Diagnosis of Tropical Biases and the MJO from Patterns in the MERRA Analysis Tendency Fields

BRIAN E. MAPES
Rosenstiel School of Marine and Atmospheric Sciences, University of Miami, Miami, Florida

JULIO T. BACMEISTER
National Center for Atmospheric Research,* Boulder, Colorado

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ABSTRACT

The Modern-Era Reanalysis for Research and Applications (MERRA) is realistic, including its Madden–Julian oscillation (MJO), which the underlying model [Goddard Earth Observing System, version 5 (GEOS-5)] lacks. In the MERRA budgets, analysis tendencies (ATs) make evolution realistic despite model shortcomings. The ATs are the negative of physical process errors, if dynamical tendencies are accurate. Pattern resemblances between ATs and physical tendencies suggest which processes are erroneous. The authors examined patterns of tropical ATs in four dimensions and found several noteworthy features. Temperature AT profiles show that moist physics has erroneous sharp cooling at 700 hPa, a signature of misplaced melting and perhaps excessive pre-cipitation evaporation. This excites a distinctive (fingerprint) erroneous short vertical wavelength temperature structure, perhaps a cause of the GEOS-5 too-slow convectively coupled waves. The globe’s largest AT of 200-hPa wind stems from overactive heating over the intra-Americas seas region in summer, with the same moist physics fingerprint. The erroneous heating produces a baroclinic vortex that is countered by ATs opposing its temperature and momentum fields in a thermal wind balanced sense. Lack of restraint in the deep convection scheme is also indicated in MJO composites, where the water vapor AT is anomalously positive on the leading edge, indicating a premature vapor sink. Since GEOS-5 lacks an MJO, this diagnosis suggests that the transition from shallow to deep convection (moistening to drying) is crucial in the real-world MJO. This is not news, but its diagnosis by ATs provides an objective, repeatable way to measure the effect that could be a useful guide in model development.

1. Introduction

There are many ways to learn from the confrontation of an atmosphere model with observations, in service of model improvement. The study of initial tendencies [or errors in one-time-step forecasts, Klinker and Sardeshmukh (1992)] is appealing because the effect of a model process error is localized. However, initialization shock may dominate the results, making interpretation subtle (e.g., Judd et al. 2008). At the other extreme of time scale, the biases of unstrained model runs can also be hard to interpret since interacting errors have time to pervade all aspects of the simulation. In between the first time step and free model climatology lies the process of error growth and spread, which may yield long-term errors quite different from the original source of the error (e.g., Rodwell and Jung 2008). At still longer lead times, other coupled model components (land and ocean) can further evolve the errors (e.g., Song and Mapes 2012). A “seamless” suite of data assimilation and forecast activities, with initialized forecasts examined at various lead times, is arguably the best way to evaluate and improve models of both weather and climate (Jeuk en et al. 1996; Phillips et al. 2004; Rodwell and Palmer 2007; Boyle et al. 2008; Andersson et al. 2005; Martin et al. 2010).

Data assimilation can also teach us about nature, not just about model errors. While model accuracy is helpful in ensuring the realism of analyzed states, small model

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Corresponding author address: Brian E. Mapes, Rosenstiel School of Marine and Atmospheric Sciences, University of Miami, Miami, FL 33149.
E-mail: mapes@miami.edu

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errors can actually be informative if they act as space–
time “fingerprint” patterns that facilitate process interpretation. Lessons about nature are probably clean-
est when the model exerts little of its own influence, but
rather acts only as a quantitative framework of governing
equations. Such is the case with the study here of the
Madden–Julian oscillation (MJO) (Madden and Julian
1994), a prominent form of variability in nature that the
free-running Goddard Earth Observing System, version 5
(GEOS-5), model lacks almost completely (see Figs. 3g,
4g, 6g, and 7g of Kim et al. 2009). That same model
(slightly updated but still lacking an MJO) underpins the
new Modern-Era Reanalysis for Research and Applica-

A novelty of the MERRA over earlier reanalyses is that its datasets include comprehensive sets of budget terms for the model state variables (e.g., wind, temper-

ture, moisture, and ozone). These Eulerian budgets balance exactly, by construction: a term on the right-

hand side of each budget called the analysis tendency
(AT) guarantees it. Construction of the ATs occurs
during a predictor–corrector or forward–backward time
integration that drives the model through a sequence of
analyzed atmospheric states (as described in section 2).

In a well-developed, comprehensive, full-physics GCM
like GEOS-5, model shortcomings are mostly second-
order weaknesses within adequate schemes, not wildly
inaccurate or missing processes. This helps us interpret
ATs: if the space–time patterns of ATs resemble the
pattern of action of one of the model’s physical ten-
dencies, this suggests which scheme is at fault—acting in
about the right place within a well-analyzed state, but in a
slightly wrong way (Schubert and Chang 1996). Along the
way, lessons can also emerge about nature, at least if
they are expressible within the framework of the ideas
and mechanisms embodied in the model’s formulation.
This study is a diagnosis of some errors of GEOS-5 via
MERRA ATs, containing some lessons about nature.

Section 2 describes the MERRA data and the inter-
pretation of analysis tendencies. Section 3 examines AT
patterns in samples and averages over various regions of
space and time. Section 4 contains the summary and
conclusions.

2. Data and methods

a. Analysis tendencies

The MERRA reanalysis is described in Rienecker
et al. (2011). It uses a version of the GEOS-5 atmo-
spheric model called GEOSAGM-Eros_7_24. Its physics are similar to prior versions including the National
Aeronautics and Space Administration Seasonal-to-
Interannual Prediction Program, version 2 (NSIPP-2),
model (Bacmeister et al. 2006; Lee et al. 2008; Mapes
et al. 2009), and the GEOS-5 model used in Kim et al.
(2009), although the reevaporation of precipitation has
been updated somewhat (relevant to discussions herein).
State estimation (analysis) is done by a 3D optimal in-
terpolation (minimization of a weighted sum of squared
errors between first-guess fields and observations), in-

gesting many types of observations both from satellites
and in situ measurements (Rienecker et al. 2008). Given
the sequence of analyzed states every 6 h, the incre-
mental analysis update (IAU) (Bloom et al. 1996) tech-
nique builds ATs that carry the model trajectory in phase
space almost exactly through the analyzed states. The
ATs are constant within 6-h model integration time
windows centered on the 6-hourly analysis times. Using
the IAU system, any version of the model can be driven
through any set of states (including other reanalyses, not
just MERRA states)—a capability called replay.

The following discussion introduces our notation
about the ATs, as used in figure captions and discussions
below. Consider an arbitrary state variable \( Z \) whose
governing equation in nature can be written in terms of
large-scale dynamical plus physical processes (partial
tendencies):

\[
\frac{dZ}{dt} = \frac{\partial Z}{\partial t} + \frac{\partial Z}{\partial t_{\text{phys}}}. \tag{1}
\]

A GCM has a corresponding governing equation for
Z, but discretized in time as indicated by \( \Delta t \) and with
approximations of the right-hand side:

\[
\Delta Z/\Delta t = dZ/dt_{\text{dyn}} + dZ/dt_{\text{param}}. \tag{2}
\]

The model dynamical tendencies \( dZ/dt_{\text{dyn}} \) consist of
advection of resolved-scale gradients by resolved-scale
flows, plus pressure gradient and Coriolis forces in the
case where \( Z \) is momentum. Given an accurate state
analysis and its gradients, \( dZ/dt_{\text{dyn}} \approx \frac{\partial Z}{\partial t_{\text{bd}}} \) since dynam-
cal core numerics errors are small. More problematic
are the “physics” tendencies \( dZ/dt_{\text{param}} \), which must try to
represent \( Z_{\text{phys}} \) including all unresolved fluid eddy flux divergences (turbulence, convection, and gravity
waves), all truly nondynamical processes like radia-
tion and molecular effects (surface conduction, phase
changes, and radiation), and all the interactions of
these things, including possible nondeterminism. In
GEOS-5, the physical tendencies \( dZ/dt_{\text{phys}} \) are broken
down according to subroutine packages: moist processes
\( dZ/dt_{\text{moist}} \) (e.g., convection, cloud, and precipitation),
turbulence \( dZ/dt_{\text{turb}} \), radiation \( dZ/dt_{\text{rad}} \) and gravity wave
drag \( dZ/dt_{\text{gw}} \).

In reanalysis (or replay) mode, the model equations are
modified by addition of an analysis tendency \( dZ/dt_{\text{ana}} \):
\[
\frac{\Delta Z_{\text{analyzed}}}{6 \text{ h}} = dZ/dt_{\text{dyn,6h}} + dZ/dt_{\text{param,6h}} + dZ/dt_{\text{ana}},
\]

(3)

which is perhaps more clearly viewed as a definition of the AT field:

\[
dZ/dt_{\text{ana}} = \frac{\Delta Z_{\text{analyzed}}}{6 \text{ h}} - dZ/dt_{\text{dyn,6h}} - dZ/dt_{\text{param,6h}}.
\]

(4)

If the large-scale state variables are accurately analyzed including their spatial gradients and time changes, then large-scale dynamical tendencies are accurate \((dZ/dt_{\text{dyn}} \approx \dot{Z}_{\text{dyn}})\) as argued above and \(\Delta Z_{\text{analyzed}}/\Delta t \approx \partial Z/\partial t\). With those assumptions, (3)–(1) give the following:

\[
dZ/dt_{\text{ana}} \approx -\left( dZ/dt_{\text{param}} - \dot{Z}_{\text{phys}} \right),
\]

(5)

or in other words, ATs can be interpreted as the negative of model physical tendency error.

The IAU produces 6-hourly piecewise-constant ATs centered on the analysis times, which are included as four-dimensional output fields in the MERRA dataset. However, it is worth noting that any scheme that draws the model toward an analyzed state sequence could be used to define ATs usefully, even simple relaxation or nudging (Jung 2011).

b. MJO definitions

The MJO results described below involve two different approaches to define the MJO phase as a basis for composites. In the first, each longitude has a different phase (front, middle, and back of the moving MJO’s central rainy or active area). In this case longitude as well as time can be pooled to make phase composites, and a few months of data are sufficient to fill 8–10 phase bins. In the second, the whole world is assigned one phase of the MJO on a given day, so “phase” thus corresponds to the longitude of enhanced convection (Wheeler and Hendon 2004, hereafter WH04). Since the dependence on longitude is retained, only temporal averaging contributes to building a composite and many more data are needed to make it smooth. A third definition used in Robertson and Roberts (2012) also assigns the whole world a single MJO phase on any given day. Figure 3 of Riley et al. (2011) illustrates our two methods of defining the MJO.

The first approach is defined from space–time filtered tropical belt \((15^\circ S–15^\circ N)\) outgoing longwave radiation (OLR) observed by satellite. The OLR time–longitude section was bandpass filtered for 20–100-day periods and planetary wavenumbers 1–9, to produce a reference time–longitude section \(\text{OLR}'(x, t)\), which passes the eyeball test (Fig. 5 below) for appropriately isolating the relevant low frequency aspects in the time–longitude section. A scatterplot of standardized OLR’ and standardized \(\partial (\text{OLR}')/\partial t\), with each longitude–time bin as its data points, makes a circular scatter in which azimuth defines MJO phase and radius is amplitude (see Fig. 3 of Riley et al. 2011; Fig. 2 of Yasunaga and Mapes 2012). Dividing phase into 10 bins leaves enough data in each bin for a smooth composite with just a few MJO cycles (four months of data). However, aspects of the MJO that depend on longitude are sacrificed in the averaging. In some plots below, Indian and Pacific Ocean longitudes were averaged separately, although this functions more as a significance check (emphasizing the similarities) than an estimate of longitude dependence (the differences). This was our first approach, conducted initially with 2.5° “scout” versions of MERRA and later repeated with final MERRA data, for two 120-day periods of intense MJO activity: January–April 1990 and November 1992–February 1993. The first period was the highest peak in a long-term index of MJO variance for which MERRA data were available when the research began, while the second was chosen because it included the Tropical Ocean and Global Atmosphere Coupled Ocean–Atmosphere Response Experiment (TOGA COARE) field program. For these two periods, a comprehensive composite of all (more than 100) MERRA dataset variables was made and perused. The similarity of results between these two MJO-active periods gives us confidence that the conclusions reported here are robust. We focus here on the 1990 results, in part to emphasize that the special observations of 1992–93 are not critical for this exercise. Microwave rainfall estimates over ocean, obtained from Remote Sensing Systems (http://www.ssmi.com), were used as an independent check on MERRA rainfall. It is noteworthy that the 2.5° scout data gave composite results almost identical to the much larger final MERRA dataset.

Our second approach to the MJO definition uses the Real-time Multivariate MJO index (RMM). WH04 defined its components (RMM1 and RMM2) as the leading pair of principal components in an analysis of the combined vector of standardized and lightly high-pass filtered OLR, 850-hPa zonal wind and 250-hPa zonal wind time–longitude sections. In this RMM-based MJO definition, longitude and latitude dependences are retained since RMM1 and RMM2 are simply daily time series. We composited 1979–2005 MERRA data in the WH04 octants of RMM1–RMM2 phase space. For these composites we also rebinned the data from \(2^\circ \times 2^\circ\) resolution \((540 \times 360\) arrays, discarding the 361st latitude, the North Pole) to \(3^\circ \times 5^\circ\) \((108 \times 36\) arrays). Data...
are on 42 pressure levels (25 levels in the troposphere with 25–50-hPa spacing). RMM phases thus range from 1 to 8.

3. Results: Analysis tendencies and their interpretation

This section examines the MERRA tropical ATs in different scales, domains, and contexts based on the most outstanding findings of our comprehensive examination.

a. Vertical structure: A full-resolution sample of $dT/dt_{ana}$

Figure 1 shows $dT/dt_{param}$ and $dT/dt_{ana}$ at a single grid point over the equatorial western Pacific in late December 1992, the place and time of the TOGA COARE field campaign. The MERRA total physical heating (Fig. 1a) is top heavy in profile and intermittent in time, and shows a distinctive stripe of low or negative values at 700 hPa, also seen in prior studies such as Fig. 4 of Mapes et al. (2009), Figs. 1 and 3 of Hagos et al. (2010), and Fig. 9 (case 1) of Ling and Zhang (2011). Moist heating $dT/dt_{moist}$ provides most of this total (not shown), and further breakdowns are shown later. The analysis tendency (Fig. 1b) consistently opposes the stripe of moist cooling at 700 hPa, suggesting that it is erroneous, and also has a negative stripe at 550 hPa (the 0°C level in the tropics).

Based on these AT stripes, under interpretation (5) above, we suspected that the model was melting its precipitation at the wrong level, near 700 hPa instead of 550 hPa in the tropics. In the model code, freezing and melting were both assigned a time scale of 5000 s, a time chosen to express ice nucleation delays in the freezing process. For melting, 5000 s is so long (5-km fall at a typical snowfall speed of 1 m s$^{-1}$) that a secondary cleanup line of code is actually handling most snow melting, at the first altitude (going downward) where $T$ exceeds 5°C. Thus melting is, indeed, occurring too low in the MERRA version; newer versions of GEOS-5 have updated this treatment based on the research presented here. Precipitation reevaporation also shows a sharp vertical gradient in the 600–700-hPa range (as shown below in Fig. 6c) and may also contribute some of the physics error deduced from the AT vertical structure. The reevaporation is mostly of nonconvective rain (not shown) and it corresponds to a cloud void beneath rain-generating upper cloud, suggesting that it is strong enough to drive a resolved-scale downdraft (Fig. 8c of Mapes et al. 2009). Reevaporation cooling was deliberately increased during past model development in order to limit convection–low level convergence interactions that lead to a double ITCZ bias in the Pacific (Bacmeister et al. 2006).

Vertically thin localized cooling (such as melting) drives gravity wave motions that are dispersive according to vertical wavelength, yielding wavelike temperature anomalies with short vertical wavelengths that extend above and below the localized cooling. This wavelike-forced $T$ pattern can then couple to convective mass flux profiles through buoyancy sorting, producing thin layered inflows and outflows sometimes seen near but also extending above and below the melting level in
Doppler radar data (Mapes and Houze 1995). Based on this physics, the erroneous vertical temperature wave implied by the \( \sim 300\)-hPa vertical wavelength in Fig. 1b may be a consequence of thin-layer physical heating errors in as few as one layer. But if model melting is misplaced in the vertical from 550 to 700 hPa, it implies a dipole error with twice the magnitude of melting: both too little cooling at 550 hPa and too much at 700 hPa. The same short-wavelength \( T \) profile in connection with rain events can be seen in Fig. 8f of Mapes et al. (2009).

There is also another kind of very indirect evidence of a short vertical wavelength heating and \( T \) error in GEOS-5: convectively coupled waves travel at about 7 m s\(^{-1}\) (Fig. 6b of Lee et al. 2008), much slower than in observations and approximately consistent with the idea of a gravity wave of \( \sim 300\)-hPa vertical wavelength as seen in Fig. 1b coupling to convection. Might the altitude of melting be important in setting the phase speed of convectively coupled waves? The answer depends on a combination of the heating profile’s vertical fine structure and the convection scheme’s sensitivity profiles, beyond the present scope.

b. The strongest feature of \( U_{200} \) AT climatology

The MERRA annual mean climatology (1979–2005) of \( du/\Delta t_{\text{ana}} \) at 200 hPa is shown in Fig. 2, in the region of one of its most intense features, regridded to \( 3.3^\circ \times 5^\circ \) resolution. The largest value exceeds \( -3 \) m s\(^{-1}\) day\(^{-1}\) in the annual mean over the western Atlantic at about 25\(^\circ\)N, and the time–latitude climatology in Fig. 2b reveals that it occurs in summer when sea surface temperature (SST) is warmest. A similarly timed positive value is seen at 10\(^\circ\)–15\(^\circ\)N, suggesting that these are part of a couplet.

GEOS-5 tends to produce too much deep convection and rainfall over the Atlantic warm pool (AWP) region in summer when driven with observed SST fields (standard diagnostics not shown), like many contemporary GCMs (Biasutti et al. 2006; Misra et al. 2009). This problem is indicated in MERRA by the vertically integrated AT for water vapor, \( d(q_v)/\Delta t_{\text{ana}} \) (Fig. 3). Positive AT values there suggest that the model physics has an overactive moisture sink (precipitation). We speculate that the convection scheme cues too strongly on surface-based parcel instability, which is closely tied to warm SST, and is too insensitive to the middle-level dry air, an important suppressing factor for convection in the AWP region.

An overactive moisture sink implies an excessive moist heating in the model, which must produce erroneous potential vorticity (PV) via its vertical derivative. We can discern the balanced wind and thermal structure of this erroneous PV vortex in Fig. 4a, which shows a cross section of the ATs of temperature (colors) and \( u \) (contours). Cyclonic \( du/\Delta t_{\text{ana}} \) torques at 200 hPa indicate that wind observations oppose the model’s tendency to produce an excessive anticyclone above its excessive heating. Meanwhile, anticyclonic torques near 600 hPa suggest that the model has an erroneous cyclonic tendency, consistent with a PV source due to an excessive vertical heating gradient \( dQ/dz \) there. Consistently, \( dT/\Delta t_{\text{ana}} \) is negative in between, in the 200–600-hPa layer, and positive at 700 hPa,
which also indicates via the $T$ field directly an excessive $dT/dt_{\text{param}}$ heating dipole with (minus) the profile of $dT/dt_{\text{ana}}$. Figure 4b shows that the physical heating (open contours) closely follows the pattern that the ATs are opposing, supporting the interpretation (5) of ATs as the negative of physical (mostly moist) heating errors. Rain events in Fig. 8b of Mapes et al. (2009) leave a temperature residue of similar vertical structure, so Fig. 3’s balanced climatological vortex of errors appears to be a convectively driven feature writ large. In this case, the heating has excessive magnitude, and its peculiar profile (discussed above in section 3a) is the fingerprint of MERRA’s moist heating processes that aids in attribution.
c. MJO composites of ATs

Since MERRA tracks nature in time, we can use independent satellite observations of the MJO as the basis for compositing MERRA ATs and other fields. Robertson and Roberts (2012) conclude that “MERRA has produced a very credible picture of intraseasonal variability as judged by comparisons with radiative fluxes and precipitation data that are independent of the assimilation,” and we find the same using OLR (not shown) and SSM/I rainfall estimates (in Fig. 7 below), encouraging the use of independent measurements as a basis for composites.

Figure 5 shows the strong MJO activity of January–April 1990, with 15°N–15°S OLR (left panel colors) and OLR’ filtered to MJO frequencies and wavenumbers (open contours on both panels). Figure 5b shows the phase strips used to construct our composites. Phase 0 is most suppressed (OLR’ maxima), and phase 5 is most active (OLR’ minima), as the antipodes of 10 equally spaced azimuth bins in OLR’ versus dOLR’/dt space. Many studies use 8 phase bins, but we (following Riley et al. 2011) happened to choose 10 initially, and that resolution proves convenient below. Contouring makes such binning details unimportant, except that plot axis labels go from 0 to 9 rather than 0 to 7 or 1 to 8.

Selected terms in the MJO composite temperature budget are shown in Fig. 6. Note that mean fields and MJO variations are combined in Fig. 6; these are not anomalies. Since the MJO is low frequency and cyclical, heat storage $\Delta T/\Delta t$ is tiny as $dT/dt_{\text{dyn}}$ and $dT/dt_{\text{phys}}$ nearly balance (not shown). Moist processes (Fig. 6c) produce most of the physical heating, and again the sharp vertical gradient from 550 to 700 hPa is seen. Evaporation of precipitation (Fig. 6d) is centered at 750 hPa and provides a substantial part of the vertical gradient near 600 hPa, which is sharper than that in Fig. 5 of Bacmeister et al. (2006) as the parameterization has changed since then. The profile structure in $dT/dt_{\text{ana}}$ (Fig. 6d) seems to align with the moist heating profile.
finestructure, and not with that of radiative heating (not shown), again providing fingerprint-type evidence that moist heating rather than cloudy radiation is the dominant process driving the layered structure of errors.

Moisture budget processes (Fig. 7) are revealing about the model’s difficulties in simulating the January–April 1990 MJOs. Starting at the lower left, Fig. 7d shows that unassimilated rainfall estimates by satellite indicate a tripling of rainfall from phase 0 to 5 for the composite MJO as defined here, with the Indian sector (red) rainier than the Pacific (blue) on average. MERRA (land plus ocean) has a positive rain bias compared to SSM/I (ocean only) across all phases, and also a smaller composite MJO amplitude (Fig. 7c). Robertson and Roberts (2012) also find that the MERRA MJO is credible but a bit weak in its rainfall amplitude, consistent with the notion that the model lacks the oscillation mechanisms and is being forced to undergo it only by the observations it assimilates. Phase 2 as defined here is the peak of MERRA’s excessive rain bias. Moisture ATs in Figs. 7a,b confirm that MERRA’s moisture sink is most excessive in phase 2, although this is just a modest deviation from a time-mean tropical moisture profile bias that prevails across all phases, with a distinctive vertical profile (Fig. 7a). GEOS-5 developers call this bias “the mushroom” after its appearance in zonal mean cross sections.

Convective mass flux (Fig. 7e) also shows a distinct upper-level enhancement in phase 2, indicating that the model is premature in its onset of deep convection in the MJO onset phase, well before the peak rainfall (at phase 5–6). Interestingly, observations composited in the same way (albeit from different years, in the CloudSat era, 2006–09) suggest some interpretations of the model’s difficulties. Figure 7f shows randomly drawn samples of CloudSat echo objects (Riley et al. 2011), each centered on its appropriate phase (phase is defined continuously here, but the x axis is labeled with 10 values for convenience). Deep convection does indeed occur in phase 2, in fact with the highest echo-top altitude of the whole display. It is isolated and narrow, however, quite distinct from the wide, overlapping mesoscale echo objects in the main active phases (3–6 in this random sample from MJO events in 2006–09). Also consistently, lightning
peaks in off-peak phases of the MJO (Morita et al. 2006), indicating intense but sparse convection in conditions like phase 2. Based on all of these indications, it appears that the lifted-parcel instability driving isolated cumulonimbus clouds is strong in early MJO phases, so perhaps it is unsurprising that GOES-5 parameterized convection, which is based on vertically integrated buoyancy or cloud work function (Moorthi and Suarez 1992) might overreact to that instability. Hypotheses to improve the model would be to increase its sensitivity to dry air, as suggested also around Fig. 3, or to find some way to parameterize a distinction between isolated and organized deep convection. MERRA’s prematurely widespread deep convection development is also seen as a phase shift of its mid and high cloud-related fields relative to the Moderate Resolution Imaging Spectroradiometer (MODIS) and other satellite observations (Fig. 4 of Robertson and Roberts 2012).

By using many years (1979–2005) instead of just four months of MERRA data, we can add spatial detail to this diagnosis of MJO moist processes and their errors in GEOS-5. Figure 8 shows the MERRA MJO anomalies of precipitation and column integrated $d(q_v)/dt_{ana}$ compositing according to the Wheeler–Hendon RMM phase definition, averaged over 20°S–20°N. Phase 8 is repeated as phase 0 for contouring purposes. Positive rain anomalies (green) of about 1 mm day$^{-1}$ move...
across the Indo-Pacific sector (60°E–180°) from phases 2 to 6. Before (east of) these rain anomalies are positive AT anomalies (red, ≈0.1 mm day$^{-1}$) that show the model’s overactive physical moisture sink (premature deep convection or inadequate surface flux) in those regions and times. Lines at phases 2 and 3 delineate when this leading positive AT feature is over the Pacific, although the effect is even stronger over the Indian Ocean in phase 8.

Figure 9 shows a spatially distributed view of moisture budget terms for phases 2 (top three panels) and 3 (bottom three panels). MERRA precipitation composites show the maximum (red areas in Figs. 9a,d) moving from the eastern Indian to western Pacific Ocean during
these phases. Ahead of the peak rainfall anomalies, over the whole western Pacific, positive $d(q_v)/dt_{ana}$ and vertically distributed $d(q_v)/dt_{ana}$ suggest, once again, that the model physics tendency has a negative error there (excessive moisture sink in premature deep convection or inadequate source in surface flux). The vertical structure of $d(q_v)/dt_{ana}$ in the bottom panel of each phase (Figs. 9c,f) is broadly consistent with that of Fig. 7a and indicates that the physics error is an excessive sink at low levels and source at upper levels, again suggesting premature transition to deep convection. Robertson and Roberts (2012) find consistent results about the MERRA AT structure across the MJO, as defined in their different way. They also examined the divergence of the low-level wind ATs, and found evidence of convergent wind tendencies in the boundary layer playing a role in organizing MJO precipitation, so momentum physics errors, and not just the thermodynamic ones emphasized here, may be a part of GEOS-5’s poor MJO simulation.

Finally, in light of the Indian Ocean signature in Fig. 8, we consider a case study of special interest: October–November 2011 during the Dynamics of the Madden–Julian Oscillation (DYNAMO) field campaign on MJO initiation. Figure 10 shows the MERRA rain rate, precipitable water, and $d(q_v)/dt_{ana}$ for this 61-day period. Two main intraseasonal rain peaks are seen in late October and late November in association with precipitable water peaks. The water vapor AT is, indeed, at its most positive when the real-time multivariate MJO index (RMM) phase is 8 (dotted lines), consistent with the composite results of Fig. 8; a hopeful indicator that these 2 months of DYNAMO-sampled MJO activity may be representative of the MJO generally.

4. Summary and conclusions

We have examined the MERRA analysis tendency fields in height, latitude longitude, and time (season, MJO phase, and instantaneous). Besides showing the model’s mean biases, which could be known by subtracting averaged free running simulation output from averaged observations, ATs show patterns of model error within realistic and real-world-synchronized sequences of atmospheric states. From these patterns and (5) a few findings emerged about MERRA’s underlying model version called GEOSagcm-Eros_7_24:

1) The model has erroneous short vertical wavelengths in its vertical heating profile (Fig. 1b). These errors come mainly from moist heating (Fig. 6b), which has a steep vertical gradient at midlevels due to delayed melting of precipitation too far below the 0°C level as well as concentration of the evaporation of precipitation at about 700 mb (Fig. 6c).

2) The model produces excessive deep convection (moist heating and drying) over the Atlantic warm pool in summer (Fig. 3), where it drives an anomalous baroclinic vortex (Fig. 4), and on the leading edge of the MJO (Figs. 6, 8, and 9), where instability is large (e.g., lightning and tall narrow clouds are observed). The well-known insensitivity of convection schemes to dryness (Derbyshire et al. 2004) may be the common culprit in both errors.

We can further deduce from the fact that GEOS-5 lacks the MJO entirely in free running mode (Kim et al. 2009) that the moisture AT diagnosis points to shallow-to-deep convection transition as a likely key process in the real-world MJO. This is not a new idea (Kemball-Cook and Weare 2001; Kikuchi and Takayabu 2004; Kiladis et al. 2005; Masunaga et al. 2006; Benedict and Randall 2007; Zhang and Song 2009; Masunaga 2009; Katsumata et al. 2009), but having a repeatable, objective method to measure the effect in a mathematical confrontation of model with observations could be uniquely helpful for turning this familiar notion into a path toward well-calibrated model improvements.

The tactic of replaying existing analyses using IAU is very appealing, in comparison to expensive raw-data assimilation, but the use of even simpler linear relaxation to estimate ATs may suffice (Jung 2011). We hope such activities become more routinely available in the future, both to improve models and to advance understanding of imperfectly simulated but well-analyzed phenomena.
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