoon trough region where long-term (1988-2010) mean July-November

850-hPa relative vorticity is positive. The region with the significant positive relative vorticity is very similar to that shown in Figure 7. The spatial correlation distribution between the observed interannual variability of TCs and the APCC MME hindcast VOR (Figure 7(b)-(c) and (e)-(f)) is higher in this particular region, which is in agreement with the observations (Figure 7a and d). The high anomaly correlation between the APCC MME and the observed VOR (Figure 2b) and the significant correlation between the APCC MME VOR and the observed interannual variability of the WNP TCs led us to select VOR averaged over the part of the western and eastern Pacific (0°-20N°, 140°E-170°W) as one of the potential predictors in the system.

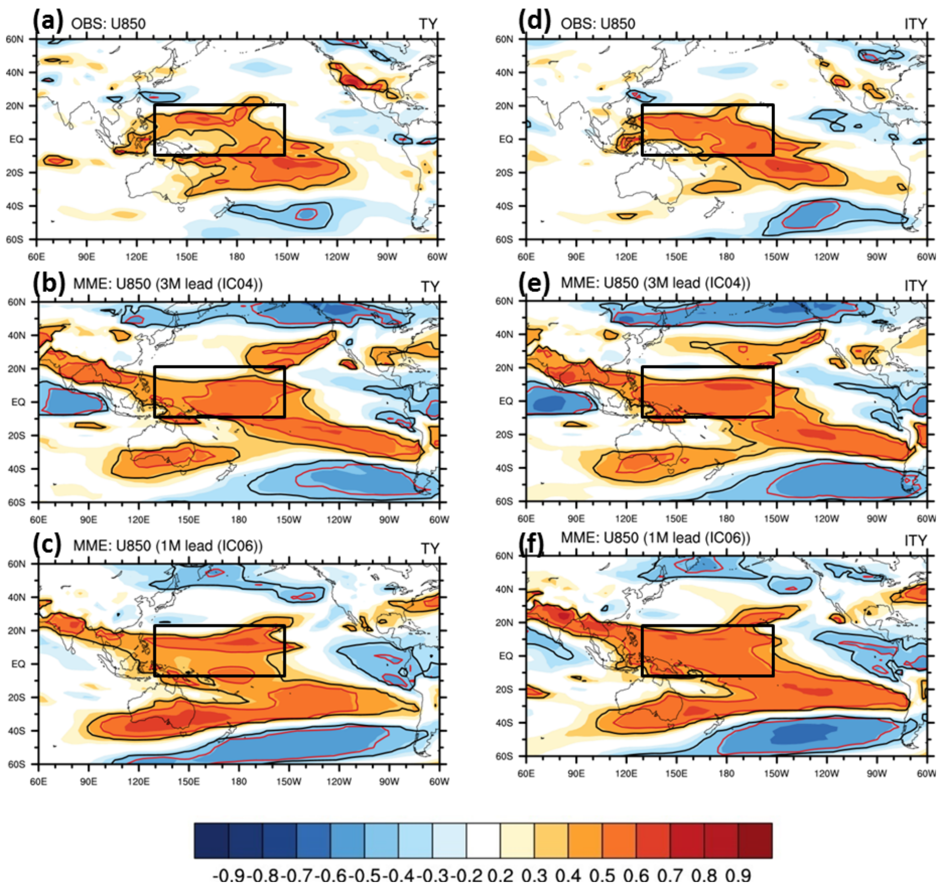

Figure 8 Same as in Figure 5, but for U850.

It is important to consider steering flow variations for predicting the interannual variability of TC movement in the WNP (Chan 1994). In particular, the steering flow conditions can be considered one of the crucial predictors for dynamical-statistical TC prediction. The correlation of the observed U850 with the detrended interannual variations in TCs (Figure 8a and d) is characterized by significant positive correlations in the equatorial central and western Pacific, with maximum values exceeding 0.6. Such significant positive correlations are also well represented in the APCC MME hindcasts (Figure 8b-c and 8e-f). Westerly low-level zonal wind anomaly is related to the interannual variability of TC activity in the WNP. Note that the only large discrepancy between the observations and the APCC MME hindcasts is that a significant correlation is observed over a wider extent in the Pacific in the case of APCC MME hindcasts than in the case of the observations. The spatial correlation patterns of U200 are very similar to those of U850, though they have opposite signs (Figure 9); that is, the correlation between the observed and the APCC MME hindcast JASO U200 is characterized by significant negative correlations in the equatorial central and western Pacific, indicating that the easterly upper-level zonal wind anomaly is related to the interannual changes in TCs in the WNP. On the basis of the performance of the APCC MME hindcasts in predicting the observed low and upper-level zonal wind and the relationship between the zonal wind and interannual variability of the WNP TCs, we used U850 and U200 averaged over the region 10°S-20N°, 130 °E-150°W as potential predictors in the prediction system.

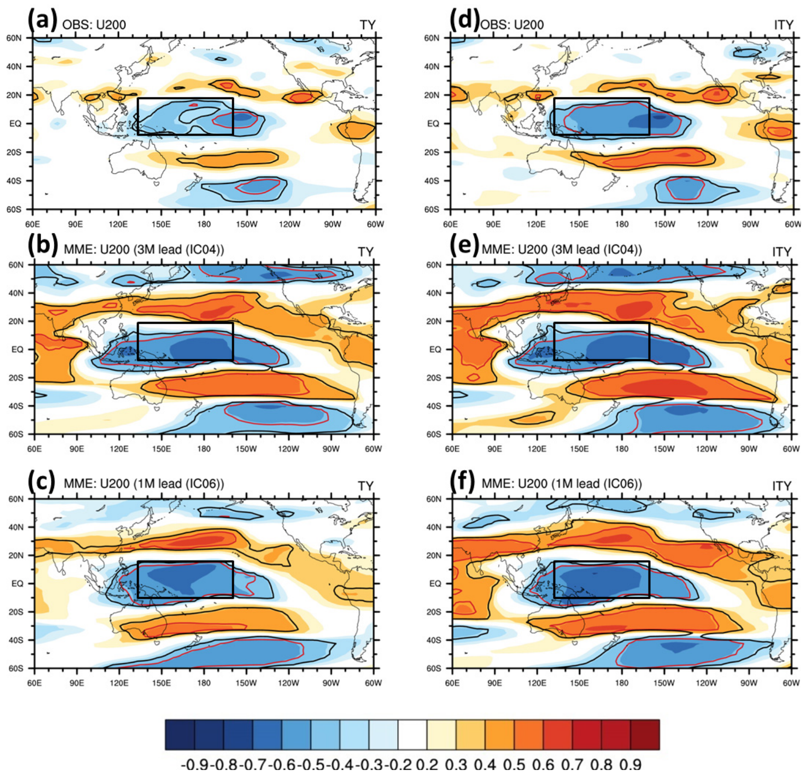

Figure 9 Same as in Figure 5, but for U200.

The APCC MME hindcast skill for the five potential predictors is further investigated. Figure 10 shows the time series of JASO predictors averaged over the region indicated in the Figures 5-9, both for observations and APCC MME hindcasts. The APCC MME hindcast SST are equal to or less than the observed SST values (Figure 10a). In particular, the 1982, 1987, and 1997 El Niño events are well reproduced in the hindcasts. The corresponding linear trends of the MME hindcast SST are similar to those of the observations, especially at 1- and 2-month forecast lead time. The hindcast VWS is much stronger than that observed throughout most of the 27-yr period (Figure 10b). The hindcast VOR and U850 are generally weaker than the corresponding observed values, while the hindcast U200 is stronger than the observed U200 (Figure 10c-e). With the exception of VOR and U200, the linear trends of the MME hindcasts are in general similar to those of the corresponding observations, and there are no clear differences between the linear trends of hindcasts with different lead times.

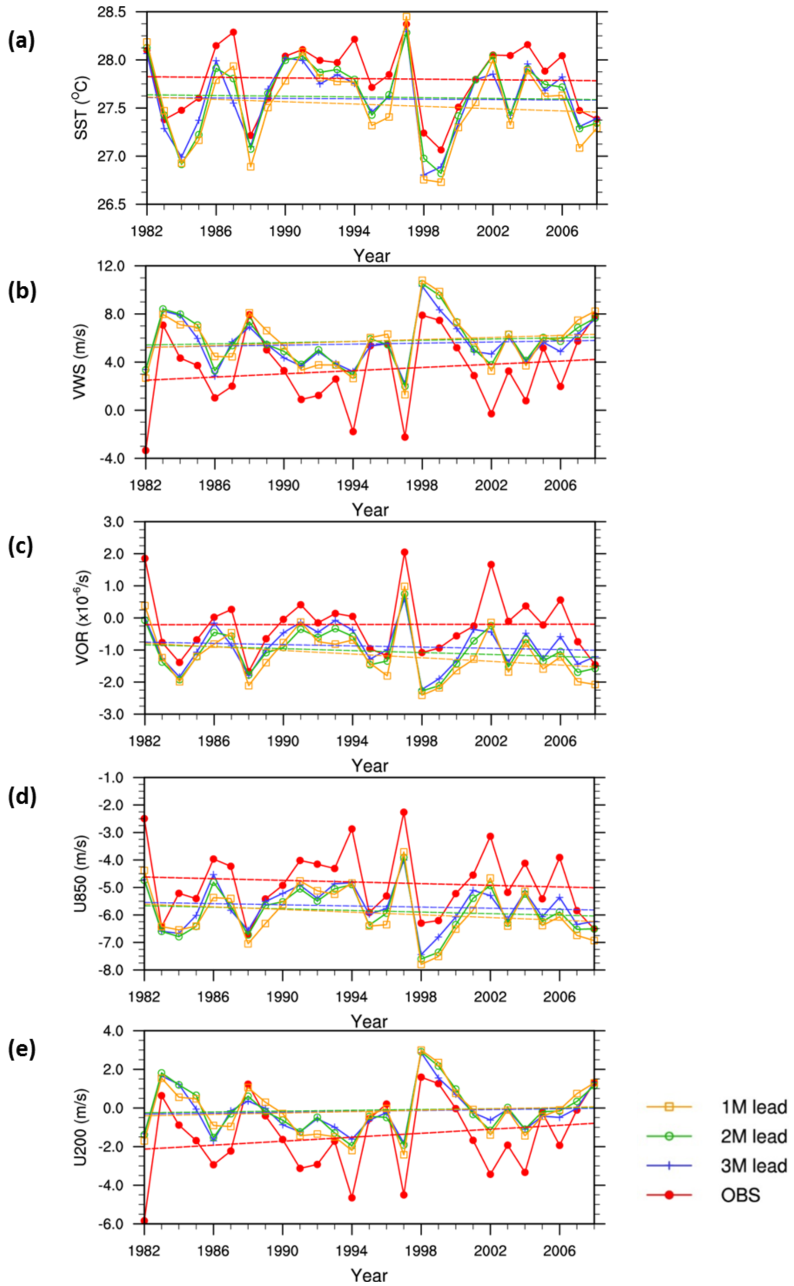

Figure 10 The time series (27 years; 1982-2008) of JASO (a) SST (a) SST, (b) VWS, (c) VOR, (d) U850, and (d) U200 averaged in boxes shown in Figures 5-8 from observations (red solid) and APCC MME hindcasts with April (3-month lead; yellow), May (2-month lead; green), and June (1-month lead; blue) ICs. Dashed straight lines indicate the linear trends of the corresponding time series.

In spite of the mean biases and slightly different trends, the APCC MME is skillful in predicting the interannual variability of large-scale environmental fields. The correlation coefficients between the observations and the APCC MME hindcasts with different forecast lead times are listed in Table 3. The correlations for the detrended time series of SST, VWS, and U850 are the same as those for the original time series; however, in the case of VOR and U200, the correlations are slightly higher for the detrended time series than for the original series. This is because unrealistic downward (upward) trends in the APCC MME VOR (U200) hindcasts are removed. In general, the correlations of time series become higher as the lead time decreases.

Table 3 Correlations between the time series (1982-2008) of the observations and MME hindcasts for each IC and for the detrended time series

Predictor	ICs	Area-averaged	Detrended
SST	3M lead 2M lead 1M lead	0.87 0.89 0.89	0.87 0.88 0.89
VWS	3M lead 2M lead 1M lead	0.85 0.87 0.93	0.85 0.87 0.93
VOR	3M lead 2M lead 1M lead	0.80 0.86 0.90	0.81 0.88 0.94
U850	3M lead 2M lead 1M lead	0.86 0.89 0.93	0.86 0.89 0.93
U200	3M lead 2M lead 1M lead	0.82 0.83 0.89	0.82 0.84 0.90

We next examine the correlations between the five potential predictors from the APCC MME hindcasts and the TCs detrended time series (Table 4). As can be expected, the interannual variability of TCs is significantly correlated with higher SST, weaker VWS, stronger VOR, and stronger westerly (easterly) U850 (U200), which is in good agreement with the observations. Note that the correlations for VWS, U850, and U200 become stronger as the lead time decreases.

Table 4 Correlations of the five predictors with the detrended time series for TCs over the period 1982-2008. The five predictors are derived from observations and APCC MME hindcasts for the JASO season with April-June initial conditions.

Predictand		Predictor				
		SST	VWS	VOR	U850	U200
TY	OBS	0.62	-0.50	0.31	0.50	-0.49
	3M lead	0.54	-0.61	0.53	0.56	-0.62
	2M lead	0.56	-0.63	0.51	0.56	-0.66
	1M lead	0.50	-0.62	0.42	0.54	-0.67
ITY	OBS	0.74	-0.60	0.45	0.58	-0.61
	3M lead	0.63	-0.63	0.58	0.58	-0.65
	2M lead	0.67	-0.66	0.58	0.61	-0.68
	1M lead	0.63	-0.67	0.53	0.61	-0.70

3) Predictor screening and selection

All the predictors can partially explain the seasonal TC activity in the WNP; however, the inclusion of as many potential predictors as possible in the multivariate regression does not necessarily provide better predictability. A careless combination of all predictors in the multivariate regression may lead to poor prediction (Wilks 2006). The potential predictors in this study are mutually correlated because they are controlled by large-scale circulations such as ENSO or the WNP summer monsoon (Chan and Liu 2004; Kim et al. 2010). Therefore, we try to select a best set of predictor variables from pools of potential predictors by forward selection. That is, the regression is repeated as the number of potential predictors increases, and the best set of predictors is determined by comparing the regression results at each stage of the forward selection. We use the goodness-of-fit measures such as mean squared errors (MSE), R^2 (i.e., the coefficient of determination), and the F-ratio in order to select the best predictors (Wilks 2006). At each step, we choose the best predictor that has the smallest MSE, highest R^2, and the largest F-ratio. From the second step, another predictor variable is additionally chosen if the addition of the variable produces larger decreases in MSE and larger increases in R^2 than in the previous step.

Table 5 Goodness-of-fit measures: mean squared errors (MSE), R^2 and F-ratio in each stage of the forward selection procedure. In LAD regression, the dependent variable is the observed interannual variability of TYs and the independent variable(s) is (are) obtained from APCC MME hindcasts with April-June ICs. Bold and shaded values denote that the predictor is selected at each stage of forward selection.

Step	Statistics	SST	VWS	VOR	U850	U200
April ICs (3M lead)						
1	MSE R^2 F-ratio	5.96 0.29 10.19	5.32 0.37 14.38	6.12 0.27 9.22	5.87 0.30 10.72	**5.23** **0.38** **15.06**
2 +U200	MSE R^2 F-ratio	5.46 0.35 6.42	5.23 0.38 7.24	5.25 0.37 7.15	5.23 0.38 7.24	-
May ICs (2M lead)						
1	MSE R^2 F-ratio	5.88 0.30 10.61	5.18 0.38 15.47	6.37 0.24 7.91	5.91 0.29 10.44	**4.85** **0.42** **18.19**
2 +U200	MSE R^2 F-ratio	4.95 0.41 8.32	4.84 0.42 8.76	4.72 0.44 9.33	**4.65** **0.45** **9.63**	-
3 +U200 +U850	MSE R^2 F-ratio	4.86 0.42 5.57	4.71 0.44 5.98	4.70 0.44 6.01	-	-
June ICs (1M lead)						
1	MSE R^2 F-ratio	6.43 0.23 7.58	5.12 0.39 15.94	6.93 0.17 5.24	6.07 0.28 9.55	**4.67** **0.44** **19.87**
2 +U200	MSE R^2 F-ratio	4.27 0.49 11.57	4.02 0.52 13.03	**3.99** **0.52** **13.19**	4.03 0.52 12.99	-
3 +U200 +VOR	MSE R^2 F-ratio	4.02 0.52 8.30	4.07 0.51 8.11	-	4.08 0.51 8.07	-

Table 5 presents the statistics when the interannual variability of TY is the predictand. In the first step, we consider all five potential predictors from the APCC MME hindcasts with April ICs and the predictor that provides the best simple LAD regression, as indicated by the smallest MSE, the largest R^2, and the largest F-ratio, is chosen. The best predictor is U200. Of the remaining four variables, the one that yields the best predictions that also includes U200 is chosen. In the second step, however, none of the four predictors produces larger decreases in MSE and increases in R^2 in comparison with the statistics in the first step. Hence, U200 from the APCC

MME hindcasts with April ICs is the only selected predictor for developing a regression equation for the interannual variability of TY. For developing a statistical model with the APCC MME hindcasts with May ICs, U200 is chosen as the best predictor in the first step. Of the remaining four variables, U850 is selected as an additional good predictor in the next step, since the addition of U850 produces larger decreases in MSE and larger increases in R^2 as compared to the statistics in the first step. In the case of the APCC MME hindcasts with June ICs, U200 and VOR are finally chosen as good predictors of the statistical model for the interannual variability of TY predictions. The predictors are selected for each predictand in the same manner and summarized in Table 6. Of all five potential predictors, one or two are selected for each predictand. Wang et al. (2009) demonstrate that a statistical model based on simultaneous relationships may not require as many predictors as a model based on lagged relationships.

Table 6 List of predictor(s) for LAD regression selected by the forward selection procedure

Predictand	ICs	Selected predictor(s)
TS	3M lead 2M lead 1M lead	VWS, SST U200, SST U200, VOR
TY	3M lead 2M lead 1M lead	U200 U200, U850 U200, VOR
ITY	3M lead 2M lead 1M lead	U200 U200, U850 U200

Note that the predictors selected by forward selection are to some extent correlated to each other. Therefore, we examine the variance inflation factors (VIF) to measure the impact of collinearity among the predictors in a regression model. The VIF is always greater than or equal to 1, and a VIF exceeding 10 is usually regarded as the critical threshold to identify collinearity in a regression (Davis et al. 1986; O'Brien 2007; Villarini et al. 2011; Kim et al. 2012). Among the VIFs for the predictors for each predictand, the maximum VIF is found to be 7.81 for VOR for the predictand TY with a 2-month lead time, suggesting that the predictors selected above are acceptable for use in the statistical models to predict the interannual variability of TYs.

3.3 APCC MME-based statistical prediction of seasonal TC activity

1) Cross-validation of seasonal TC activity with APCC MME hindcasts

We have adopted the procedure followed by Wang et al. (2009) for the empirical prediction system of the WNP TCs activity with the APCC MME hindcasts. The procedure comprises three steps to make forecasts of the WNP TCs activity for a target year. The first step involves a simple (one predictor only) or multiple (multiple predictors) LAD regression analysis between the area-averaged APCC MME hindcasts predictor(s) anomalies in JASO season and the observed interannual variation in the WNP TCs over the whole hindcast period. The target year is removed from the regression analysis. In the next step, the regression coefficients are applied to the corresponding predictors from the APCC MME forecasts for the target year to obtain the forecasts of the interannual variability of TC activity. The final step is to calculate the total number of TCs for the target year by adding the predicted interannual variability of TC activity obtained from the regression analysis to the long-term mean of the seasonal TC activity. The skill of the APCC MME hindcasts for predicting seasonal TCs activity is leave-one-out cross validated.

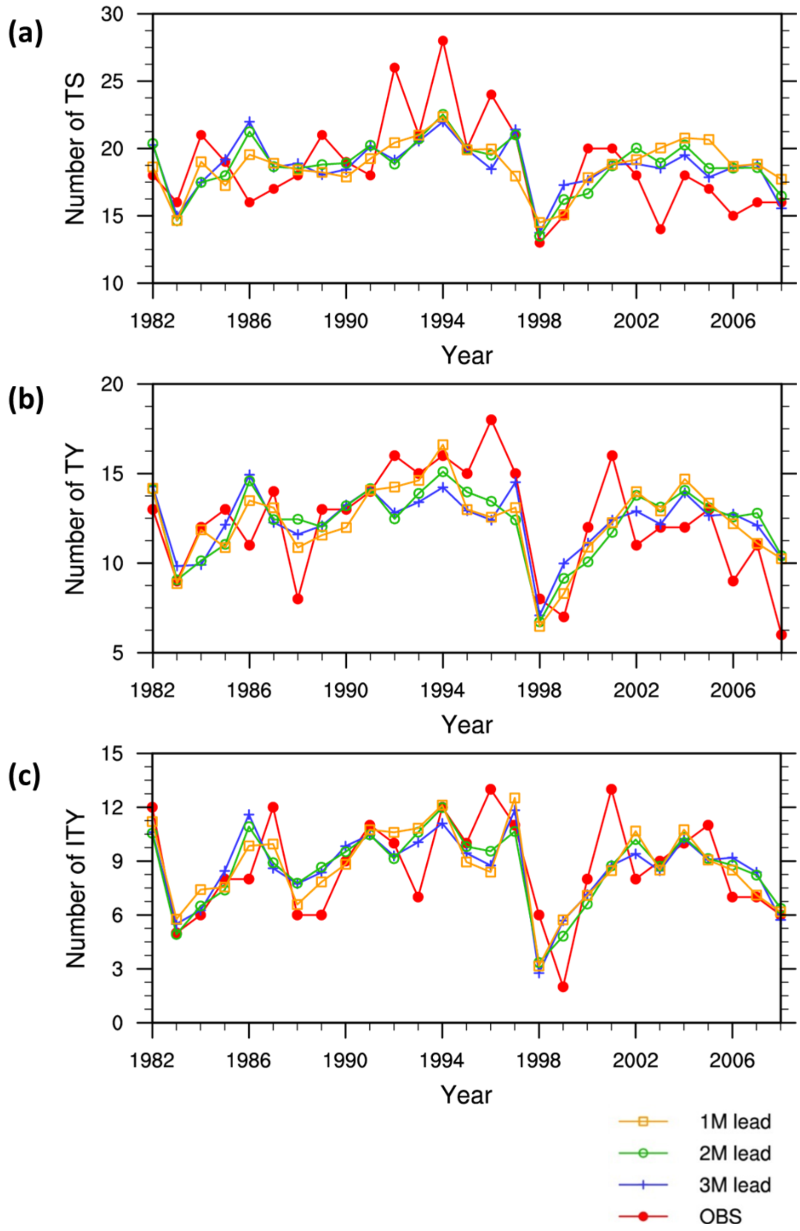

Figure 11 Time series (27 years; 1982-2008) of observations and hindcasts of JASO seasonal TCs predicted from the statistical model based on predictands (TS, TY, and ITY) and predictors selected from APCC MME hindcasts with April-June initial conditions.

Figure 11 shows the hindcasts of the WNP seasonal TCs for the period 1982-2008 calculated using the APCC MME-based statistical model. The APCC MME hindcasts predict the general fluctuations of TCs, and the prediction is in agreement with the actual observations. In particular, the MME hindcasts capture the distinct features of fluctuations of TC activity; the TCs numbers dramatically dropped in 1998-1999 and again increased after 1999. In addition, the hindcasts reasonably represent the observed two major inactive TC seasons of 1983 and 1998-1999 (La Niña year). Meanwhile, the hindcasts underestimate the number of TSs in the active seasons of 1992, 1994, and 1996 (Figure 11a). in the case of TYs and ITYs, the hindcasts capture to some extent the active TC seasons of 1992 and 1994 (Figure 11b-c), but miss the active seasons of 1996 and 2001. Intuitively, the skill for the seasonal TY and ITY activity prediction (Figure 11b-c) seems to be better than that for TS prediction (Figure 11a).

The forecast skill is quantitatively assessed by the temporal correlation between the observed and forecasted seasonal TC activity. The forecast skill is also evaluated using the root mean square error (RMSE). Table 7 lists the prediction skill of cross-validated seasonal TC activity with the APCC MME hindcasts. Overall, the prediction skill for TY and ITY activity is higher than that for TS activity with lower RMSE and higher correlation coefficients. The prediction skill for TYs is higher than that for TSs. The forecast skill generally tends to improve with a shorter lead time, with the exception of TY and ITY activity prediction at 2-month leads. The prediction skill for the TY and ITY activity at 2-month lead time is lower than that at 3-month lead time but higher than that at 1-month lead time. All the correlation coefficients of cross-validated seasonal TC activity are statistically significant, with the exception of TS prediction at 3-month lead time.

Table 7 Prediction skill (measured by the root mean square error, i.e., RMSE, and the correlation coefficients) of cross-validated seasonal TC activity with APCC MME hindcasts. Values in bold with asterisk marks denote correlation coefficients that are significant at the 0.01 level of significance.

Predictand	ICs	RMSE	Correlation coeff.
TS	3M lead	3.00	0.48
	2M lead	2.93	**0.51***
	1M lead	2.83	**0.56***
TY	3M lead	2.40	**0.58***
	2M lead	2.47	**0.56***
	1M lead	2.19	**0.67***
ITY	3M lead	2.12	**0.63***
	2M lead	1.98	**0.68***
	1M lead	2.04	**0.67***

2) Comparison of seasonal TC activity during JASO with APCC MME real-time forecasts

The APCC MME-based statistical model developed in this study is further analyzed by comparing it with operational TC forecasts over the WNP basin issued previously by TSR (Tropical Storm Risk; Rockett and Saunders 2002). Laboratory for Atmospheric Research in CityU (City University of Hong Kong; Chan et al. 1998, 2001) has also issued seasonal forecasts of TC activity since 2000; however, they have not issued forecasts for the WNP TC activity since 2012 because their prediction scheme is currently under revision. Since the APCC MME real-time forecast made by one-tier models (Table 2) is available only from 2012, the TC activity forecast from the APCC MME-based statistical model is compared with that from TSR for the years 2012 and 2013. Table 8 lists the forecasts of the WNP TCs for the 2012 and 2013 seasons with the APCC MME-predicted JASO predictors at various lead times and those issued by TSR (Rockett and Saunders 2002) for early May and early July. The actual number of TCs occurring in each year is also listed in Table 8. The forecasts based on the LAD regression equations are rounded to the nearest integer to obtain the number of TCs.

Table 8 Forecasts of the WNP TCs using the APCC MME-based predictors for JASO with April-June initial conditions and those issued in early May and July by TSR for the 2012 and 2013 TC seasons. The actual number of the WNP TCs during JASO from JTWC over the two years is also listed.

Predictand	Year	APCC			TSR		JTWC
		April ICs	May ICs	June ICs	Early May	Early July	
TS	2012 2013	18 17	17 17	18 18	25.5 (±4.6) 25.6 (±4.2)	26.8 (±4.2) 25.4 (±4.3)	17 -
TY	2012 2013	11 11	10 10	11 11	15.6 (±3.5) 16.0 (±3.4)	16.7 (±3.4) 15.8 (±3.4)	11 -
ITY	2012 2013	7 7	7 7	7 7	8.5 (±2.6) 8.9 (±3.0)	9.2 (±2.4) 8.4 (±2.4)	8 -

A comparison of the APCC forecasts and the observations (JTWC) for the 2012 season suggests that the seasonal TC forecasts based on the APCC MME operational seasonal forecasts have high prediction skills in the case of WNP TC seasons (JASO). The APCC MME predicts similar TC activity during JASO seasons irrespective of the forecast lead times. Since the TSR forecast spans the entire WNP season from January 1 to December 31 but the TCs formed during JASO form about 80% of the annual number of TCs in the WNP, the APCC MME seasonal TC forecasts can be complementary to the TSR forecasts. Furthermore, the APCC MME operational seasonal forecasts can be used to provide more timely information on the WNP TCs.

4. SUMMARY AND DISCUSSION

4.1 Summary

This paper describes the development of an APCC MME-based dynamical-statistical model for predicting TC activity during the WNP TCs season. A distinguishing feature of this model is that the predictors are physically relevant concurrent seasonal large-scale environment variables derived from a dynamical MME seasonal prediction system. Therefore, the advantage of this method is that (1) it offers a combination of the statistical and dynamical methodologies, thus providing better skill than either statistical or dynamical method (Wang et al. 2009; Kim and Webster 2010), and (2) the MME prediction, using which the predictors are chosen for the statistical model, has higher predictive skill than the other individual models considered for the seasonal forecasts (Palmer et al. 2004; Hagedorn et al. 2005; Weigel et al. 2008; Wang et al. 2009). We used 54 ensemble members in total, derived from five different seasonal prediction models. The predictive skill of the APCC MME is generally better than that of single models for the large-scale variables during TC seasons.

We examined the relationship between the interannual variability of TCs and the observed and APCC MME-based potential predictors (i.e., SST, VWS, VOR, U850, and U200) in JASO season. The interannual variability of TCs is significantly correlated with higher SST, weaker VWS, stronger VOR, and stronger westerly (easterly) U850 (U200) in the APCC MME predictions; these results agree well with the actual observations. On the basis of these results, we selected a set of best predictors from pools of potential predictors by forward selection. One or two predictors were selected for each predictand (i.e., tropical storms, typhoons, and intense typhoons). This procedure helps avoid the possibility of poor prediction arising from a careless combination of all predictors in multivariate regression (Wilks 2006). Thus, we developed an APCC MME-based dynamical-statistical model on the basis of the statistical relationship between the interannual variability of the actual number of the WNP TCs during the active TCs season and the APCC MME-based variability of the selected key predictors for the summer season (July-October).

Leave-one-out cross validation results of the APCC MME-based dynamical-statistical model demonstrate the skill of this model in predicting the interannual variability of TCs when using the predictors derived from the APCC MME seasonal prediction; the correlation coefficients between the hindcasts and the observations range from 0.51 to 0.68. Overall, the prediction skill for the frequency of typhoons and intense typhoons is higher than that of tropical storms. In addition, the forecast skill generally tends to improve with as the lead time decreases for almost all predictands. A comparison between the observed numbers of TCs and the APCC MME real-time forecasts of TCs demonstrates that the APCC MME seasonal prediction has good predictive skill for forecasting the TC activity in the WNP during JASO. In addition, since the APCC MME seasonal TC forecasts are more timely compared to those from the other operational center (i.e., TSR), the MME could provide more valuable information to the end-users—in particular, the residents of tropical cyclone-prone areas in the Asia-Pacific region.

4.2 Discussion

Several aspects of the prediction system require improvement through further in-depth studies. For example, confining the forecasting target region to regions along the coastline—for e.g., Korea, China, Japan, and Taiwan—are required for providing more reliable information about regional TC landfalls (e.g., Saunders and Lea 2005; Elsner and Jagger 2006; Kim et al. 2010). For this purpose, the reliable forecasts of TC tracks as well as TC frequency and intensity based on the MME seasonal forecasts are indispensable. Various works have developed Track-pattern-based prediction models for seasonal TCs have been developed in various works. Literature suggests that a track-pattern-based approach would be helpful for gaining a more physical understanding of the forecast skills (e.g., Camargo et al. 2007; Chu et al. 2010; Kim et al. 2011). This method also would be more helpful for decision makers in the TCs-prone regions to be more proactive.

Furthermore, the key drivers of the seasonal TC forecasts in the WNP and the sources of forecast skill and/or uncertainty in the seasonal TC forecast have to be examined. In particular, an investigation of the physical explanations for the seasonal TCs forecasts would allow a deeper understanding of MME performance and thus help realize more reliable seasonal TC forecasts based on the MME.

The main aims of this research are to provide value-added reliable seasonal climate information through seasonal TC forecast outlooks and to verify the results. Given reliable results from the in-depth studies described above, the seasonal TC outlook will comprise information for prediction, monitoring, and verification; in other words, it will provide (1) predictions of the frequency and pattern of typhoons in the coming season in the WNP and in the specific region (2) a statement of the prevailing global weather patterns and climatic conditions and (3) a statement of the reliability of this outlook in light of the current conditions.

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