Forecast Skill of Madden-Julian Oscillation Events in a Global Nonhydrostatic Model during the CINDY2011/DYNAMO Observation Period

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Abstract

Near real-time week-long forecasts of Madden-Julian Oscillation (MJO) events using a regionally stretched global nonhydrostatic model were executed for the intensive observation period of the Cooperative Indian Ocean experiment on intraseasonal variability in the year 2011 (CINDY2011)/Dynamics of the Madden-Julian Oscillation (DYNAMO) field program. Forecast skill was validated using a real-time multivariate MJO (RMM) index and the forecast skill scores. The scores indicated a dependency on the initial MJO amplitude and phase. The errors were smaller in forecasts initialized in the active period of the MJO. A tendency for over-amplification (under-amplification) in forecasts initialized at phases 2–6 (7–8, 1) and earlier (delayed) phase propagation in the forecasts initialized at phases 1–3 (5–6) was identified. This was related to systematic positive biases in RMM1 and RMM2. The RMM1 error dominated in wind fields without significant contributions from convection. The RMM2 error grew in both convection and wind anomalies after the 5-day lead time, causing reduction in the MJO skill score. These results suggest that improvement in the basic model fields, i.e., large-scale circulations and a link between convection and dynamics, should extend the predictability of MJO in this framework.

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1. Introduction

The Madden-Julian Oscillation (MJO; Madden and Julian 1971, 1972) is a dominant tropical phenomenon with an intraseasonal time scale (40–60 days) that influences the global atmosphere, including mid-latitude weather, monsoon onset, tropical cyclogenesis, and the occurrence of severe rainfall events. Because of its broad impact on global weather, an understanding and accurate prediction of the MJO are important for potential improvements in extended-range forecasts (Gottschalck et al. 2010; Vitart and Molteni 2010; Straub 2013). An international observation project, Cooperative Indian Ocean experiment on intraseasonal variability in the year 2011 (CINDY2011)/Dynamics of the Madden-Julian Oscillation (DYNAMO), was conducted over the Indian Ocean in 2011–2012 (Yoneyama et al. 2013). The goal of the project was to improve our understanding of the onset mechanism and dynamics of the MJO and our ability to simulate and forecast the MJO in models. Multi-national operational centers and research institutes provided forecasts and analysis data throughout the intensive observation period (IOP; from 1 October 2011 to 31 January 2012). Forecasts were also provided by a real-time forecast system developed at the Japan Agency for Marine-Earth Science and Technology (JAMSTEC). This forecast system is unique in that it uses a global nonhydrostatic model with

explicit representation of moist convection. The MJO forecast skill of this system during the IOP is discussed herein.

2. Forecast settings and analysis method

The forecast system is based on the Nonhydrostatic Icosahedral Atmospheric Model (NICAM; Satoh et al. 2008). NICAM is designed for global cloud-resolving numerical experiments and employs nonhydrostatic governing equations on a quasi-uniform (icosahedral) grid system. For near real-time forecasts, the regionally stretched version (Tomita 2008a) was used with grid sizes of 14 km at 8°S, 80°E and 56 km at the opposite side of the globe (Fig. S1). This allowed the tropical warm pool domain to be covered with grid sizes that marginally resolve mesoscale convective systems. This framework provides a seamless treatment of convection and associated fields in a large-scale domain (Oouchi et al. 2012). Vertically, 40 stretched layers were taken ($z = 80$ m to 38 km). Moist processes were explicitly calculated using a six-category bulk cloud microphysical scheme (Tomita 2008b). Turbulent and atmospheric radiation processes were calculated using a modified Mellor-Yamada level 2 scheme (Mellor and Yamada 1982; Noda et al. 2010) and MSTRNX (Sekiguchi and Nakajima 2008), respectively. Sea surface temperature (SST) was predicted using a slab ocean model. The initial data for the atmosphere, land surface, and slab ocean models were interpolated from the 1.0-degree gridded National Centers for Environmental Prediction (NCEP) final analysis. A week-long forecast was produced daily using the initial data at 0000 UTC throughout the IOP. Neither assimilation nor a nudging technique was used, except for SST, which was nudged to the initial value at a relaxation time of five days to avoid systematic drift.

The forecast skill of the MJO in numerical weather prediction models was evaluated by the real-time multivariate MJO (RMM) index proposed by Wheeler and Hendon (2004, hereafter referred to as WH04) and forecast skill scores based on the RMM index (Lin et al. 2008; Vitart and Molteni 2010). These are standard measures for the MJO forecast skill of operational models (Gottschalck et al. 2010; Matsueda and Endo 2011). Following WH04, a time series of 2.5-degree gridded daily anomalies of outgoing longwave radiation (OLR) and zonal velocity at 200 and 850 hPa (U200 and U850, respectively) was obtained by subtracting the first three harmonics of the annual cycle from the forecast data and then removing the averages of the previous 120 days. NCEP–National Center for Atmospheric Research (NCAR) Reanalysis (Kalnay et al. 1996) and National Oceanic and Atmospheric Administration (NOAA) daily interpolated OLR data were used to calculate the observed anomalies. The averages in the period of 1979–2008 were used to estimate the annual cycle. The anomalous OLR, U200, and U850 were meridionally averaged at 15°S–15°N and projected on the first and second principal modes of an empirical orthogonal function (EOF1 and EOF2) to obtain the observed RMM1 and RMM2. The EOF data and source code provided by the Centre for Australian Weather and Climate Research (<http://cawcr.gov.au/staff/mwheeler/maproom/RMM/>) were used, and the RMM in the forecasts was calculated by the same procedure. The annual cycle and 120-day averages were not available in the forecast data and thus observed values were used.

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Fig. 1. (a) Time-longitude sections of outgoing longwave radiation (OLR) anomalies in NOAA daily interpolated OLR (15°S–15°N) and (b) the phase diagrams of the real-time multivariate MJO index (RMM; WH04) using NCEP–NCAR reanalysis zonal winds and NOAA OLR. In (a) red contour lines show the OLR reconstructed from the RMM at -5 W m^{-2} . The convectively active periods are also marked in (a) MJO1 (15 Oct. 2011–9 Nov. 2011), MJO2 (20 Nov. 2011–11 Dec. 2011), and MJO3 (15 Dec. 2011–2 Jan. 2012), and in (b) MJO1 (blue line), MJO2 (red line), and MJO3 (green line).

3. Results

Figure 1 presents the time-longitude sections of the observed OLR and the RMM diagrams during the CINDY2011/DYNAMO IOP. Three convective events that migrated eastward over the Indian Ocean and the western Pacific occurred (MJO1, MJO2, and MJO3, Fig. 1a). The periods of the convectively active phases of the three MJO events were defined by the 15°S–15°N averaged OLR anomaly reconstructed from RMM1 and RMM2 to be $< -5 \text{ W m}^{-2}$ in the 30°–180°E domain in this study (MJO1 from 15 Oct 2011–9 Nov 2011, MJO2 from 20 Nov 2011–11 Dec 2011, and MJO3 from 15 Dec 2011–2 Jan 2012)¹. The location of the convective peak shifted eastward (60°E in MJO1, 80°E in MJO2, and 90°E in MJO3) as the minimum OLR values decreased (Fig. 1a). In the RMM diagram, MJO1 was characterized by a marked amplitude over the western Indian Ocean (phases 1–2; Fig. 1b) and MJO2 by a peak amplitude over the central to eastern Indian Ocean (phases 2–4; Fig. 1b). MJO3 appeared as a local loop over the Maritime Continent and western Pacific (phases 5–6; Fig. 1b).

The MJO forecast skill scores (Lin et al. 2008; Vitart and Molteni 2010; Gottschalck et al. 2010; Rashid et al. 2011; Matsueda and Endo 2011); root-mean-square error (RMSE), bivariate correlation (COR), phase error (PERR), and amplitude error (AERR) were used to validate the results. The formulations are given by

$$\text{RMSE}(t, \tau) = \sqrt{(a_1(t) - b_1(t, \tau))^2 + (a_2(t) - b_2(t, \tau))^2}, \quad (1)$$

$$\text{COR}(t, \tau) = \frac{a_1(t)b_1(t, \tau) + a_2(t)b_2(t, \tau)}{\sqrt{a_1(t)^2 + a_2(t)^2} \sqrt{b_1(t, \tau)^2 + b_2(t, \tau)^2}}, \quad (2)$$

$$\text{PERR}(t, \tau) = \tan^{-1} \left(\frac{a_1(t)b_2(t, \tau) - a_2(t)b_1(t, \tau)}{a_1(t)b_1(t, \tau) + a_2(t)b_2(t, \tau)} \right), \quad (3)$$

$$\text{AERR}(t, \tau) = \sqrt{b_1(t, \tau)^2 + b_2(t, \tau)^2} - \sqrt{a_1(t)^2 + a_2(t)^2}, \quad (4)$$

where $a_1(t)$ and $a_2(t)$ are the RMM1 and RMM2 observed on day t and $b_1(t, \tau)$ and $b_2(t, \tau)$ are the RMM1 and RMM2 in forecasts at a lead time of τ days. The initiation date of each forecast is $t - \tau$.

¹ This definition is different from that based on other criteria (e.g., wave-number-frequency filtering). MJO3 may not necessarily be identified as an MJO event because of the short inactive period after MJO2.

Fig. 2. MJO forecast skill scores averaged in the IOP are depicted: (a) (e) Root-mean-square error (RMSE), (b) (f) bivariate correlation (COR), (c) (g) phase error (PERR), and (d) (h) amplitude error (AERR). The abscissa is the lead time. In (a)–(d) the scores are stored by the MJO amplitude: > 1 (closed circles) and < 1 (open circles). In (e)–(h) the scores are stored by the MJO phase at the initial time (indicated by different colors). The phase 0 is defined by the MJO amplitude < 1 .

Figure 2 shows the average skill scores sorted by the MJO amplitudes (Figs. 2a–d) or phase (Figs. 2e–h) at the initial time. The numbers of samples with amplitudes < 1 and > 1 were 37 and 86, respectively, and those initialized at phases 1, 2, 3, 4, 5, 6, 7, and 8 with amplitudes > 1 were 8, 11, 5, 19, 18, 15, 5, and 5, respectively. The scores were better when there was a significant initial MJO amplitude than when there was a weak amplitude (Figs. 2a–d). The dependence on the initial MJO phase (Figs. 2e–h) indicates a steeper growth of the RMSE in the initial phases 2–5 than in phases 6–8 and 1 (Fig. 2e), and a rapid reduction in COR in phases 2 and 6 (Fig. 2f). Correspondingly, positive (negative) AERR values were significant in the initial phases 2–6 (7–8, 1) in Fig. 2h, and positive (negative) PERR values were pronounced in phases 1–3 (5–6) in Fig. 2g. On average, positive PERR and AERR developed after the 5-day lead time (Figs. 2c, 2d).

In order to understand the reasons for the PERR and AERR in the forecasts, it is useful to examine the predicted RMM1 and RMM2 ($b_1(t, \tau)$, $b_2(t, \tau)$) in comparison with those observed ($a_1(t)$, $a_2(t)$). Figure 3 presents the RMM time series in the forecasts during the IOP. Systematic positive biases in both RMM1 and RMM2 appeared in the forecasts (Figs. 3a, 3b), except for RMM2 in the developing stage of MJO1 (16–25 October 2011). The positive biases in RMM1 steadily grew after the 3-day lead time (Fig. 3a), and those in RMM2 were more pronounced in the increasing period of RMM2 (phases 3–6), especially after the 5-day lead time (Fig. 3b). The effects of the positive RMM biases on PERR and AERR are presented in Table S2, where $e_i = b_i - a_i$ ($i = 1, 2$) are the errors in the predicted RMM. The positive RMM1 (RMM2) biases account for the earlier propagation (Fig. 3c) in phases 2–3 (3–4) of MJO1 and 2 and the over-prediction of MJO amplitude (Fig. 3d) in phases 3–6 (5–6). In early October (phases: 6–7), the positive biases led to delayed phase propagation with larger amplitudes (Figs. 3c, 3d; Table S2), and in mid-October and mid-November (phases: 8–1), the positive error in RMM1 contributed to under-prediction of MJO amplitude (Fig. 3d; Table S2).

The positive biases in RMM1 (Fig. 3a), which appeared similarly in all the week-long forecasts, imply a tendency of the model to develop the anomaly fields with the EOF1 structure. The zonal

Fig. 3. Time series of (a) RMM1, (b) RMM2, (c) MJO phase, and (d) MJO amplitude in NICAM real-time forecasts for the IOP. Lines with different colors indicate the lead time. The observed values are also depicted (black lines).

Fig. 4. Zonal profiles of EOF1 (solid lines) and EOF2 (dashed lines) for 15°S–15°N averaged for (a) OLR, (b) U200, and (c) U850 (after Fig. 1 of WH04).

profiles of EOF1 and EOF2 in OLR, U200, and U850 are presented in Fig. 4. Figure 5 shows the differences between the forecasts and observation in OLR, U200, and U850, averaged among all the cases. Flattening of zonal contrast in the mean OLR (Figs. 5a, 5d) and intensification of zonal circulation centered around 160°E (Figs. 5b, 5c, 5e, 5f) developed as the lead time proceeded. The biases in U850 and U200 after the 3-day lead time resembled the EOF1 profiles (Figs. 4b, 4c, 5b, 5c) and the OLR biases with suppressed convection over the Indian Ocean resembled the EOF2 profile (Figs. 4a, 5a). The intensification of U200 in 0°E–30°E and 60°W–120°W and U850 around 120°E after the 5-day integration implies a growth of wind biases similar to the EOF2 profiles (Figs.

Fig. 5. Zonal profiles of the 15°S–15°N averaged difference between forecasts and observations in (a) OLR, (b) U200, and (c) U850 anomalies. The lead time is indicated by different colors. The IOP-averaged (d) OLR, (e) U200, and (f) U850 in observations (NOAA and NCEP-NCAR reanalysis, solid lines) and forecasts (at the 7-day lead time, dashed lines) in 15°S–15°N are also plotted.

4b, 4c, 5b, 5c). The contributions of these biases to the MJO forecast error are quantified in the following.

Errors in the predicted RMM, $e_i(t, \tau)$ ($i = 1, 2$) on day t at a lead time of τ days, can be divided into six components by associated variables and initial-time dependence:

$$e_{i,j}(t, \tau) = \text{EOF}_{i,j} \cdot (\text{VAR}_{\text{mean},j}(\tau) - \text{VAR}_{\text{obs,mean},j}) + \text{EOF}_{i,j} \cdot (\text{VAR}_{\text{anom},j}(t, \tau) - \text{VAR}_{\text{obs,anom},j}(t)), \quad (5)$$

where VAR_j ($j = 1, 3$) denotes OLR, U200, and U850 anomalies (Section 2), with the subscript “obs” indicating those in the observations, and EOF_j denoting the component of a respective variable. The subscripts “mean” and “anom” indicate the initial-time-independent (average of all the forecasts) and dependent components, respectively. In the same way as the RMM calculation, each variable was normalized by a respective factor, given by WH04.

Figure 6 shows each component of e_i ($i = 1, 2$) as a function of the lead time. The U850 and U200 components were dominant in e_1 (Figs. 6a, 6b) with a negative contribution from OLR (suppressed convection). Initial-time-independent components [the first term in Eq. 5, Fig. 6a] overwhelmed the standard deviations of the time dependent components [the second term in Eq. 5, Fig. 6b] after the 3- (6-) day lead time in e_1 (e_2). This explains the steady positive bias in RMM1 after the 3-day lead time (Fig. 3a) and the growth of PERR and AERR after the 5-day lead time (Fig. 2). A time series of the time dependent errors for the 7-day lead time is presented in Fig. 7. e_1 was roughly in phase with a_1 for the period of MJO1 and MJO2 (Figs. 3a, 7a). This implies an am-

Fig. 6. (a) Time independent (averages during the IOP) RMM1 errors (solid lines) and RMM2 errors (dashed lines) in OLR (red), U200 (blue), U850 (green), and their sum (black) as a function of the lead time. (b) Same as (a), but for the standard deviation of time-dependent RMM errors.

Fig. 7. Time series of the time-dependent (a) RMM1 and (b) RMM2 errors in OLR (red), U200 (blue), U850 (green), and their sum (black) for the 7-day lead time. A 1–2–1 filter was used to smooth out noise. The observed RMM1 (a_1) and RMM2 (a_2) are also depicted (black dashed lines).

plication of b_1 both for the positive and negative a_1 , which was overwhelmed by the effects of the mean positive biases (Fig. 6). e_2 preceded a_2 by approximately a quarter to a half wavelength (Figs. 3b, 7b). The sum of the mean positive bias and the time-dependent errors resulted in a large (small) e_2 in the increasing (decreasing) period of a_2 (Figs. 3b, 7b). The errors in OLR and wind were nearly in phase with each other for e_2 (Fig. 7b), suggesting that e_2 was more relevant to the link between convection and circulation than e_1 was.

4. Discussion and conclusions

This study considered the MJO events that occurred during the CINDY2011/DYNAMO IOP. The forecast skill in the onset period of the MJO was better for MJO1 than for MJO2 (Fig. 3). MJO1 had a significant amplitude in the Western Hemisphere (Fig. 1b) and a marked amplitude over the western Indian Ocean (Figs.

3a, 3b, 3d; phases 1–2). The significant MJO signal at the initial time favored the model to retain the MJO related fields during the forecast period. In contrast, MJO2 started with a weak MJO amplitude (Figs. 3a, 3b, 3d), where the model biases led to larger AERR and PERR [$|e_i(t, \tau)| \approx |a_i(t)|$ in Eqs. S1, S2]. Therefore, the errors were more apparent in MJO2 than in MJO1. In the following period, including the MJO3 event, both RMM1 and RMM2 retained positive values (phases 5–6), and the systematic biases clearly appeared as over-amplification (Figs. 3a, 3b, 3d, Table S2).

The better MJO skill scores for the significant initial MJO amplitudes were consistent with the results of Lin et al. (2008). They also examined the dependence of the MJO skill scores on the initial MJO phase and found better performance for cases initialized in phases 1–3 than in phases 4–8. They also stated that the average amplitudes in these two groups were not significant and attributed the phase dependence to the location of convection associated with the MJO. Matsueda and Endo (2011), utilizing The Observing System Research and Predictability Experiment (THORPEX) Interactive Grand Global Ensemble (TIGGE) data, assessed the MJO forecast skills in state-of-the-art operational models and their dependence on the initial MJO phase. They showed that the phase dependence varied among the five best numerical weather prediction models and stressed the advantage of the multi-center grand ensemble approach. They discussed the different performances among the centers in terms of the degrees of a typical problem, such as the Maritime Continent predictability barrier (Seo et al. 2009).

In this study, the dependence of the MJO forecast skill (AERR, PERR) on the initial MJO phase was primarily explained by the model biases: (1) to enhance zonal circulation, which is similar to the EOF1 structure and (2) to reduce the zonal contrast of convection, including significant convection suppression over the Indian Ocean (EOF2). This reduction in the zonal contrast of convection was accompanied by the growth of EOF2 wind anomalies after the 5-day lead time, which led to reduction of the MJO skill score. Straub (2013) investigated the MJO initiation processes over the Indian Ocean in the real atmosphere and those in the RMM index. By showing that the RMM index primarily reflected the wind anomalies, Straub (2013) concluded that the RMM index is not an appropriate measure of convective MJO initiation, but rather represents the growth of global-scale tropical circulation anomalies that in many cases precede the onset of large-scale deep convection. Therefore, the wind biases in the current forecast system may be crucial to the predictability of the MJO initiation. Straub (2013) also revealed the existence of “local” precursor signals in wind fields and convection prior to the amplification of the RMM, which are relevant to the OLR biases over the Indian Ocean in this study. Proper representation of convection and circulation is required at the local scale as well as at the global scale.

In our forecasts during the CINDY2011/DYNAMO IOP, convection was suppressed over the Indian Ocean, where the finest grid sizes were used. One of the concerns is the applicability of the horizontally varying grid spacing (14–56 km) to the MJO forecasts/simulations. Several simulations using the original version of NICAM with a globally uniform grid size of 14 km (Miura et al. 2007, 2009; Liu et al. 2009; Oouchi et al. 2009) provide a promising perspective, although the use of a 14-km mesh in the nonhydrostatic model with explicit moist physics (i.e., without using convective parameterization) is a rough treatment. An investigation of the impacts of the use of horizontally stretched grid system, resolution, and model physics on the MJO forecast skill is in progress. The generality of the findings from this study is unknown, but an improvement of the basic biases in the model will lead to the extension of the MJO predictability in the model.

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Supplement

Supplement Figure S1 shows the grid-size distribution used in the forecast system. PERR and AERR [Eqs. 3 and 4, respectively] can be rewritten as

$$\text{PERR}(t, \tau) = \tan^{-1} \left(\frac{a_1(t)e_2(t, \tau) - a_2(t)e_1(t, \tau)}{a_1(t)^2 + a_2(t)^2 + a_1(t)e_1(t, \tau) + a_2(t)e_2(t, \tau)} \right), \quad (\text{S1})$$

$$\text{AERR}(t, \tau) = \sqrt{\frac{a_1(t)^2 + a_2(t)^2 + 2(a_1(t)e_1(t, \tau) + a_2(t)e_2(t, \tau)) + e_1(t, \tau)^2 + e_2(t, \tau)^2}{a_1(t)^2 + a_2(t)^2}}, \quad (\text{S2})$$

where $b_i(t, \tau) = a_i(t) + e_i(t, \tau)$ and $e_i(t, \tau)$ is the error in the forecasts on day t at a lead time of τ days for $i = 1, 2$. Supplement Table S2 summarizes the effects of positive $e_i(t, \tau)$ on PERR and AERR when the other is negligible and $e_1 < -2a_1$ for phases 7–2 ($a_1 < 0$) and $e_2 < -2a_2$ for phases 5–8 ($a_2 < 0$) in Eq. S2.

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