Techniques and experiences in real-time prediction of the MJO: The BMRC perspective

Matthew Wheeler, Harry Hendon, and Oscar Alves

Bureau of Meteorology Research Centre P.O. Box 1289k, Melbourne, Vic, Australia m.wheeler@bom.gov.au

1. Introduction

This paper describes the current activities being conducted at the Australian Bureau of Meteorology's Research Centre (BMRC) on the prediction of the MJO. Given the close proximity of Australia to the main area of action of the MJO, it is thought that useful weather forecast products for the Australian region will result. Three different approaches have been explored and/or implemented. This paper discusses each in turn, and goes further to discuss the plans we have for future work on this subject.

2. Wavenumber-frequency filtering of satellite-observed OLR

This simple approach to forecasting the MJO involves Fourier filtering of daily-updated satellite-observed outgoing longwave radiation (OLR). As has been described by Wheeler and Weickmann (2001), the technique takes the most recent year of observed anomalies for all longitudes, pads with zeroes, and filters for the frequencies (periods between 30 and 96 days) and planetary zonal wavenumbers (eastward 1 through 5) characteristic of the MJO. The filtered fields obtained for times before the last day in the series of observations may be used for monitoring, while the filtered fields obtained for times after the end point may be used as a forecast. The technique has been applied to several forms of zonally-propagating tropical variability (e.g. the convectively coupled equatorial Kelvin, Rossby, and mixed Rossby-gravity waves), but shows most skill for the MJO. It has been implemented at BMRC since early 2001, and before that has been run and continues to run at the NOAA Climate Diagnostics Center. Output is displayed as maps and time-longitude plots at http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/maproom/OLR_modes/index.htm .

An example of the output produced by the technique is displayed in Fig.1. This output was produced and displayed on the web on the 6^{th} February, 2002. It is indicating the occurrence of active MJO convection (blue shading) for longitudes around 120°E at that time, and predicts that the convection will subsequently move to the east. Suppressed convective conditions (orange shading) are forecast to follow, to be centred at 80° E in the 7-day forecast.

The skill of the technique, as determined by 10 years of hindcasts, was shown in Wheeler and Weickmann (2001) to be about equal to the other published (but not operationally implemented) empirical MJO forecast schemes of Waliser et al. (1999) and Lo and Hendon (2000). "Useful" skill is thought to extend out to about 15-20 days in those regions with a strong MJO convective signal (i.e., mostly the Indian Ocean to west Pacific). However, given that the scheme is only predicting the occurrence of planetary scale variations in tropical OLR, its "use" has primarily only been made by weather forecasters as a guide (e.g. forecasters in the Darwin Regional Forecasting Centre). The difficulty of applying the output OLR field to weather parameters of interest has led us to develop a new approach as described in the next section. Notwithstanding this difficulty, this filtering approach is thought to be useful and interesting enough for us to continue its calculation and display.



Figure 1 Example output of two-dimensional filtering approach when last day of observed data was for 5th February, 2002 (as indicated by horizontal solid line). For times before the 5th of February, the shading is the actual observed daily OLR anomalies, for times after, the shading is the forecasted MJO OLR field out to a 14-day forecast. Contours are the filtered MJO field, dashed for positive.

3. All-season real-time multivariate MJO (RMM) index

For this, our newer approach to empirical prediction, we have focussed first and foremost on the development of a suitable index of the MJO that can be determined in real-time. As with the prediction of other climate-scale phenomena, determining the state of the oscillation in real time is a large part of the empirical prediction problem. The previously discussed approach, together with others that employ forms of band-pass time filtering, suffer from having their near-end-point values change as new information arrives. For example, when the filtering of Fig.1 is re-calculated, but with observed values extending up to the 10th of February, the MJO-filtered values obtained for the 5th of February will be different. Among other things, we have sought to overcome this undesirable characteristic in our new approach. In particular, we find that a suitable index for the MJO can be obtained that avoids time filtering by projecting daily observations onto carefully designed spatial patterns of the MJO, an extension of the work of Lo and Hendon (2000).

More specifically, we have chosen spatial patterns from EOFs of the combined fields of near-equatoriallyaveraged 850 hPa zonal wind, 200 hPa zonal wind, and OLR (Fig.2). Projection of the observed daily data onto the leading pair of multiple-variable EOFs, with the annual cycle and components of interannual variability removed, yields principal components (PC) time series that vary mostly on the intraseasonal time scale only. This projection thus serves as an effective filter for the MJO without the need for conventional time filtering, making the PC time series an effective index for real time use.



Figure 2. Spatial structures of EOFs 1 and 2 of the combined analysis of 15°S to 15°N-averaged OLR, 850 hPa zonal wind, and 200 hPa zonal wind. As each field is normalized by its global (all longitudes) variance before the EOF analysis, their magnitude may be plotted on the same relative axis. Multiplying each normalized magnitude by its global variance gives the field anomaly that occurs for a one standard deviation perturbation of the PC, as given for the absolute maxima of each field.

We call the pair of PC time series that form the index the Real-time Multivariate MJO series 1 (RMM1), and 2 (RMM2). Values for the years of 2001 and 2002 are displayed in Fig. 3. Their predominantly intraseasonal variation is obvious. In real-time. they are calculated and displayed at http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/maproom/RMM/index.htm. A full description of their calculation and behaviour is given in Wheeler and Hendon (2003). Despite the fact that RMM1 and RMM2 describe evolution of the MJO along the equator that is independent of season, the coherent off-equatorial behaviour exhibits strong seasonality. In particular, the northward propagating behaviour in the Indian monsoon and the southward extreme of convection into the Australian monsoon are captured by the seasonindependent index.



Figure 3 The RMM1 and RMM2 time series for the years of 2001 and 2002. No time filtering has been applied.



Figure 4 MJO observations (black points connected by blue line) and 15-day forecast (triangles connected by black line) as represented in phase space defined RMM1 and RMM2. This was an actual forecast produced on the 29th of May using RMM1 and RMM2 observed on the 28th of May as the predictors. Small numbers indicate the day of observation, or day of forecast. Large numbers indicate the defined MJO phase.

The use of lagged multiple linear regression to make forecasts of the two indices, with themselves (at lag 0) as predictors, has been explored. The prediction equations are of the form $RMM1(t+\tau) = a1 + b1 \times RMM1(t) + c1 \times RMM2(t)$ and $RMM2(t+\tau) = a2 + b2 \times RMM1(t) + c2 \times RMM2(t)$, where the regression coefficients (a's,b's, and c's) are a function of lag (τ) and are also made to be a smoothly varying function of the time of year. When presented in the phase space defined by RMM1 and RMM2, predictions by such a technique follow an anti-clockwise path, spiraling towards the origin (Fig.4). The skill of such forecasts, as measured by the correlation coefficient between the predicted and verifying values, is 0.52 at a 15-day lag for RMM1, and 0.48 for RMM2 (for December through March forecasts only).

In a similar fashion, any field can be used as the prediction and in a lagged multiple linear regression with RMM1 and RMM2 as predictors. Thus forecasts can be made of an entire latitude/longitude field. Real time forecasts with such a method are currently displayed on the aforementioned web page, an example of which is provided in Fig. 5.

Further applications of RMM1 and RMM2, through their relationship with synoptic weather, have been investigated. One example is the relationship with the probability of extreme weekly rainfall for points across northern Australia. Using eight MJO phases as defined by the RMM phase space (Fig. 4), the probability of weekly rainfall exceeding the highest quintile in the "Top End" region around Darwin varies from less than 12% in Phases 1 and 2, to greater than 36% in Phases 5 and 6 (see Wheeler and Hendon 2003). As the RMM indices are calculated in real time, such information can be easily adapted into a forecast. We have plans to develop such real time probabilistic precipitation forecasts. Plans are also in place

to develop probabilistic forecasts of the occurrence of tropical cyclones, given the known modulation of TCs by the MJO (e.g., Hall et al. 2001).



Figure 5 Lagged regression forecast of OLR anomalies (shading) and 850 hPa wind anomalies (vectors) of the MJO for the same 15-day forecast period as presented in Figure 4. Day 0 refers to the time of the initial condition on the 28^{th} of May. Day 15 is the forecast for the 12^{th} of June. Contour interval is 7.5 W m⁻² with no zero contour shown. Orange shading for OLR > 7.5 W m⁻² and blue for OLR < -7.5 W m⁻². This was an actual forecast produced on the 29^{th} of May.

Certain advantages have thus been achieved from the development of the RMM indices. One is that they are of sufficiently high quality to be used for diagnostic studies, yet are also able to be used in applications to prediction. Applications are easy as the whole state of the MJO is reduced to just two numbers. Conversely, however, by describing the MJO with just two numbers we may be missing some of its predictable signal. There is also the inherent caveat that the indices, by design, are only concentrating on the MJO, and presumably also miss some of the predictability provided by other forms of intraseasonal variability. On a region-by-region basis, better statistical predictions may be produced by searching for predictors that are relevant for that particular region (e.g., Webster and Hoyos 2003). It is anticipated that we will investigate such matters further in the future.

4. Coupled ocean-atmosphere dynamical forecast model – POAMA

The Predictive Ocean Atmosphere Model for Australia (POAMA) is a modern seasonal to inter-annual forecast system based on a coupled ocean/atmosphere model (Alves et al. 2003). It uses the latest version of BMRC's unified climate/Numerical Weather Prediction atmosphere model (BAM) coupled to the Australian Community Ocean Model (ACOM2). It has a sophisticated ocean data assimilation system that incorporates

the latest oceanic observations into the initialisation procedure for the model forecasts. It is also one of the few seasonal prediction models that uses real atmospheric initial conditions, taken from the Bureau's operational weather forecast system (GASP). 9-month forecasts are run once per day. Although its main purpose has been to predict the evolution of the El Nino-Southern Oscillation (ENSO), the atmospheric model is also able to simulate some semi-realistic aspects of the observed MJO. These facts conspire to make POAMA a potentially useful forecast tool for the MJO, hence its inclusion in this paper.

The specific version of the atmospheric model chosen for POAMA (BAM 3.0d) uses the Tiedtke (1989) mass flux scheme for its convective parameterization, but with a closure based on CAPE relaxation instead of the original moisture convergence. This change results in the appearance of very different tropical intraseasonal variability in the model. Prior to the change the model had no sign of any enhanced eastward propagating variability in the tropics. With the CAPE relaxation, however, the model has enhanced power for eastward propagating, low-wavenumber waves much like that observed, except with a somewhat broader spectral peak. In the low-level zonal winds, peak power in the model occurs at a period of about 70 days, while that in the observations is about 40-50 days, a seemingly good match (Fig. 6). In the precipitation field, however, the peak power in the model occurs at both a higher wavenumber and lower frequency than that observed (not shown). The model also exhibits generally greater power. Despite these and other shortcomings, the mere presence of such MJO-like enhanced eastward propagating variability in the model is encouraging for further study.



Figure 6 Wavenumber-frequency power spectrum of 15°S to 15°N –averaged 850hPa zonal wind for (a) 19-year BAM atmospheric model run with specified climatological SSTs, and (b) 19-years of NCEP/NCAR Reanalysis data (1981 to 1998). Red shading indicates greatest power.

Operational real-time forecasts with the model began on the 1st October, 2002. We thus have over a year of real forecasts to analyse for the MJO. One methodology of analysis that we have adopted is to project the

model forecasts onto the same two EOFs as determined from the observations for the RMM indices (Fig.2). Fig. 7 panels (b) and (c), show the result of applying such an analysis to five consecutive forecasts during a period in which the convection was initially in the Indian Ocean (b), and Maritime Continent/West Pacific (c). The corresponding observations are panel (a). Although the MJO had a similar strength at the times of initialization (as seen in Fig.7a), the forecasts when initialized from the Indian Ocean produced a much stronger MJO (as indicated by the large amplitude anti-clockwise circles the forecast paths trace). The forecasts initialized from the Maritime Continent/West Pacific, by comparison, are much weaker and more random.

The explanation for the vastly different behaviour of the forecasts, depending on what state the MJO is initially, may be partly attributable to a mismatch between the model's natural climate and what it receives from the initial conditions. It is known that the atmospheric model, when run freely on top of observed SSTs, tends to produce less precipitation over parts of the equatorial Indian Ocean than what is produced by the GASP analysis (as used in the initial condition). The mean winds from the coupled model's atmosphere are also different to those of the GASP analyses. Thus the initialization of the coupled model with atmospheric fields consistent with enhanced MJO-like convection over the Indian Ocean creates a great deal of "shock" to the coupled model, resulting in greatly enhanced MJO-like variability (as demonstrated in Fig.7b). When initialized from a state in which the MJO convection is enhanced over the West Pacific, on the other hand, the model appears to see little difference with its natural state, and does not react as strongly (Fig.7c).





Fig. 7. As in Fig.4 except for (a) observations from the 10^{th} November 2002 to the 1^{st} January 2003, (b) five individual POAMA forecasts initialized from the days of 8^{th} to 12^{th} November 2002, and (c) five POAMA forecasts initialized from 26^{th} to 30^{th} November. Each black dot indicates the projection onto the observed RMM EOFs for a single day of data, and the lines join consecutive days. In (b) the initial conditions all occur in phase 3. In (c) the initial conditions occur in phases 5 and 6. Forecast days 1 through 51 are displayed in (b), and forecast days 1 through 15 are displayed in (c).

Another difficult issue to overcome with the analysis of the MJO in the coupled model is the creation of anomaly fields with respect to the coupled forecast's naturally drifting state. Anomaly fields are necessary for the calculation of most indices of the MJO (as in Fig.7). For the seasonal forecast products, the natural drift of the coupled model is taken into account by referencing all anomalies relative to the model forecast climatology as developed from 15 years of hindcasts. Due to a lack of a complete history of GASP analyses, however, the hindcasts were made using atmospheric initial conditions from a run of the model forced with observed weekly Reynolds's SSTs. In the creation of intraseasonal anomalies, there is thus a mismatch between the GASP analyses used in the real forecasts and the internally generated model initial conditions used in the hindcasts. In Fig.7 we have partly overcome this by using NCEP Reanalysis as the climatology at forecast day 0, blending to the climatology from the hindcast experiments at forecast day 60. This definition of the climatology is purely subjective. In future versions of POAMA, NCEP Reanalyses will be used for the atmospheric initial conditions of the hindcasts, which should act to remove some of the bias. For a truly robust system, however, the whole assimilation and prediction cycle should be within the same model, and that model should be one that contains variability with some resemblance to the MJO. Such a system is a long way off at BMRC. Dynamical nudging may be one method to achieve the desired result.

References

Alves, O., G. Wang, A. Zhong, N. Smith, F. Tzeitkin, G. Warren, A. Schiller, S. Godfrey, and G. Meyers, 2003. POAMA: Bureau of Meteorology operational coupled model seasonal forecast system. Proceedings of the National Drought Forum, Brisbane, April 2003.

(See also http://www.bom.gov.au/bmrc/ocean/JAFOOS/POAMA/)

Hall, J. D., A. J. Matthews, and D. J. Karoly, 2001. The modulation of tropical cyclone activity in the Australian region by the Madden-Julian oscillation. *Mon. Wea. Rev.*, **129**, 2970-2982.

Lo, F., and H. H. Hendon, 2000. Empirical extended-range prediction of the Madden-Julian oscillation. *Mon. Wea. Rev.*, **128**, 2528-2543.

Tiedtke, M., 1989. A comprehensive mass flux scheme for cumulus parameterization in large-scale models. *Mon. Wea. Rev.*, **117**, 1779-1800.

Waliser, D. E., C. Jones, J.-K. E. Schemm, and N. E. Graham, 1999. A statistical extended-range tropical forecast model based on the slow evolution of the Madden-Julian oscillation. *J. Climate*, **12**, 1918-1939.

Webster, P. J., and C. Hoyos, 2003. Prediction of monsoon rainfall and river discharge on 15-30 day time scales. *Submitted to Bull. Amer. Met. Soc.*

Wheeler, M. C., and H. H. Hendon, 2003. An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *In review for Mon. Wea. Rev.* (manuscript available at http://www.bom.gov.au/bmrc/clfor/cfstaff/matw/publications.htm)

Wheeler, M., and K. M. Weickmann, 2001. Real-time monitoring and prediction of modes of coherent synoptic to intraseasonal tropical variability. *Mon. Wea. Rev.*, **129**, 2677-2694.