The real-time identification of equatorial waves in analyses and forecast

Report of WCSSP Southeast Asia Project

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1. Introduction

Equatorial waves are fundamental components of the tropical atmosphere and are important for understanding the behaviour of the tropical atmosphere. A number of observational studies have shown that a large proportion of the tropical convection is associated with equatorial wave modes (e.g., Hendon and Liebmann 1991; Wheeler and Kiladis 1999; Yang et al. 2007a, b; Kiladis et al 2009). In this project we have examined the observed statistical relationship between equatorial waves and rainfall in Southeast Asia (Ferrett al, 2019). It is shown that increases in amount of precipitation and the likelihood of extreme precipitation in Southeast Asia are linked to Kelvin, westward-moving mixed Rossby-gravity (WMRG) and n=1 Rossby (R1) waves. Heavy precipitation can be up to four times more likely to occur during a period with high amplitude waves in Southeast Asia, indicating that the probability of extreme precipitation is highly dependent on equatorial wave activity.

These equatorial waves provide a potentially important source of predictability for tropical precipitation and high impact weather. Therefore, it is crucial to evaluate and improve model ability in representing and forecasting equatorial wave modes and their associated precipitation; such analysis requires a methodology for identifying equatorial waves in observations and forecasts in real-time.

There are two main methods for identifying equatorial waves in observational data. The first following Wheeler and Kiladis (1999) is based on filtering observed data (usually outgoing longwave radiation, OLR) in wavenumber-frequency space in narrow spectral bands related to the dispersion relationship from equatorial wave theory on a resting basic state. The second following Yang et al. (2003) is to project the winds and geopotential height onto the theoretical equatorial wave structures, following the application of a broad spectral filter to separate eastward and westward moving waves. Neither of these methodologies lend themselves easily to real-time application, because of the need for a Fourier filter in frequency space introduces undesirable edge effects near the analysis time.

Wheeler and Weickmann (2001) developed the wavenaumber-frequency filtering method for real-time monitoring and prediction by extending the length of the data by filling future values with zeros (padding). The resulting anomalies can be used for monitoring near the end of the dataset and provide a "statistical" prediction of the evolution of these modes. This methodology shows some prediction skill for the MJO and various equatorial waves, the padding with zero decays the amplitude rather quickly near the end of the record and in the future. For the Kelvin Wave, R1, WMRG, the normalized RMSE at lead time zero (analysis time) compared to a diagnostically filtered dataset (i.e. with full knowledge of the future evolution) is in the range 0.5-0.7 (their Figures,13,17,21) This methodology has been extended by Carl Shrek (https://ncics.org/portfolio/monitor/mjo/) to include a rescaling of total variance to maintain the amplitude, and inclusion of 45 day OLR forecasts from CFS. These wave-number frequency methods using OLR filtered in a smaller domain of wavenumber-frequency suffer from two potential weaknesses. First the small regions of wave-number frequency space can be susceptible to errors induced by changes in frequency due to either changes in the dispersion relationship associated with e.g. sheared background flow or Doppler shifting by the background flow; or due to edge effects introduced in the real-time methodology. Secondly the reliance on identifying the convective signal can lead to the failure to identify equatorial modes in regions which may not be convectively active, and because they are identified from a convective signal they cannot easily be used to relate the precipitation signal to the wave independently.

In this project, we have extended the methodology of Yang et al (2003) to provide a novel real-time technique for operational monitoring of observed and forecast equatorial waves from their dynamical structures. This report is organized as follows. Section 2 gives a brief introduction of the equatorial wave theory and a description of the methodology used to identify equatorial waves. Section 3 presents the modifications to this technique to identify equatorial waves in real-time and operational forecasts, and the evaluation of the methodology. Summaries and discussions are given in Section 4.

2. Basic equatorial wave theory and methodology for identification equatorial waves

2.1 Basic theory

Equatorially trapped waves are obtained as solutions to the adiabatic, frictionless equations of motion on an equatorial β-plane, linearized about a state of rest and separation of the vertical structure from that in the horizontal (Matsuno 1966; Gill 1980). The horizontal and temporal behaviour of horizontal winds (u, v) and geopotential height (Z) satisfy the linearized shallow water equations with gravity wave speed c, the separation constant from the vertical structure equation that can also satisfy relevant surface and upper boundary conditions. This is possible only for discrete values of the separation constant, $c_{e.}$ In an atmosphere with a constant buoyancy frequency with a rigid lid upper boundary condition, the vertical modes are sinusoidal in height, with corrections for the density variation.

For the horizontal equations, u, v and Z fields can be taken to be of the form:

$$\{u, v, Z\}=\{U(y), V(y), Z(y)\} \exp[i(kx- \omega t)]. \qquad (1)$$

where k is the zonal wavenumber and ω is the frequency. As in Gill (1980) the equatorial wave solutions are most easily formulated in terms of new variables, q, r and v where

$$q = u + gZ/c_e,\ r = u - gZ/c_e \qquad (2)$$

There is the Kelvin wave solution with zero v and dispersion relation $\omega = kc_e$, and there are solutions with non-zero v with the dispersion relation

$$\frac{\omega^2}{c_e\beta} - c_e\frac{k}{\omega} - \frac{c_e}{\beta}k^2 = (2n+1), \quad for\ n = 0, 1, 2 \ .... \qquad (3)$$

where n is the meridional mode number and β is $\partial f/\partial y$. Since the Kelvin wave satisfies this relation with $n = -1$, this notation is conventionally used to label it. The Kelvin wave is eastward moving. The n=0 mode is the mixed Rossby-gravity (MRG) wave which has both eastward (EMRG) and westward-moving (WMRG) solutions. For n=1 and higher there are low frequency westward-moving equatorial Rossby waves and both eastward and westward-moving high frequency gravity wave solutions.

According to Gill (1980) the meridional (y) structures of equatorial waves can be described by parabolic cylinder functions:

$$D_n\left(\frac{y}{y_0}\right) = \exp\left[-\frac{1}{4}\left(\frac{y}{y_0}\right)^2\right] P_n\left(\frac{y}{\sqrt{2}y_0}\right) \quad , \qquad (4)$$

where $$y_0 = (\frac{c_e}{2\beta})^{1/2} \ , \qquad (5)$$

is the meridional scale, P_n is proportional to a Hermite polynomial of order n, and the waves are trapped at the equator on a scale $y_t = \sqrt{2}\, y_0$.

The first ~~three~~four functions have the forms:

$$D_0, D_1, D_2, D_3 = \left\{1, \frac{y}{y_o}, [\left(\frac{y}{y_0}\right)^2 - 1], [\left(\frac{y}{y_0}\right)^3 - 3\left(\frac{y}{y_0}\right)]\right\} \exp\left[-\frac{1}{4}\left(\frac{y}{y_0}\right)^2\right], \quad (6)$$

Guided by basic equatorial wave theory, the parabolic cylinder function expansions of q, v and r are organized and described as follows:

$$\begin{array}{llll} q = & q_o D_o & + q_1 D_1 & + \sum_{n=1}^{n=\infty} q_{n+1} D_{n+1} \\ v = & 0 & + v_o D_o & + \sum_{n=1}^{n=\infty} v_n D_n \\ r = & 0 & + \ 0 & + \sum_{n=1}^{n=\infty} r_{n-1} D_{n-1} \\ & \uparrow & \uparrow & \uparrow \\ & n=-1 & n=0 & n=1,2... \end{array} \quad (7)$$

These functions form a complete and orthogonal basis, and the projections in Eq. (7) are quite general, with q_0D_0 describing the Kelvin wave, q_1D_1 and v_0D_0 describing n=0 MRG waves, and $q_{n+1}D_{n+1}$, v_nD_n and $r_{n-1}D_{n-1}$ describing $n\geq1$ equatorial Rossby waves and gravity waves. The theoretical horizontal structures of some of the gravest equatorial waves are shown in Fig.1. If the low-level convergence (or cyclonic circulation especially for R1 and R2) provides the organization for convection, then we would expect this convection to occur in the blue shaded (blue contours) regions in Fig.1. This relationship has been revealed in observational studies (e.g.,Yang et al. 2007a,b and Ferrett et al. 2019).

2.2 Methodology to identify equatorial waves

The key points of the analysis method developed in Yang et al. (2003) are as follows:

1) Use Eq. (2) to formulate equatorial wave solutions in terms of v and two new variables, q and r,   with c_e being deduced from a specified y_0 from Eq. (5).

In this analysis y_0 =6^{o} is used and the corresponding c_e is about 20 m s^{-1}, as previous studies using ERA data indicate that y_0 =6^{o} gives a best fit to data by minimizing the root mean square errors of the v , q, and r fields in the tropics. This c_e is used only to create the new dependent variables q and r from u and Z and later to reverse the variable transform.

It is interesting to note that the meridional scale is not only related to the c_e (Eq.5) but also to the equivalent depth h, therefore

$$y_0 = (\frac{c_e}{2\beta})^{\frac{1}{2}} = (gh)^{\frac{1}{4}}/(2\beta)^{1/2}. \qquad (8)$$

Hence

$$h \sim y_0{}^{4} \text{ and } c_e \sim y_0{}^{2} . \qquad (9)$$

The powers of y_0 in Eq. (9) suggests that the horizontal structure functions used here would be much less sensitive than the vertical structures and the phase speeds, indicating the robustness of the projection methodology.

2) Filter data in a wavenumber and frequency domain.

The v, q and r in the tropical belt (24^{o}N and 24^{o}S) are separated into eastward and westward-moving components using a space-time spectral analysis which transforms data from the x-t domain into the k-ω domain by performing 2-D FFT in the zonal and time direction (Hayashi 1982). The data is filtered using a specified spectral domain with k=2~40 and period =2~30 days. The Kelvin wave is filtered in the eastward-moving domain (positive k), and WMRG, R1 and R2 waves are filtered in the westward-domain (negative k).

3) At each vertical level project the filtered data onto the horizontal structures of equatorial waves. The Fourier coefficients (e.g., V(y), for each k and ω) of eastward or westward-moving v, q and r are separately projected onto the meridional structures of the equatorial waves as described in Eq. (7) to obtain the equatorial wave modes at each level.

4) Transform the Fourier coefficients of *v*, *q* and *r* for each wave mode back into physical space, and then deduce *u* and *Z* for each wave mode from the projected *q* and *r* using Eq. (2).

This level by level projection allows the data itself to show the vertical structures, without assuming a vertical structure, and obtain amplitudes for horizontal winds and geopotential height separately without assuming that the amplitude coefficients for the three variables are related via dispersion relations. This methodology has been successfully employed in a wide range of studies to investigate the horizontal and vertical structures of convectively coupled equatorial waves both in observations (e.g., Yang et al. 2007a,b,c) and models (Yang et al.2009), the variation and vertical propagation of equatorial waves in different phases of QBO (Yang et al. 2011, 2012), the influence of ENSO on equatorial waves and tropical convection (Yang and Hoskins, 2013, 2016), and connection between African easterly wave and equatorial waves (Yang et al. 2018), and in this project to identify the relationship between precipitation and equatorial waves in southeast Asia (Ferrett et al, 2019). Furthermore, the absence of a reliance on narrow wave-number frequency bands to identify the waves should reduce the impact of edge effects in real-time applications.

To develop the above methodology for real-time application we need to modify the filtering step (2) and evaluate the impact of the edge effects of the filtering on the diagnosed waves.

3. Methodology for real time identification and prediction of equatorial waves

3.1 Procedures and data used

Met. Office 6-hourly analysis and forecast data for 2015-2018 are used, re-gridded to 1 degree x 1 degree. Dynamical fields (*u*, *v* and Z) are projected ~~equatorial~~ onto eastward-moving Kelvin waves and westward-moving WMRG, R1 and R2 waves using the methodology described above, with modifications to the filtering technique.

Real-time filtering approach.

For real-time filtering we propose a methodology in which, for each day, we create a 90 day time-series constructed from 83 days of 6 hourly analysis data and 7 days of 6 hourly global forecast data. The 90-day time series data is filtered in a zonal wavenumber-frequency domain of k=2-40 and period=2-30 days and then projected into different wave modes following the methodology above (see Figure 2a) We label the last time of analysis data as the analysis (T+0), previous days as T-1 day, T-2 days,… and subsequent days as T+1 day, T+2 days,…. with the days T+1 and onwards providing a projection of the forecast on to the equatorially trapped waves. Sensitivity tests with time series of lengths 120, 180, and 360 days gave similar results for amplitude and phase of the diagnosed waves. We refer to this data-set as the "Real-time" wave dataset, T+0 as the real-time analysis, and T+1 and onwards as the real-time forecast.

Evaluation data set

To evaluate the real-time methodology we create a wave dataset taking full account of future data. To mimic the real-time methodology, and to ensure that any differences between the real-time wave analysis and diagnostic wave analysis are not due to differences in the filtered periods, for each day we filter a ninety day time series of observed winds and geopotential centred on the analysis time T+0, and project this dataset onto the equatorial wave modes (see Figure 2b). We refer to this dataset as the "Diagnostic-analysis"

To test the impact of the edge effect of the filtering at the ends of the dataset in the real-time methodology we construct a further wave dataset, by repeating the real-time methodology, replacing the 7 day forecasts with analysis data (mimicking a perfect forecast). We refer to this dataset as the "Perfect Forecast" wave dataset (Fig.2a).

To explore the value of using the forecast data, we create one more additional wave dataset ~~created~~ by repeating the real-time methodology but~~y~~ replacing the forecast data with zeroes, (see Figure 2a), referred to as the ‘Padded’ wave dataset.

3.2 Results

Results presented here will be focused on one year, 2016, as the other three years give very similar features. Since at a given latitude, the zonal wind of the Kelvin wave and the meridional winds of the $n \geq 0$ equatorial waves can represent the whole meridional structure, we will present these winds at a latitude where their amplitude are near their maximum: Kelvin wave u on the equator, WMRG v on the equator, R1 v at 8^{o}N and R2 v at 13^{o}N.

3.2.1 Evaluation of amplitude and phase of diagnosed equatorial waves

Impact of the real-time filtering

To examine the impact of the real-time filtering methodology we compare the waves diagnosed from the Perfect Forecast wave dataset with those from the Diagnostic-analysis. The amplitude and phase propagation of waves can be clearly demonstrated in a longitude-time Hovmöller diagram. Figure 3 shows Hovmöller diagram of the Kevin wave u at 850hPa from the Diagnostic-analysis (Fig.3a) and Perfect forecast dataset at day 0 (analysis time, Fig.3b) and day 2 (Fig.3c). By eye, the wave amplitude and zonal phase behaviours look very similar in the three cases. This is confirmed by the differences between the Perfect Forecast dataset and Diagnostic-analysis shown in Figs.3d, e. It is seen that the differences are generally small, being less than 0.5m s^{-1} in most of the time and space domain. It is interesting that the differences appear to be mainly on lower frequencies, indicating the edge effect is small at high frequency. It is noted that there are phase jumps (discontinuities) around 35E and 280E, in the regions of the eastern central-African highlands and the Andes.

For the westward-moving equatorial waves, WMRG, R1 and R2, as in the case for the Kelvin wave, their amplitude and zonal propagation behaviours in the Perfect forecast dataset are very similar to those of Diagnostic-analysis (not shown), with very small differences between them, especially for R1 and R2 waves.

<u>Impact of an imperfect forecast</u>

To examine the wave behaviours in Real-time forecast, Fig. 4 shows the Kevin wave identified from Real-time dataset. The Diagnostic-analysis is shown again in Fig.4a for comparison, and the Real-time Analysis at day 0 and the day 2 forecast waves are shown in Figs.4b, c, respectively. The difference fields are shown in Figs.4d, e. The real-time analysis (day 0) shows a quite similar amplitude and phase propagation pattern to that of Diagnostic-analysis, with the difference between them being small (Fig.4d), although the impact of the imperfect forecast can be seen (by comparison with Figure 3d). For the day 2 forecast, the pattern of strong waves is also reasonably well simulated, for example around the middle of April or the middle of June. However, it is clear that there are systematic errors which seems to be associated with the two highlands around 35E and 280E (Figs.4d,e), and the error grows with the forecast lead time.

Figure 5 shows WMRG waves in Real-time wave dataset, the wave pattern is generally well simulated at day 0 (real-time analysis) and at day 2 (forecast). The topography-related bias can also be seen for the WMRG but is weaker than that for the Kelvin wave. R1 and R2 waves are also very well simulated by the Real-time methodology and their topography-related errors are less clear (not shown).

Since the bias looks quite stationary, although it has some seasonal variation for WMRG, to examine the bias the 12-month mean amplitudes of the Kelvin wave zonal wind, and WMRG, R1 and R2 meridional winds at their maximum latitudes are shown in Figure 6 for the Perfect forecast wave dataset (left) and Real-time wave-dataset (middle) for a selection of times between T-4 days and T+6 days. For comparison the 12-month mean of the waves in Diagnostic-analysis (black solid) is also shown in each panel. The three blue lines are for T -4, T-2 and T+0 (analysis), and 4 red lines for day T+1, T+2, T+4 and T+6. It is seen that the time mean zonal wind of the Kelvin wave is close to zero in the Diagnostic-analysis, consistent with what would be expected for a wave-like field. For the Perfect forecast wave dataset, the mean amplitudes of the Kelvin wave at day -4 to 0 (blue) are close to that in Diagnostic-analysis, whereas the mean amplitude beyond day 0 (red) starts to show some departure from the zero, but large departure is only shown for large lead time (day +4 to +6) and mainly around 35E and 280E, close to the topography. Errors in the other wave fields are much smaller.

On the other hand, time mean Kelvin wave zonal wind amplitudes for the Real-time wave dataset (middle column) have much larger departures, especially around the two highland areas, with an easterly bias to the west and westerly bias to the east at the two longitudes. On close inspection, it is interesting to see that peaks of the wind bias shift eastward with the leading time in both areas. In contrast the peaks of bias for westward-moving waves tend to shift westward with lead time, and may be an indication of spurious wave generation by processes in the vicinity of the orography.

To remove the bias we propose, for each lead time, removing a mean of the previous 30 days wave analysis (T+0) or forecast (T+1 to T+7) for the given lead time. We choose a 30 day running mean to capture the longest wave periods in the dataset whilst minimizing the amount of data which needs to be stored to calculate the bias. The right column of Fig. 6 shows the 12-month mean for Real-time wave dataset after the 30-day mean is removed. It is clear that the bias has been greatly reduced. (N~~n~~ote that no bias correction has been made for

T<0, but it could in principle be done as even at T<0 the wave data is influenced by forecast errors).

Figure 7 shows Hovmöller diagrams of the Kelvin wave at Real-time wave dataset with a lead-time dependent 30-day time mean removed. It is seen that the forecast waves at day 2 (Fig 7c) now more resemble those of Diagnostic-analysis, and the differences between the day 2 forecast and Diagnostic (Fig.7e) are dominated by errors with spatial and temporal characteristics of the observed wave field.

The three westward-moving waves in the Real-time wave-dataset with the 30-day mean removed are shown in Figs. 8-10, respectively. It is encouraging to see that similar to that for the Kelvin waves, the amplitude and phase evolution of the three westward-moving waves is well captured by forecast.

After showing the wave behaviours for the Perfect forecast and Real-time wave-datasets, it is of interest to evaluate the benefit of including the forecast data in the real-time methodology by examining the waves in the Padded wave dataset. Figure 11 gives an example for the Kelvin wave. It is clear that wave analysis (T+0) from the padded dataset differs greatly from that in the Diagnostic-analysis, with little skill in capturing wave behaviours. This suggests that the forecast data is indeed useful not only in providing future information about the equatorial waves, but also in identifying the waves in real-time. However in the absence of forecast data the padded approach could probably be improved by increasing the length of the time series both backwards in time and by padding with more zeros (c.f. the methodology of Wheeler and Weickmann)

3.2.2 Validation of wave variance, errors and correlation

To examine the variability of equatorial waves, Figure 12 shows the standard deviation of the four waves in the Perfect forecast dataset (left), Real-time dataset without removing previous

30-day mean (middle) and Real-time dataset with the 30-day mean removed for days 0-7 (right). It is seen that for all waves in the Perfect forecast dataset, and R1 and R2 in Real-time dataset, their standard deviation at all lead times is very close to those in the Diagnostic-analysis (black), except for the westward moving waves at day 6 around 40^{o}E where there is a spike. For Kelvin and WMRG waves in the Real-time dataset, their standard deviations are also close to those in Diagnostic-analysis at days -4 to 0, but from day 2 their variability is weaker than those in Diagnostic-analysis. The Real-time dataset with 30-day mean removed (right) has very similar variability to that before the removal of the 30 day mean, but with the spike around 40^{o}E for the three westward-moving waves being removed, indicating the removing the 30day mean doesn't substantially reduce the diagnosed wave amplitude

To quantify the errors in a statistical way, the root mean square errors (RMSE) for the four waves identified with different procedures are calculated and standardised by the standard deviation of the wave mode in the Diagnostic-analysis. RMSEs are relative to the Diagnostic-analysis. Figure 13 shows the normalised RMSE averaged over all longitudes against lead time at both 850 hPa and 200 hPa. For the Perfect forecast (solid), the RMSE for each wave is less than 0.2 at day -4. It increases slowly, with the lead time, to about 0.3 to day 4. After day 4 the errors increase faster but they are generally less than 0.5 at day 6. At the last day (day 7) the errors jump to 0.75~ 0.95 due to edge effect being largest there. For the Real-time dataset (dashed) before day 0 the RMSEs are comparable to those in Perfect forecast dataset but increase more rapidly from day0, reaching around 0.7 at day 4, 0.8 at day 5 and 1.0 at day 7. As expected, the errors in the Padded dataset (dotted) are much larger than those of either of the other methods at all lead times, although it is worth noting that the error in the Padded method at day 0 is slightly reduced compared to the error in the Perfect Forecast at day 7, which would be equivalent to the error without any procedures in a real-time analysis method which didn't do anything to mitigate the edge-effects of the filter.

Figure 14 shows the correlations of each wave in the different datasets with those in Diagnostic-analysis. Correlations are calculated with samples at all longitudes and time (360 longitudes*366 days). The correlation shows a similar signature to the RMSE. Correlations in the Perfect forecast dataset (solid) are quite high and drop slowly with lead time, being larger than 0.9 up to day 6. For the Real-time dataset (dashed), although their correlations drop rapidly after day 1, they are still larger than 0.5 at day 6, and remain above 0.7 up to days 4-5 depending on the wave.

Again as expected, the correlations at T+0 for the Padded dataset (dotted) are much lower than that in Real-time analysis at T+0.

4. Summary and discussion

A novel technique for real-time identification of dynamical equatorial wave modes in analysis and forecast data is successfully developed based on well tested methodology for identifying equatorial waves from the horizontal structures of wave modes. The real-time methodology appends 7 days of operational global forecast data on to an analysis time series. The dynamical fields are then filtered in a specified broad zonal wavenumber-frequency domain and projected into horizontal structures of the wave modes. This methodology is distinctly different from previous methodologies that identify equatorial waves by filtering OLR over a small domain confined by dispersion relations.

The technique is tested using the four year Met. Office analysis and forecast data in 2015-18. The waves investigate are equatorial Kelvin, westward moving Mixed Rossby-Gravity Wave (WMRG), and n=1 (R1) and n=2 (R2) Rossby waves.

The methodology is evaluated by first assessing the impact of the filtering procedure by using a “Perfect Forecast” dataset against a Diagnostic-Analysis with full knowledge of the future wave behaviour. Correlations and RMSE shows the impact of the filtering procedure to be small at analysis time (T+0) with error growing only slowly to T+6.

In the Real-time dataset the errors at analysis time (T+0) are only slightly larger than for the Perfect forecast dataset. Some biases in time mean equatorial wave winds in the Real-time forecast are identified, which appear to be topography-related, appearing around the two highland regions of eastern central Africa and the Andes. Since the bias is quite stationary with some small seasonal variation, simply removing the previous 30-day mean for each wave at each lead time greatly reduces the bias. Forecasts with the bias removed can simulate wave amplitude, phase evolution and variability reasonably well up to forecast lead times 4-5 days (Normalized RMSE < 0.7-0.8, correlation >0.6-0.7) These results are encouraging, indicating that the real-time technique is able to identify the waves ~~analyses~~in the analysis ~~-~~in real-time and the model has some skill in forecasting the equatorial waves.

For comparison, the technique is also applied to time series of analysis data with the last 7 days being padded to zero. The result shows very little skill in capturing equatorial wave behaviours, demonstrating that the forecast data is not only useful in providing future information of equatorial waves, but also in identifying the waves in analyses.

Based on above analysis, we recommend that the technique can be applied to operational real-time identification of equatorial waves in analyses and global forecast models.

Next, we will use the 4 year real-time forecast data to further evaluate the skill of the forecast model for predicting the phase and amplitude of the waves and to examine the ability of the Met Office global operational forecast model in representing the observed relationships between equatorial waves and high impact weather across Southeast Asia. It is anticipated that through tracking the evolution of amplitude and phase of equatorial waves and their relations to convection and high impact weather throughout the forecasts would provide useful information on the prediction of tropical convection and high impact weather events.

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