Moist Process Biases in Simulations of the Madden–Julian Oscillation Episodes Observed during the AMIE/DYNAMO Field Campaign

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ABSTRACT

Two Madden–Julian oscillation (MJO) episodes observed during the 2011 Atmospheric Radiation Measurement Program MJO Investigation Experiment (AMIE)/DYNAMO field campaign are simulated using a regional model with various cumulus parameterizations, a regional cloud-permitting model, and a global variable-resolution model with a high-resolution region centered over the tropical Indian Ocean. Model biases in relationships relevant to existing instability theories of MJO are examined and their relative contributions to the overall model errors are quantified using a linear statistical model. The model simulations capture the observed approximately log-linear relationship between moisture saturation fraction and precipitation, but precipitation associated with the given saturation fraction is overestimated especially at low saturation fraction values. This bias is a major contributor to the excessive precipitation during the suppressed phase of MJO. After accounting for this bias using a linear statistical model, the spatial and temporal structures of the model-simulated MJO episodes are much improved, and what remains of the biases is strongly correlated with biases in saturation fraction. The excess precipitation bias during the suppressed phase of the MJO episodes is accompanied by excessive column-integrated radiative forcing and surface evaporation. A large portion of the bias in evaporation is related to biases in wind speed, which are correlated with those of precipitation. These findings suggest that the precipitation bias sustains itself at least partly by cloud radiative feedbacks and convection–surface wind interactions.

1. Introduction

Despite decades of work, simulating the Madden–Julian oscillation (MJO; Madden and Julian 1971, 1972) in climate models and understanding the instabilities that drive it remain a significant challenge. However, some progress has been reported in recent years. For example, Hung et al. (2013) found that, in general, models participating in phase 5 of the Coupled Model Intercomparison Project (CMIP5) perform better than those that participated in phase 3 of CMIP (CMIP3) in representing MJO variance and the ratio of eastward-propagating to westward-propagating signals. They show that about one-third of the CMIP5 models simulate the spectral peak of MJO precipitation between 30 and 70 days. However, they also note that many of the models suffer from persistent biases of equatorial precipitation. Research toward improved understanding and modeling of the MJO has been progressing on two fronts. One approach is directed toward improvements in the parameterization of convective processes and their interaction with the large-scale environment in models, and the other is aimed at enhancing the theoretical understanding of the instability mechanisms that could result in intraseasonal-scale oscillations in convection.

On the parameterization front, several authors have pointed to various processes as important for improving simulations of the MJO. Among these are increased mixing entrainment and detrainment associated with convection (e.g., Kim et al. 2012; Klingaman et al. 2015; Hannah and Maloney 2014) and improved sensitivity of the depth and strength of convection to environmental humidity due to strengthened coupling between clouds and their surrounding environments (Kim and Kang...
2012), Chikira and Sugiyama (2013) reported sensitivity of their MJO simulation to the inclusion of vertically varying entrainment that depends on the environment in their new cumulus scheme. The gradual evolution of diabatic heating from shallow to deep and later to stratiform precipitation has also been proposed to be a critical process in the simulation of the MJO (e.g., Fu and Wang 2009; Seo and Wang 2010; Hagos et al. 2011; Benediet et al. 2013). Models that link moisture convergence with convection have demonstrated some success (e.g., Liu et al. 2005). Another process whose role is increasingly recognized in recent years is cloud radiative feedback (Landu and Maloney 2011; Kim et al. 2015). In a recent study, for example, Kim et al. (2015) showed a statistical relationship between the CMIP5 models’ representation of this effect and their performance in simulating the amplitude of the MJO. Del Genio et al. (2015) examined sensitivity of MJO simulation to entrainment, rain evaporation, downdrafts, and cold pools. They found that for the various configurations, a version that produces strong column heating for weak precipitation also produces improved initiation and progression of MJO. However, improvements in MJO simulations are often accompanied by degradation of the simulated mean state. For example, Kim et al. (2011) showed that the parameterization changes that improved the simulation of the MJO in their model resulted in excessive precipitation over the western Pacific Ocean.

On the theory front, the MJO is believed to be an outcome of a complex interplay of moisture mode instability, wind-induced surface heat exchange, cloud-radiation feedbacks, and advection processes. Moisture mode instability is related to a positive feedback loop that arises from strong codependence between precipitation and saturation fraction, which is column precipitable water divided by its saturation value. Raymond and Fuchs (2009) showed that a simplified model with strong coupling between convection and moisture produces a MJO-like disturbance in an environment with weak dry air advection. The apparent improvement in the simulation of the MJO with increased entrainment in some cumulus parameterizations discussed above provides support for this hypothesis. Longwave radiative forcing associated with moisture and cloud anomalies is also often cited as the main source of moist static energy for the MJO (Andersen and Kuang 2012; Sobel et al. 2014). For example, in the Chikira and Sugiyama (2013) cumulus scheme, radiative heating anomalies moisten the lower and middle troposphere through vertical advection. Finally, a convection–surface flux feedback through nonlinear wind-induced surface heat exchange (WISHE) was proposed by Maloney and Sobel (2004) as a potential instability mechanism for the MJO. In their atmospheric model coupled with a slab ocean model, latent heat flux anomalies lag the maximum precipitation anomalies, as is often observed. However, the eastward wind exceeds the phase speed of the simulated MJO such that the moist static energy anomalies associated with latent heat flux anomalies can be advected ahead of the MJO precipitation anomalies. Furthermore, Back and Bretherton (2005), Araligidad and Maloney (2008), and Sobel et al. (2010) all showed evidence that the variability of latent heat fluxes has a significant impact on the intraseasonal variability of precipitation. Other theoretical studies emphasize the role of cloud radiative feedback as an instability mechanism essential for intraseasonal oscillations (Raymond 2001; Bony and Emanuel 2005; Sobel and Maloney 2013). In such theories, the heating and vertical motion associated with the cloud radiative feedback provides additional moistening, rendering the intraseasonal modes unstable.

This study aims to bridge the gap between current theoretical understanding of MJO processes on the one hand and evaluation and improvement of cumulus parameterizations on the other using data collected during the 2011 Atmospheric Radiation Measurement Program (ARM) MJO Investigation Experiment–Dynamics of the MJO (AMIE/DYNAMO) field campaign (Yoneyama et al. 2013). We examine the contributions of model biases associated with the processes discussed above to the overall model biases in the simulation of precipitation, evaporation, column radiative forcing, and the overall spatiotemporal structure of the two MJO episodes observed during October and November of 2011.

2. Data and analyses

The data used in this study include three sets of large-scale precipitation products, two of which were collected from ground-based radars during 2011 AMIE/DYNAMO, Yoneyama et al. (2013) field campaign (October–December 2011), extended surface meteorology and radiation measurements from a Research Moored Array for African–Asian–Australian Monsoon Analysis and Prediction (RAMA; McPhaden et al. 2009) buoy, and the Tropical Rainfall Measuring Mission (TRMM) 3B42 data (TRMM 3B42; Huffman et al. 2007) merged precipitation dataset (August 2008–July 2013).

During AMIE/DYNAMO, two precipitation radars were deployed on Addu Atoll, Maldives: the National Center for Atmospheric Research (NCAR) dual-polarimetric, dual-wavelength (S and Ka band) S-PolKa radar (0°37.826’S, 73°6.175’E) and the Texas A&M Shared Mobile Atmospheric Research and Teaching Radar (SMART-R; 0°36.453’S, 73°5.748’E). Three sets of large-scale mean precipitation products were derived from these two radars and the TRMM 3B42 data that...
cover an area of roughly 300-km diameter marked by the left circle in Fig. 1a. A large-scale single-column model forcing dataset is derived using the constrained variational objective analysis approach (Zhang and Lin 1997; Zhang et al. 2001). While two sounding arrays (multiple sounding sites enclosing an area) were available during AMIE/DYNAMO (Johnson and Ciesielski 2013), they enclosed areas of roughly $8^\circ \times 8^\circ$ that are significantly larger than a single ground-based precipitation radar. Because of the lack of a sounding array that corresponds to the size of the radar domain, the forcing data were developed based on the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis (ERA-Interim) but constrained with the observed surface rainfall as well as observed top-of-atmosphere and surface radiation based on the method developed by Zhang et al. (2001). Three versions of the forcing data using the above-mentioned precipitation products are used to account for uncertainties in the rainfall estimates. The forcing dataset is used as a proxy for observations in this study rather than to drive model simulations (as they are commonly used). The length of the forcing time series is 90 days (1 October–31 December 2011). The mean thermodynamic profiles from the forcing datasets are used to calculate the column saturation fraction (SF) as defined by Raymond and Fuchs (2009):

$$SF = \frac{\text{CPW}}{\text{CPW}_{\text{sat}}}$$

where CPW is the column-integrated precipitable water and the subscript sat denotes the saturated value (i.e., the maximum amount of water vapor that the column can hold).

While the AMIE/DYNAMO variational forcing dataset is relatively short (3 months), the three different versions of the forcing datasets partially compensate for the short record of the observations. In comparison, surface meteorology data from the RAMA buoy located at $0^\circ$N, $80.5^\circ$E are available from August 2008 to July 2013. The extended buoy time series allows us to calculate more robust statistical relationships between variables. Surface evaporation is calculated using the COARE 3.0 algorithm (Fairall et al. 2003), which is a bulk flux algorithm used to estimate surface fluxes from a time series of wind speed, temperature, moisture, and the gradients of each variable between the sea surface and the lowest layer of the atmosphere. To provide a collocated surface flux and precipitation observational dataset, 3-h mean rain rate from the TRMM 3B42 product is spatially averaged within a $3^\circ \times 3^\circ$ box centered on the RAMA buoy.

Two sets of column-integrated net radiative forcing are used in this study. One of them is provided by the variational forcing dataset, calculated by subtracting the net radiative fluxes between the top of atmosphere and the surface, both of which are obtained from ERA-Interim. The other one is derived from the combined retrieval algorithm (CombRet; Comstock et al. 2013). The CombRet product during AMIE/DYNAMO combines the ARM vertically pointing cloud radar–lidar instruments on Gan ($0^\circ41.251^\prime$S, $73^\circ9.00^\prime$E) and the S-PolKa precipitation radar to retrieve microphysical properties and their radiative heating profiles from both nonprecipitating and precipitating hydrometeors (Feng et al. 2014). The total radiative heating profiles, including both water vapor and hydrometeors, are vertically integrated to obtain the column net radiative forcing.
3. Models and simulation design

Three sets of experiments are performed and analyzed: (i) a limited-area 3-km horizontal grid spacing (cloud permitting) model without cumulus parameterization (CPM; Fig. 1a), (ii) a suite of limited-area-model simulations with seven different state-of-the-art cumulus parameterizations at 30-km horizontal grid spacing, and (iii) global variable-resolution simulations with two different cumulus parameterizations at 30-km horizontal grid spacing over the tropical Indian Ocean and gradually coarsening to a 120-km grid spacing elsewhere (Fig. 1b). The first two sets of experiments use the Weather Research and Forecasting (WRF; Skamarock et al. 2008) Model version 3.5.1, and the third set use the nonhydrostatic Model for Prediction Across Scales–Atmosphere (MPAS-A, hereafter MPAS; Skamarock et al. 2012) version 2.0. The MPAS is formulated using unstructured Voronoi tessellations and a C-grid discretization. It allows for both quasi-uniform discretization of the sphere as well as local refinement (Ringler et al. 2008; Ju et al. 2011; Hagos et al. 2013, 2015) and is based on the work of Thuburn et al. (2009) and Ringler et al. (2010). The circles in Fig. 1a mark the area of large-scale precipitation coverage on Addu Atoll in the Maldives and the RAMA buoy. Figure 1b shows the Voronoi mesh for the MPAS simulation. The 30-km grid spacing circular region covers the entire tropical Indian Ocean basin as does the rectangular WRF domain. The output from the 3-km CPM simulation is regridded into 30-km grid spacing by averaging over a $10 \times 10$ gridpoint box for comparison to the other simulations. All simulations are run for the 2-month period between 1 October 2011 and 30 November 2011. Tables 1 and 2 list the components of the model setup that are common to all WRF and MPAS simulations, respectively. Table 3 briefly describes the cumulus parameterizations examined in this study and defines the simulation acronyms used in the figures.

4. The nature of model biases

To examine the performance of the model simulations, some basic features of the MJO are considered. Figure 2 shows the Hovmöller diagrams of precipitation averaged between $5^\circ$S and $5^\circ$N. Figure 2a shows the observed daily precipitation from the TRMM 3B42 dataset. The eastward propagation of precipitation associated with the October and November MJO episodes during the second halves of October and November are apparent. Precipitation is suppressed across the tropical Indian Ocean during the first two weeks of both months. The model performance in capturing the precipitation associated with the two MJO episodes varies significantly from simulation to simulation. The CPM (Fig. 2b) captures the eastward propagation, but precipitation is generally overestimated during both the active and suppressed phases of the MJO. The simulation with the SAS cumulus scheme (Fig. 2d) also captures the eastward-propagating waves, and, in agreement with the observations, its precipitation during the suppressed phase is quite weak. The eastward propagations in the WRF simulations with the BMJ (Fig. 2e), ZM5 (Fig. 2f), and G3DS (Fig. 2j) cumulus schemes as well as the MPAS simulation with the Kain–Fritsch (KF) scheme (MPASKF; Fig. 2k) are obscured by westward-propagating

### Table 1. Configuration common to all WRF simulations performed in this study.

<table>
<thead>
<tr>
<th>Physics scheme or initial condition</th>
<th>Parameterization or set up</th>
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</thead>
<tbody>
<tr>
<td>Longwave radiation scheme</td>
<td>Rapid Radiative Transfer Model (Mlawer et al. 1997)</td>
</tr>
<tr>
<td>Boundary layer scheme</td>
<td>Yonsei State University (Hong et al. 2006)</td>
</tr>
<tr>
<td>Microphysics scheme</td>
<td>Morrison (Morrison et al. 2009)</td>
</tr>
<tr>
<td>Shortwave radiation scheme</td>
<td>Rapid Radiative Transfer Model (Cavallo et al. 2011 and references therein)</td>
</tr>
<tr>
<td>Lateral and surface boundary conditions</td>
<td>ERA-Interim, applied 6-hourly</td>
</tr>
<tr>
<td>Sea surface temperatures</td>
<td>ERA-Interim, prescribed, applied 6 hourly</td>
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### Table 2. Configuration common to all MPAS simulations performed in this study.

<table>
<thead>
<tr>
<th>Physics schemes or initial condition</th>
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</tr>
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<tbody>
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<td>Yonsei State University (Hong et al. 2006)</td>
</tr>
<tr>
<td>Microphysics scheme</td>
<td>WRF single-moment 6 class (WSM6; Hong and Lim 2006)</td>
</tr>
<tr>
<td>Shortwave radiation scheme</td>
<td>Iacono et al. (2008)</td>
</tr>
<tr>
<td>Surface boundary conditions</td>
<td>GFS, applied 6-hourly</td>
</tr>
<tr>
<td>Sea surface temperatures</td>
<td>GFS, prescribed, applied 6-hourly</td>
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signals during the suppressed MJO phases according to TRMM. In the WRF simulations using the KFE (Fig. 2g) and GFE (Fig. 2i) schemes and the MPAS simulation with the MTK scheme (MPASTK; Fig. 2l), MJO active phase precipitation between the locations of the Addu Atoll and the RAMA buoy is weak compared to the observations. In general, significant precipitation during suppressed periods of MJO according to TRMM observations is the most common bias across most of the simulations.

Based on the recommendations of the U.S. Climate Variability and Predictability Program (CLIVAR) MJO working group for the first-level diagnostics of the MJO in models (Waliser et al. 2009), a univariate empirical orthogonal function (EOF) analysis is performed on unfiltered meridionally averaged precipitation fields shown in Fig. 2. This is done in order to obtain a more quantitative measure of model MJO biases and assess their links to biases found in various fields observed during AMIE/DYNAMO. Figure 3 shows the comparison of the first two principal components (PCs) and first two EOFs from the model simulation between the locations of the Addu Atoll and the RAMA buoy is weak compared to the observations. In general, significant precipitation during suppressed periods of MJO according to TRMM observations is the most common bias across most of the simulations.

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As discussed in the introduction, current theories of MJO dynamics emphasize the role of three moist processes and associated relationships among specific variables. Thus, biases in the relationships could be important sources of biases in MJO simulation. For example, moisture mode instability theory would suggest that biases in either the saturation fraction or the relationship between precipitation and saturation fraction, or perhaps some combination of both, could be contributing to the excessive precipitation. Similarly, according to the WISHE theory of the MJO, biases in wind speed as well as the dependence of evaporation on wind speed could affect the simulation of MJO. If indeed the moisture–cloud radiative feedback is central to the

### Table 3. Cumulus parameterization schemes used in this study.

<table>
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<tr>
<th>Scheme</th>
<th>Brief description</th>
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<tr>
<td>Betts–Miller–Janjić (BMJ; Janjić 1994)</td>
<td>Column moist adjustment scheme relaxing toward a well-mixed profile. It has no explicit updraft or downdraft and no cloud detrainment.</td>
</tr>
<tr>
<td>Grell 3D Ensemble (G3DS; Grell and Dévényi 2002)</td>
<td>Multiclosure, multiparameter scheme with a very large number of ensemble members.</td>
</tr>
<tr>
<td>Grell–Freitas Ensemble (GFE; Grell and Freitas 2014)</td>
<td>Multiclosure, multiparameter scheme with a very large number of ensemble members that tries to smooth the transition to cloud resolving scales. It has explicit updrafts and downdrafts and includes cloud and ice detrainment.</td>
</tr>
<tr>
<td>Modified Tiedtke (MTK; Tiedtke 1989; Zhang et al. 2011 and references therein)</td>
<td>Mass flux scheme with a CAPE-removal time-scale closure. It includes shallow convection, convection originating above the boundary layer, momentum transport, and cloud and ice detrainment.</td>
</tr>
<tr>
<td>KF–Cumulus Potential (KF-CUP; Berg and Stull 2005; Berg et al. 2013)</td>
<td>KF scheme modified to better account for shallow convection by linking boundary layer turbulence and shallow clouds.</td>
</tr>
<tr>
<td>Simplified Arakawa–Schubert (SAS; Han and Pan 2011)</td>
<td>Mass flux scheme with both deep and shallow convection and momentum transport.</td>
</tr>
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</table>
MJO simulations, biases in moisture as well as the dependence of cloud radiative forcing on moisture would affect the simulation of MJO. While nonlinear and feedback processes are likely to confound the sources of errors in MJO, analysis using a linear statistical model could provide some insight into the direct role of the above-discussed relationships in the fidelity of MJO simulation. In the next section, the representation of

FIG. 2. Hovmöller diagrams of precipitation (mm h\(^{-1}\)) averaged between 5°S and 5°N latitude from TRMM 3B42 and the 11 simulations. The dashed lines mark the longitudes of Addu Atoll and the RAMA buoy measurements.
these relationships in the models is compared with observations, and the contribution of biases in their representation in the overall model performance is quantified using statistical models.

5. Contributions of process biases

a. The relationship between saturation fraction and precipitation

As discussed in the introduction, moisture mode theory requires a strong relationship between precipitation and saturation fraction. To examine this relationship in the observations, first the precipitation for the 90 days of the observation period are computed from the daily S-PolKa, SMART-R, and TRMM rain-rate time series and are combined with the corresponding saturation fraction values from the forcing data. The joint time series from the three precipitation products over 90 days contains 270 data points. The saturation fractions are then sorted in increasing order and equally partitioned into 15 bins each containing 18 data points. The saturation fraction values from the model simulations are also divided into the bins constructed from the observations, and the average model rain rates are calculated for the corresponding saturation fraction bin. Figure 4 shows the relationship between rain rate and saturation fraction from observations and various simulations. Since rain rate is a strongly increasing function of saturation fraction, the logarithm of rain rate is plotted. The log-linear relationship between saturation fraction and rain rate is apparent in both observations and model simulations. Similar relationships between precipitable water and precipitation have been observed in other contexts as well (e.g., Wentz and Spencer 1998; Peters and Neelin 2006; and references therein). The slopes of the simulated relationships are in general slightly different from the slope of the observed relationship. This is especially true at low saturation fractions where the modeled precipitation is relatively higher than the observed precipitation.
observations for comparable saturation fractions. Such excessive frequency of weak precipitation is a common deficiency in many global as well as regional model simulations (e.g., Sun et al. 2006; Stephens et al. 2010; Hagos et al. 2014).

Even though this bias in the relationship between saturation fraction and precipitation is common, its overall contribution to the biases in the precipitation time series as well as the MJO itself is not clear. In this subsection a linear statistical model is constructed to provide a first-order estimate of the contributions from this process bias. To understand how the role of this process bias is quantified, suppose that the modeled relationship between saturation fraction and precipitation exactly matched that of the observations (i.e., no bias in the relationship between saturation fraction and precipitation and all the error in precipitation comes from erroneous saturation fractions). If that were the case we could build a linear statistical model that takes the modeled saturation fraction, finds the observed saturation fraction bin that it belongs to and randomly picks a value from the corresponding observed precipitation sample, and uses that value to construct a new precipitation time series. The only difference between the original model time series and the reconstructed one would be random error, which can be quantified and limited by repeating the exercise multiple times (see next paragraph). If there were a bias in the relationship between saturation fraction and precipitation in the model time series (as in this case), however, it would be the difference between the original time series and the reconstructed time series from the linear model. The random selection and construction of the time series is performed 100 times. A Student’s t test is performed and the differences between a simulation and the linear model are reported only if they are significant at the 99% confidence level.

The time series of the original precipitation at Addu Atoll and that obtained from the linear model that excludes the bias in the relationship between saturation fraction and precipitation can be compared (Fig. 5). The difference between the two is most apparent between 30 October and 15 November, during what is supposed to be a suppressed period (Figs. 5a,b). This is in agreement with the fact that the bias in the relationship is most apparent in the low saturation fraction values (Fig. 4). To quantify the errors and contributions of this
bias to the overall error in precipitation time series, the root-mean-square errors (RMSEs) of the model simulations with respect to the observation are calculated. The difference in the RMSEs between the original precipitation time series and that from the linear model suggests that this process bias directly accounts for up to 30% and on average 12% of the RMSE in precipitation. Having quantified the direct contribution of the bias in the relationship between saturation fraction and precipitation to the overall precipitation time series, we consider how well the two episodes of MJO are simulated if this direct contribution was absent. To that end, the output from the linear statistical model is applied to the whole domain and a corrected precipitation field is constructed. Then the EOF analysis is performed once again. Figure 6 is similar to Fig. 3, but the direct contribution of the bias in the relationship between saturation fraction and precipitation are eliminated. The improvements are apparent. The excess precipitation on the western end of the domain during both active and suppressed periods is significantly reduced (Fig. 6a versus Fig. 3a and Fig. 6b versus Fig. 3b). Furthermore the high frequency variability that dominated the original PC1 is essentially absent in the revised analysis. Thus, the direct contribution of bias in the relationship between saturation fraction and precipitation has a large impact on the simulation of MJO.

Even after accounting for the above-discussed biases, however, the MJO simulation as depicted by the EOF analyses still shows significant biases (Fig. 6). Since we have already factored in the effect of the bias in the relationship between precipitation and saturation fraction, one would expect that most of the remaining error in the MJO simulation must be related to the error in saturation fraction itself. Indeed, that turned out to be the case. Figure 7 shows the correlation of the RMSE in saturation fraction at Addu Atoll with that of the EOFs and PCs obtained from the linear model analysis. The correlations range from 0.64 to 0.87 and are all statistically significant at the 95% confidence level. That means further improvement in the simulation of MJO requires improvements in the processes that regulate the supply of moisture, which, according to existing theories, include wind-induced surface heat exchanges and cloud radiative feedbacks. These are the subjects of the subsequent subsections.

b. The relationship between surface evaporation and surface wind speed

In a manner similar to the previous analysis, the observed and modeled relationships between surface wind speed and evaporation are compared (Fig. 8). The observational dataset in this case is the multiyear RAMA buoy dataset that provides a longer data record and is more representative of a tropical oceanic environment.
than the shorter-duration AMIE/DYNAMO datasets. As expected, a more or less linear relationship is present between wind speed and evaporation. In general, the models tend to produce about 50% more evaporation for a given surface wind speed compared to the observations. The fact that this bias is fairly consistent among the simulations suggests that it is more related to the common surface and/or planetary boundary layer (PBL) schemes, including the fact that SST is prescribed in these simulations. For example, the difference between the observations and the simulations becomes larger at a higher wind speed because in the model simulations the SST is prescribed and is insensitive to surface wind speed. In reality, however, high wind speed would reduce the SSTs and hence limit the degree to which evaporation can continue to increase with wind speed (Zhang and Grossman 1996). Additionally, there are some intersimulation differences that are related to the interaction of the cumulus representation with the PBL processes. In any case, the main question we ask is, what is the direct contribution of this bias (in the relationship between surface wind speed and evaporation) to the overall bias in evaporation, which includes bias in the surface wind speed itself, using a linear statistical model similar to the one discussed in the last subsection? For a given surface wind speed, this linear statistical model assigns an evaporation value randomly selected from the

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**Fig. 7.** Scatterplots of the RMSEs in the univariate MJO metrics with the local RMSEs in saturation fraction at Addu Atoll. The former is calculated against TRMM and after the bias associated with the relationship between saturation fraction and precipitation (Fig. 5) is removed using the linear statistical model. The latter is calculated against DYNAMO’s variational forcing data from Addu Atoll.
In other words, the linear statistical model produces what the evaporation time series would have been if there were no statistically significant difference between the model simulations and observations within each wind speed bin. In other words, the linear statistical model produces what the evaporation time series would have been if there were no statistically significant difference between the model simulations and observations in the relationship between surface wind speed and surface evaporation. Figure 9 shows the original time series and that from the linear statistical model and the RMSEs from both. Comparison of the two shows that the excess evaporation associated with the bias in the relationship is fairly uniform and shows little variation with the MJO phase. This is consistent with the fact that the bias exists both in high and low wind speeds. The correction by the linear model to the first order simply shifts the modeled time series to slightly lower values. The differences between the RMSEs (Fig. 9c) shows that the bias in the relationship between surface wind speed and surface evaporation contributes between 15% and 47% of the RMSE in the time series of the latter.

c. The relationship between moisture and column radiative forcing

As discussed in the introduction, the positive feedback between moistening and cloudiness has been proposed to be an important component of MJO-like instability by several studies. In this section the biases in the relationship between saturation fractions and radiative forcings are assessed. The direct contribution of this relationship to the overall model bias in cloud
radiative forcing is quantified using a linear statistical model as discussed in the last two subsections. Once again the average cloud radiative forcing is calculated for the 15 bins of saturation fraction values discussed in the first subsection. Figure 10 shows the average forcing for two sets of observations and the model simulations. All the WRF simulations overestimate the radiative forcing for the given saturation fraction. In comparison the MPAS simulations do well in the mean radiative forcing. This difference points to the important role of stratiform clouds in radiative forcing. In general the cloud microphysics scheme used in the WRF simulations (Morrison et al. 2009) produces much larger anvil shields (not shown) than the one used in MPAS (WSM6), resulting in much higher cloud radiative forcing in the upper troposphere. Similar findings in the cloud radiative heating differences between various bulk microphysics schemes are also reported by Wang et al. (2015, see their Fig. 5).

Once again, a time series of cloud radiative forcing is constructed using the linear model like the ones discussed in the last two subsections. For a given model-simulated saturation fraction, the linear statistical model assigns cloud radiative forcing from the observation bin that it corresponds to and thereby removes the direct contribution of the bias in the relationship to overall bias in cloud radiative forcing. Figure 11 shows the comparison between the original cloud radiative forcing time series at Addu Atoll with that obtained from the linear statistical model. The WRF simulations produce weak positive column-integrated heating during active phases of the MJO, while observations show weak net cooling during these periods [as also shown by Wang et al. (2015) and Johnson et al. (2015)]. The improvement in the WRF simulations is striking, especially during the suppressed periods, 1–10 October and 1–20 November (Figs. 11a,b). This is consistent with the nature of the biases in the relationship between saturation fraction and precipitation discussed in the last subsection. Comparison of the RMSEs in radiative forcing (Fig. 11c) shows that the bias in the relationship between saturation fraction and column-integrated radiative forcing accounts for up to 78% of the error in the time series of the latter.

d. Error propagation and feedbacks

In the last three subsections, the direct contributions of errors in the representation of the dependences of precipitation on saturation fraction, evaporation on surface wind speed, and column radiative forcing on saturation fraction were quantified. But one has to keep in mind that in many of the cases the contributions of these relationships are the small fractions of the overall error in these variables. In other words much of the biases of the dependent variables (precipitation, evaporation, and radiative forcing) come directly from the input variables (saturation fraction and surface wind speed) and are propagating through the parameterization schemes. In that case, there could also be feedback processes that exacerbate the errors. One potential feedback mechanism is the impact of precipitation errors on errors in other variables that in turn affect the availability of moisture. One possible mechanism is the impact of precipitation and associated downdraft on wind speed. If erroneous precipitation results in erroneous surface wind speed, then the errors in surface wind speed will propagate to surface evaporation even if the surface flux scheme was perfect. This in turn would introduce errors in the supply of moisture and precipitation and column radiative heating, even if the errors in the representation of the relationship of the latter two variables on moisture were relatively accurate. Figure 12 shows the scatterplot of the relationship in the surface wind speed and rain-rate RMSE at the location of the RAMA buoy. As discussed above, the strong correlation (0.63) between the two errors indicates the degree to which errors are propagating from precipitation to surface wind speed via the processes discussed above, including, for example, through downdrafts and convective momentum transport potentially forming a feedback loop.

6. Discussion and conclusions

This study examines the simulation of two MJO episodes observed during the 2011 AMIE/DYNAMO field campaign using a regional cloud-permitting model (WRF), a regional model with various cumulus parameterizations
and a global variable-resolution model (MPAS) with a high-resolution region centered over the tropical Indian Ocean. The range of resolutions, parameterizations, and model dynamics used allows for a systematic evaluation of model behavior. Biases associated with three processes believed to play an important role in MJO-related instabilities are examined. These processes are moisture mode instability, wind-induced surface heat exchange (WISHE), and moisture-cloud radiative feedback. These processes are associated with specific relationships between precipitation and column saturation fraction, between surface wind speed and evaporation, and between saturation fraction and column-integrated radiative forcing. In this study, these relationships determined from model simulations are compared with observations (Figs. 4, 8, and 10, respectively). To provide guidance for parameterization development and improvement, the contributions of the biases in the simulation of each of these relationships to the overall model biases are quantified using a linear statistical model.

In comparison to the observations, the model simulations are generally found to overestimate the amount of precipitation associated with a given saturation fraction especially at low saturation fraction values. A linear statistical model is used to quantify the contribution of this bias to precipitation time series (Fig. 5) and the biases in the MJO metrics (Fig. 3 versus Fig. 6). By introducing excessive precipitation in what would otherwise be a suppressed MJO period, this bias significantly contributes to the overall bias in the MJO structure and propagation. Once the direct impact of this bias is accounted for, the RMSEs in the MJO structure are strongly correlated with the RMSEs in the saturation fraction itself (Fig. 7), which is frequently overestimated in the model simulations, particularly those that apply cumulus parameterizations. Furthermore, the model simulations are found to consistently overestimate the amount of surface evaporation associated with a given surface wind speed (Fig. 8), suggesting significant contribution from surface and PBL schemes. This bias in the relationship between surface wind speed and evaporation is found to contribute between 15% and 47% of the RMSE in the time series of the evaporation. Finally, the relationship between saturation fraction and column-integrated total radiative forcing is considered. The
model simulations often overestimate the radiative forcing associated with low saturation fraction (Fig. 10). This is consistent with the overestimation of precipitation at low saturation fraction shown in Fig. 4. The bias in the relationship between saturation fraction and column radiative forcing accounts for up to half of the RMSE in the time series of radiative forcing.

In all four of the metrics used (two PCs and two EOFs) the CPM is among the better-performing simulations (Figs. 6 and 7), and it has the smallest RMSE in the precipitation time series (Fig. 5c); also, the difference from the linear model is small, suggesting a reasonable representation of precipitation and saturation fraction relationship. However, its error in evaporation and the relationship between evaporation and surface wind speed (Fig. 8) and column-integrated radiative forcing are comparable to those of the other simulations (Fig. 10). This highlights the fact that, even with cloud-permitting simulations, errors associated with surface processes and cloud microphysics could undermine the improvement that one would get from explicit representation of convection.

In summary, the nature of the biases associated with simulating the MJO that emerges from this study is the following:

(i) The excessive precipitation at low saturation fraction directly contributes to the precipitation and radiative forcing bias, especially during what would otherwise be a suppressed MJO period.

(ii) The strong correlation between errors in saturation fraction and errors in the spatiotemporal structure of the MJO episodes, on the other hand, suggest that the excessive precipitation and cloud radiative forcing at low saturation fraction are likely undermining accurate simulation of moisture–cloud radiative feedback processes that are needed for simulations of robust MJO.

(iii) While the surface fluxes are consistently overestimated for a given surface wind speed, suggesting a prominent role in the surface and/or PBL schemes, the strong correlation between precipitation and surface wind speed errors (Fig. 12), possibly through convective momentum transport (Tung and Yanai 2002), suggests a positive feedback loop for the propagation of errors.

As noted in the introduction, theoretical understanding of the nature of MJO and its simulation using cumulus parameterizations have been rapidly progressing in parallel. Yet, significant challenges remain. This progress can be accelerated when advances in both of these two lines of activities are more integrated. This study examines the simulation of three relationships that are central to the instability mechanisms recently proposed to play important roles in the propagation of the MJO (i.e., saturation fraction versus precipitation, evaporation versus wind speed, and saturation fraction versus radiative forcing) and quantifies biases associated with errors in their model representations. While biases in these three processes contribute to model biases significantly, they certainly are not the only sources of error. While they are not our main focus, this study indicates that the role of surface flux parameterizations could be contributing significantly to model biases in the simulation of the MJO. Future work will examine biases in a set of surface and boundary layer parameterizations and their comparative impact in the simulation of tropical convection.

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Facility. The ARM variational analysis forcing data for AMIE/DYNAMO can be accessed online (http://www.arm.gov/data/eval/29). CombRet can also be accessed online (http://dx.doi.org/10.5439/1169498). The DYNAMO field campaign data used in this paper are available at NCAR’s Earth Observing Laboratory’s DYNAMO data catalog (https://www.eol.ucar.edu/field_projects/dynamo). The RAMA buoy data can be obtained from NOAA’s website (http://www.pmel.noaa.gov/tao/rama/data.html).

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