MJO potential predictability and predictive skill in IAP AGCM 4.1

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ABSTRACT

A 30-year hindcast was performed using version 4.1 of the IAP AGCM (IAP AGCM4.1), and its potential predictability of the MJO was then evaluated. The results showed that the potential predictability of the MJO is 13 and 24 days, evaluated using the signal-to-error ratio method based on a single member and the ensemble mean, respectively. However, the MJO prediction skill is only 9 and 10 days using the two methods mentioned above. It was further found that the potential predictability and prediction skill depend on the MJO amplitude in the initial conditions. Prediction initiated from conditions with a strong MJO amplitude tends to be more skillful. Together with the results of other measures, the current MJO prediction ability of IAP AGCM4.1 is around 10 days, which is much lower than other climate prediction systems. Furthermore, the smaller difference between the MJO predictability and prediction skill evaluated by a single member and the ensemble mean methods could be ascribed to the relatively smaller size of the ensemble member of the model. Therefore, considerable effort should be made to improve MJO prediction in IAP AGCM4.1 through application of a reasonable model initialization and ensemble forecast strategy.

1. Introduction

The MJO is the dominant component of tropical intraseasonal variability (Madden and Julian 1971, 1972). It can affect the atmospheric and oceanic variability over the tropics and extratropics, and it represents a major source of predictability on the intraseasonal time scale. MJO prediction makes a great contribution to sub-seasonal to seasonal forecast quality, since it links deterministic weather forecasts and probabilistic climate predictions (Zhang 2013). There is emerging interest in many research institutions and operational meteorological centers in sub-seasonal prediction, especially for the MJO and its related phenomena.

In recent decades, MJO prediction skill and its potential predictability have been widely evaluated for both dynamical and statistical methods (Waliser 2011). At the beginning of the current century, MJO prediction skill was only about 7–10 days using dynamical models (Jones et al. 2000), and could be up to 2 weeks using statistical models (Lo and Hendon 2000; Wheeler and Weickmann 2001). As MJO prediction capability depends on the forecast system and its initial conditions, with the development of more advanced climate models and high-quality data assimilation methods, MJO dynamical prediction capabilities have been greatly improved. The skillful prediction of the MJO can now reach 15–25 days, and the predictability of the MJO can extend to 4–6 weeks (Kim et al. 2014; Neena et al. 2014; Ren et al. 2015; Weaver et al. 2011; Xiang et al. 2015).

The previous versions of IAP AGCM have been widely applied for seasonal climate prediction (e.g. Lang, Wang, and Jiang 2004; Lin et al. 1998), however, they have not yet been applied for MJO prediction, due to the lack of...
and their dependence on the amplitude of the MJO in the hindcast initial conditions is presented in Section 3.2. A summary and discussion are given in Section 4.

2. Model, experiments, and methodology

The model used in this study is IAP AGCM 4.1, a newly developed version of IAP AGCM 4.0 (Zhang, Lin, and Zeng 2009). Its performance in reproducing the observed climatology has been evaluated in many studies (e.g. Sun, Zhou, and Zeng 2012; Yan, Lin, and Zhang 2014). The physical package from NCAR’s CAM5 is adopted in IAP AGCM 4.1, with the convection parameterization scheme taken as the modified Zhang–McFarlane scheme (Neale, Richter, and Jochum 2008; Richter and Rasch 2008). The horizontal resolution of the model is approximately 1.4° × 1.4°, and there are 30 levels in the vertical.

The hindcast experiment was initiated from 0000 UTC 1 March to 1800 UTC 5 March, with an interval of 6 h, covering the period 1981–2010, using the NCEP’s CFsR (Saha et al. 2010). For each day, there were four predictions, with an interval of 6 h, and a forecast lead time up to six months, and they were all treated equally as the ensemble member for that day. Therefore, there were a total of 150 predictions with a four-member ensemble for this hindcast experiment. The atmospheric initial conditions included winds, temperature, relative humidity, and surface pressure. The SST anomaly used in the hindcasts was the merged SST anomaly considering the predicted SST anomalies from the IAP eNsO ensemble prediction system (Zheng and Zhu 2010), and the persistent February SST anomalies from the OISST data-set (Reynolds et al. 2007).

The commonly used RMM (Real-time Multivariate MJO) index (Wheeler and Hendon 2004) was employed to characterize the MJO signal, with RMM1 and RMM2 as the two components of the index, and the observed MJO EOF modes were used to obtain the hindcast MJO index. The signal-to-error ratio method, based on the perfect model assumption, including the ‘single-member method’ and the ‘ensemble-mean method’ following Neena et al. (2014), was applied to evaluate the predictability of the MJO. Under the perfect model assumption, the ensemble hindcasts were considered as a pool of ‘control’ and perturbed hindcasts. The predictability of the MJO was defined as the lead-time at which the mean forecast error becomes as large as the mean signal. The MJO signal was defined as the variance of mean amplitude of the RMM index of all control ensemble members averaged within a sliding 51-day window, and the observed values prior to the hindcast initiation day were used for computing the signal to apply the same sliding window size. The error was defined as the variance of the difference between the

Figure 1. Zonal propagation of 20–80-day band-pass-filtered 850-hPa zonal wind from (a) NCEP Reanalysis-2 and (b) IAP AGCM 4.1, averaged over 10°S–10°N and regressed onto the reference time series averaged over 120°–150°E. Note: Dashed contours are for negative values and zero contours are omitted.
perturbed forecast and the control forecast, as a function of lead-time. In the single-member estimate, the RMM1 and RMM2 from any given hindcast ensemble member were considered as the ‘control’ forecast, and other ensemble members other than the ‘control’ were considered as ‘perturbed’ forecasts. There was a slight alteration in the ensemble-mean estimate; the definition of ‘control’ was the same as in the single-member method, while ‘perturbed’ in the ensemble-mean approach was the ensemble mean of all the other ensemble members other than the control. To be consistent with the predictability estimation, the average MJO hindcast skill was also measured in a similar way as the predictability estimate, substituting the observed RMMs in place of the control forecast RMMs. Furthermore, three other frequently-used measures of prediction skill – bivariate anomaly correlation (COR), bivariate RMSE, and mean square skill score (MSSS) – were also adopted to measure the forecast skill (Lin, Brunet, and derome 2008). COR measured the skill in forecasting the phase of the MJO, while the RMSE took into account errors in both phase and amplitude, and MSSS provided a relative level of skill for the MJO forecast compared to the climatological forecast that predicts no MJO signal.

3. Results

3.1. Overall MJO potential predictability and prediction skill

The predictability and prediction skill of the MJO evaluated for IAP AGCM 4.1 are shown in Figure 2. Both error growth curves have the fastest-growing period during the first week of the hindcast, and then the growth rate drops gradually thereafter. The predictability estimated by the ensemble-mean approach is higher than that by the single-member method because of the slower error growth rate and smaller initial error in the ensemble-mean method. The predictability estimated by the single-member method is about 13 days, while that estimated by the ensemble-mean method is about 24 days. Similarly, the prediction skill obtained by the ensemble-mean method is slightly better than that of the single-member method. The reason is that the ensemble-averaging process helps to reduce certain effects of the errors in the atmospheric initial conditions that dominate the single-member forecasts. The error growth curve for the single-member method is also similar to that for the ensemble-mean method; the only difference is that the ensemble-mean method has a smaller error growth rate, especially after 10 days’ forecast lead-time. In the ensemble-mean approach, the prediction skill is about 10 days; similarly, the prediction skill in the single-member method is 9 days. Such a small difference between the results of the ensemble-mean and single-member methods is due to the small size of the ensemble members used in our hindcast.

3.2. Dependence on initial amplitude

The dependence of the MJO predictability and prediction skill on the initial conditions of different MJO amplitudes

Figure 2. Mean error and mean signal estimates for MJO (a) potential predictability and (b) prediction skill. Notes: The blue and red curves are the mean error growth in the single-member method and ensemble-mean method, respectively. The black curve indicates the mean signal. The MJO predictability and prediction skill (units: d) are given in the bottom right of each panel.
are further evaluated. The amplitude of the MJO, defined as \( (\text{RMM1}^2 + \text{RMM2}^2)^{1/2} \), in the initial conditions, was classified into five categories. The 7-day running mean was applied to remove high-frequency non-MJO signals for the RMM index. For each year, if the MJO amplitude was less than 1 on 1 March and 5 March, even if the amplitude was larger than 1 during 2–4 March, it was classified into initial conditions with a weak MJO, that is, \([0,1)\). If all amplitudes were larger than 1 during 1–5 March, we treated it as the initial conditions with a strong MJO. Furthermore, the strong MJO could be further classified into four categories with different amplitude.

Figure 3 shows the predictability and prediction skill under the initial conditions with different MJO amplitude. For initial conditions with a weak MJO amplitude, the predictability is 12 days as estimated by the single-member method, while it is 18 days as estimated by the ensemble-mean method. The prediction skill is 4 and 5 days as evaluated using the single-member and ensemble-mean method, respectively. It is clearly shown that, as the MJO amplitude increases in the initial conditions, the predictability and prediction skill become better, and the prediction skill becomes closer to the predictability. For initial conditions with a strong MJO signal, the estimated predictability can reach 17 and 26 days as evaluated using the single-member and ensemble-mean methods, respectively. Their corresponding MJO prediction skills can also reach 13 and 15 days. This result indicates that MJO predictability and prediction skill rely strongly on the MJO amplitude in the initial conditions.

The MJO prediction capability of IAP AGCM 4.1 was also examined using three frequently-used measures (COR, RMSE and MSSS), following Lin, Brunet, and Derome (2008), as shown in Figure 4. The COR was the correlation...
between observed RMM1 and RMM2 and their respective forecasts, assuming a correlation coefficient of 0.5 as the minimum for useful skill. Based on this criterion, we can see from Figure 4(a) that the MJO prediction ability of IAP AGCM 4.1 is 10 days. Under the conditions of weak MJO amplitude, this model cannot give a useful MJO prediction skill, as the COR is always less than 0.5. However, its prediction skill can increase to 23 days if the initial conditions contain a strong MJO signal.

The RMSE was the RMS difference between the observed and forecasted RMM index, with \sqrt{2} taken as the maximum for useful skill. The prediction skill is around 9 days for IAP AGCM 4.1, as shown in Figure 4(b). It is interesting to note that the MJO prediction skills do not rely on the MJO amplitude in the initial conditions when using RMSE. Together with the COR results, it is indicated that the MJO phase is much easier to predict than the MJO amplitude.

MSSS was 1 minus the value of the mean square error of the model forecasted RMM index divided by the climatological RMM index variance. Assuming an MSSS of 0 as the minimum for useful skill, the overall skill of IAP AGCM 4.1 is about 9 days, and we can see that the MJO prediction skill of IAP AGCM 4.1 is worse than the climatological forecast if it is initiated from conditions with a weak MJO signal (Figure 4(c)).

4. Summary and discussion

IAP AGCM 4.1, the latest version of the IAP’s atmospheric model, has been used in climate simulation and seasonal prediction, whereas the MJO prediction skill of the model has not yet been evaluated. To help further our understanding of the MJO forecasts, and their critical role in extended range forecasting, we examined the MJO prediction skill and estimated its predictability in IAP AGCM 4.1 in this study. It was found that the MJO single-member predictability for IAP AGCM 4.1 is 13 days and the ensemble estimate of MJO predictability is 24 days – much lower than other start-of-the-art models involved in the Intraseasonal Variability Hindcast Experiment (ISVHE), where the MJO single-member predictability is about 20–30 days and the ensemble-mean predictability is about 35–45 days (Neena et al. 2014). The prediction skill in IAP AGCM 4.1 measured using the single-member approach is about 9 days, while it is 10 days using the ensemble-member approach. The ISVHE hindcast has a single-member skill of 12–16 days and an ensemble-mean skill of 15–20 days. The results suggest that the current prediction skill of IAP AGCM 4.1 needs to be greatly improved.

The dependence of the predictability and prediction skill on the MJO amplitude in the initial conditions was also explored. The single-member predictability initiated from a weak MJO was found to be 12 days, and the ensemble estimate 18 days. The predictability can increase by 7 days if the prediction is initiated from a strong MJO. Similarly, the predictability is also better if the initial conditions contain a strong MJO signal. This result indicates that MJO predictability and prediction skill initialized with strong MJO conditions is better than that with a weak MJO.

Many studies have shown that improvements in model initialization and ensemble forecasting strategies have contributed greatly to advancements in MJO prediction (Fu et al. 2011; Kang, Jang, and Almazroui 2014). In this hindcast experiment, which was originally designed for seasonal forecasting, the atmospheric initial conditions were taken from the CFSR without any careful implementation of initial atmospheric conditions. It is likely that an increase in MJO forecast skill could be accomplished with an improved initialization. Also, the skill could be further improved if a superior initial conditions perturbation method and accurate initials conditions are applied, especially at the beginning of the forecast. Meanwhile, many previous studies suggest that air–sea coupling improves the simulation and prediction performance of the MJO significantly (Fu and Wang 2004; Fu et al. 2003; Pegion and Kirtman 2008; Woolnough, Vitart, and Balmaseda 2007). The lack of air–sea coupling in IAP AGCM 4.1 may therefore also affect the forecast skill of the MJO. Therefore, prediction studies using a fully coupled global climate model will be undertaken in the future, to achieve a better understanding of the simulation and prediction of the MJO.

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