Moist static energy budget analysis of tropical cyclone formation and intensification in high-resolution climate models

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ABSTRACT

Tropical cyclogenesis and intensification processes are explored in six high-resolution climate models. The analysis framework employs process-oriented diagnostics that focus on how convection, moisture, clouds and related processes are coupled. These diagnostics include budgets of column moist static energy and the spatial variance of column moist static energy. The latter allows for the quantification of the different feedback processes responsible for the amplification of moist static energy anomalies associated with the organization of convection and cyclogenesis, including surface flux feedbacks and cloud-radiative feedbacks. Tropical cyclones (TCs) are tracked in the climate model simulations and the analysis is applied along the individual tracks and composited over many TCs. Two methods of compositing are employed: a composite over all TC snapshots in a given intensity range, and a composite over all TC snapshots at the same stage in the TC life cycle (same time relative to the time of lifetime maximum intensity for each storm). The radiative feedback contributes to TC development in all models, especially in storms of weaker intensity or earlier stages of development. Notably, the surface flux feedback is stronger in models that simulate more intense TCs. This indicates that the representation of the interaction between spatially varying surface fluxes and the developing TC is responsible for at least part of the inter-model spread in TC simulation.
1. Introduction

The study of tropical cyclones (TCs) in climate models has long been difficult because of the conflict between the high resolution necessary to accurately simulate TCs and the need to perform long, global simulations. In recent years, however, enormous progress has been made in the ability of general circulation models (GCMs) to simulate TCs from subseasonal to seasonal and longer time scales (Camargo and Wing 2016). Global forecast models have become a more reliable source of tropical cyclone (TC) genesis guidance (e.g., Halperin et al. 2016) while climate models have improved such that they can reproduce the TC climatology with some fidelity (e.g., Zhao et al. 2009; Wehner et al. 2014) and exhibit some skill in seasonal forecasting (Zhang et al. 2016; Vecchi et al. 2014; Murakami et al. 2015, 2016; Vitart et al. 2010; Chen and Lin 2011, 2013). This is largely a result of algorithmic and computational advances that have allowed for the use of high horizontal resolutions that substantially improve the simulation of TC climatology, structure, and intensity. However, biases remain. For example, low-resolution GCMs tend to simulate too few TCs globally (Camargo 2013), and even 50 km high-resolution models are generally not able to simulate the most intense storms (Shaevitz et al. 2014). While decreasing the model grid spacing can improve the low intensity bias (Manganello et al. 2012; Wehner et al. 2014; Murakami et al. 2015), it does not do so uniformly (Roberts et al. 2015), and even in models with the same resolution, there can be a substantial difference in their ability to simulate TCs (Shaevitz et al. 2014). This suggests that resolution is not the only factor controlling model simulation of TCs. In particular, TCs are tightly coupled to clouds and convection, so TC frequency, intensity, structure, and interannual variability are strongly sensitive to the details of convective parameterizations (e.g., Reed and Jablonowski 2011; Murakami et al. 2012; Zhao et al. 2012; Kim et al. 2012; Duvel et al. 2017). These biases contribute to uncertainty regarding future projections of TC activity.
(Walsh and coauthors 2016), as such projections depend on the ability of GCMs to reliably capture the features of TC activity.

Our objective is to develop process-oriented diagnostics to identify model characteristics that are responsible for proper simulation of TCs and that will explain the inter-model spread in TC frequency and intensity distributions. These diagnostics go beyond simply quantifying the simulated TC activity and focus on how simulated TCs respond to their environments, rather than how the large-scale environment itself is simulated across different models. Our study builds on the work of Kim et al. (2018), which introduced a suite of diagnostics that provided deeper insights into the representation of physical processes that are responsible for the simulation of TCs in GCMs. The Kim et al. (2018) diagnostics consist of azimuthal averages of dynamic and thermodynamic fields around the storm center and identify physical processes related to the interaction between convection, moisture, and circulation that can lead to inter-model differences in simulated TCs. Of the three models examined, they found that the one with the most intense storms had the most precipitation near the composite TC center, the strongest sensitivity of convection to moisture, and the strongest contrast in relative humidity and surface latent heat flux between the inner and outer region of the composite TCs. These results indicate the importance of moisture-convection coupling and feedbacks between the surface latent heat flux and convection. Here, we develop and apply an additional, related set of diagnostics to further analyze the role of these and other processes in simulated TCs, in six high-resolution climate models.

The paper is organized as follows. We provide a brief description of the six high-resolution models used in this study in Section 2 and describe our diagnostics and analysis methodology in Section 3. The application of these diagnostics to the six models will be described in Section 4, with a discussion of their implications in Section 5. We provide a summary of the results and conclusions in Section 6.
2. Model Simulations

a. Models

We explore TC genesis and intensification processes in six high-resolution climate model long-
term (> 20 year) historical simulations (Table 1). While long-term simulations were performed, we only have high-frequency (six-hourly) output available for a subset of several years, on which we focus our analysis. The TC statistics in those years are representative of the model climatology. Several of these simulations were also examined in complementary studies by Kim et al. (2018) and Moon et al. (2018). This six-member model ensemble is an “ensemble of opportunity” based on available simulations, rather than a coordinated intercomparison.

Three of the models were developed at the Geophysical Fluid Dynamics Laboratory (GFDL) - Atmosphere Model version 2.5 (AM2.5; Delworth et al. 2012), High Resolution Atmospheric Model (HiRAM; Zhao et al. 2009), and Forecast-Oriented Low Ocean Resolution (FLOR; Vecchi et al. 2014) version of Coupled Model 2.5 (CM2.5; Delworth et al. 2012). AM2.5 and HiRAM are atmosphere-only simulations forced with observed sea surface temperatures from HadISST1.1 (Rayner et al. 2003), while FLOR is a coupled simulation in which SSTs are calculated interactively by its oceanic component and nudged toward the observed SSTs with a 5-day nudging time scale. This ensures the model mean state remains close to that observed. The ocean component of FLOR has 1° x 1° horizontal resolution, zooming to 1/3° meridional spacing near the equator with 50 vertical levels, and an ocean-atmosphere coupling interval of 1 hour. The atmosphere-component of FLOR is AM2.5. All three GFDL models are run with 50 km horizontal resolution and 32 vertical levels in the atmosphere. All three models use the same finite volume dynamical core on a cubed-sphere grid (Putman and Lin 2007), with the same divergence damping coefficient (Zhao et al. 2012), the same time steps, and the same physics-dynamics coupling interval.
(the gravity wave, advective, and physics time steps are 200, 600, and 1200 s, respectively, and
the radiation is called every 3 hours). AM2.5 and FLOR use the same Relaxed Arakawa-Schubert
convection scheme (Moorthi and Suarez 1992), while HiRAM uses a version of the Bretherton
et al. (2004) shallow convection scheme, modified to simulate both deep and shallow convection
(Zhao et al. 2012); all other physics packages are the same (GFDL Global Atmospheric Model De-
development Team 2004). Therefore, AM2.5 and FLOR differ only in that FLOR is coupled while
AM2.5 is atmosphere-only, and AM2.5 and HiRAM differ only in their convection schemes.

Two of the additional atmosphere-only models we analyze are versions of the National Center for
Atmospheric Research (NCAR)/Department of Energy (DOE) Community Atmosphere Model,
version 5 (CAM5; Neale et al. 2012) with both the spectral element (CAM-SE; Dennis et al.
2012) and the finite volume (CAM-FV; Lin and Rood 1996, 1997) dynamical cores. CAM-SE
is configured with the variable-resolution option (Zarzycki et al. 2014), with 0.25° grid spacing
over the North Atlantic and 1° grid spacing elsewhere as in Zarzycki et al. (2017). The raw
data are remapped to a globally-uniform 0.25° latitude-longitude grid, although we restrict our
analysis to the North Atlantic where the native resolution is highest. CAM-FV is configured with
global 0.25° grid similar to the work of Wehner et al. (2014). CAM5 utilizes 30 vertical levels
with a model top of approximately 2 hPa. Both CAM-SE and CAM-FV use similar versions of
the CAM5 physics parameterizations, including the same deep (Zhang and McFarlane 1995) and
shallow convective (Park and Bretherton 2009) schemes, moist boundary layer turbulence scheme
(Bretherton and Park 2009), and Rapid Radiative Transfer Model for GCMs (RRTMG; Mlawer
et al. 1997) scheme. Therefore, CAM-SE and CAM-FV differ primarily in their dynamical cores,
which has previously been shown to impact the simulation of TC climatology in the model (Reed
et al. 2015). The prescribed SST and sea-ice boundary dataset for both simulations is provided
from Hurrell et al. (2008).
The sixth atmosphere-only model simulation we analyze is one member of the M2-AMIP (for Modern-Era Retrospective Analysis for Research and and Applications, Version 2 (MERRA-2; Gelaro et al. 2017) Atmospheric Model Intercomparison Project (AMIP)) set of simulations (Col-llow et al. 2017, 2018) performed with the NASA Goddard Earth Observing System Model Ver-sion 5, version 5.12.4 (GEOS; Rienecker et al. 2008; Molod et al. 2015). This version of the atmosphere component of GEOS is the same model that was used for MERRA-2, the most re-cent NASA re-analysis data product, but the simulation we analyze is a free-running version of the model initialized in November 1979 and driven by the MERRA-2 SST and sea-ice boundary conditions (Bosilovich et al. 2015). GEOS employs a finite volume dynamical core (Putman and Lin 2007) with a c180 cubed-sphere grid (an approximate horizontal resolution of 50 km), which is then spatially interpolated to a 0.625° x 0.5° longitude-latitude grid. The native model vertical grid has 72 terrain-following hybrid-eta levels. GEOS employs a Relaxed Arakawa-Schubert convection scheme (Moorthi and Suarez 1992) and parameterizations for longwave (Chou and Suarez 1994) and shortwave (Chou and Suarez 1999) radiation; other details on the physics packages can be found in Molod et al. (2015).

b. TC detection and tracking

TC-like vortices (which we refer to as ‘TCs’) are detected and tracked from the model fields using standard tracking algorithms from each modeling group, which produce, for each TC, a time series of the TC’s center longitude and latitude, minimum sea level pressure, and maximum wind speed corrected to a surface (10 m) value ($V_{max}$). We use $V_{max}$ to characterize the TC intensity.

The TCs in the HiRAM simulation are tracked using the routine described in Zhao et al. (2009), which is based on Vitart et al. (1997, 2003) and Knutson et al. (2007). This algorithm locates grid points with an 850 hPa relative vorticity maximum, local sea level pressure minimum, and warm
core, and tracks the storm by searching for a vortex in the next snapshot within a distance of 400 km and connecting the snapshots. It requires that storms last at least 3 days and have a maximum surface wind speed greater than 17 m s\(^{-1}\) during at least 3 (not necessarily consecutive) days.

The tracking scheme used in AM2.5 and FLOR is similar to that used in HiRAM and is described in Murakami et al. (2015) and Harris et al. (2016). This algorithm uses local sea level pressure minimum and a warm core criteria to detect TCs and requires that storms last at least 3 days, be warm-core for at least 2 days, and have a maximum surface wind speed greater than 15.75 m s\(^{-1}\) during at least 36 hours while the storm has a warm core.

The TCs in the CAM-SE simulation are tracked using TempestExtremes (Ullrich and Zarzycki 2017; Zarzycki et al. 2017), while the TCs in the CAM-FV simulation are tracked using the detection algorithm from Zhao et al. (2009). TempestExtremes (Ullrich and Zarzycki 2017; Zarzycki et al. 2017) searches for a local minimum in sea level pressure and a collocated local maximum in geopotential thickness between the 300 and 500 hPa levels (which indicates a warm core). Candidate cyclones are then stitched together in time, with storms needing to be equatorward of 40° latitude for at least 60 hours (not necessarily consecutive) and separate trajectories which terminate and begin within 12 hours and 10°s of one another are merged to eliminate double-counting of broken tracks.

The TCs in the GEOS simulation are tracked using the Camargo and Zebiak (2002) tracking algorithm, which has been widely applied to various global and regional climate models (e.g., Camargo 2013). This algorithm uses basin-dependent thresholds of low level vorticity, surface wind speed, and vertically integrated temperature anomaly to detect TCs, then tracks the low level vorticity center forward and backward in time from each point that has met the detection criteria. For this study, we additionally require that the vortex have a maximum surface wind greater than 15.2 m s\(^{-1}\) for 3 days (not necessarily consecutive). If this threshold is not applied, the Camargo and
Zebiak (2002) algorithm detects many more weak storms, which shifts the intensity distribution in GEOS towards weaker wind speeds and increases the sample size of total storms, but does not otherwise have a significant impact on our results or conclusions.

3. Analysis Methodology

For all models except CAM-SE, we use two years of 6-hourly output to apply our analysis along individual simulated tropical cyclone tracks. Eight years, 1992-1999, are analyzed for the CAM-SE simulation, so that the number of TCs analyzed is comparable to the other models, since we only analyze TCs in the North Atlantic in CAM-SE, compared with the global distribution of TCs in the other models. GCM outputs are saved with a 6-hour time interval on model levels (several of the models provided output at 3-hour or 1-hour time intervals, but since we track the tropical cyclones in 6-hour increments, we do not make full use of the higher temporal sampling). We perform our analysis in $10^\circ$ boxes centered on each TC and following each TC. When making composites, we exclude points over land and TCs that have moved poleward of $30^\circ$. The number of TCs analyzed in each model is shown in Table 2.

We compute budgets of column-integrated moist static energy and spatial variance of column-integrated moist static energy. Moist static energy is approximately conserved under moist adiabatic processes and its column integral is unchanged by convection. The analysis framework for the variance budget was first developed by Wing and Emanuel (2014) to understand the physical mechanisms of self-aggregation of convection in idealized simulations. It has since been applied to simulations of tropical convection in a variety of idealized and realistic configurations (Arnold and Randall 2015; Wing and Cronin 2016; Coppin and Bony 2015; Holloway and Woolnough 2016; Becker et al. 2017; Holloway 2017) and to cloud-resolving model simulations of tropical
cyclones (Wing et al. 2016). Column-integrated moist static energy, $\hat{h}$, is given by

$$
\hat{h} = \frac{1}{g} \int_{p_b}^{p_t} (c_p T + gz + L_v q) dp,
$$

(1)

where $p_t$ is the pressure at the model top, $p_b$ is the pressure at the bottom, $q$ is water vapor mixing ratio, and all other variables have their usual meaning. Usually, one would perform the integral using the surface pressure as $p_b$. Here, we perform our analysis on model levels using the 4-D varying pressure (calculated using the surface pressure and the appropriate relation for each model’s hybrid vertical coordinates). This causes difficulties with the evaluation of the column integral, since one of its bounds (the surface pressure) decreases dramatically over the life cycle of a tropical cyclone. To avoid complications in the interpretation of the variability of moist static energy in and around the TC due to decreasing column mass, we interpolate the moist static energy to a fixed pressure level of $p_b = 920 \text{ hPa}$, and integrate from there to the next model level above, and then through the rest of the column on model levels. This may introduce some error to the closure of the moist static energy budget, as the other terms (described below) are evaluated at the surface rather than at 920 hPa. The budget for column-integrated moist static energy is given by

$$
\frac{\partial \hat{h}}{\partial t} = F_k + N_L + N_S - \vec{u} \cdot \nabla \hat{h},
$$

(2)

where $F_k$ is the surface enthalpy flux, $N_L$ is the column longwave radiative flux convergence, and $N_S$ is the column shortwave radiative flux convergence. Each of these terms (as well as advection, the last term on the right hand side of Equation (2)) is a source or sink of $\hat{h}$. $F_k$, $N_L$, and $N_S$ are output as temporal averages (6-hourly for HiRAM, AM2.5, and FLOR, 3-hourly for CAM-SE and CAM-FV, and 1-hourly for GEOS); we average consecutive periods together to derive a value centered around the time of the TC snapshot. $\hat{h}$ is computed as described above, using instantaneous output at the time of the TC snapshot, and $\frac{\partial \hat{h}}{\partial t}$ is computed using a centered finite difference. Given the uncertainties associated with calculating the advection of moist static energy
from offline model output, we calculate the advective term as a residual from the rest of the budget. All terms are computed at each grid point within the $10^\circ$ box centered on the TC.

The budget for the spatial variance of $\hat{h}$ is given by

$$\frac{1}{2} \frac{\partial \hat{h}'^2}{\partial t} = \hat{h}' \frac{\partial \hat{h}'}{\partial t} = \hat{h}' F_{k} + \hat{h}' N_L' + \hat{h}' N_S' - \hat{h}' (\vec{u} \cdot \nabla h)',$$

where primes indicate anomalies from the mean of the $10^\circ \times 10^\circ$ box centered around a TC. As convection organizes and the TC forms, the convecting areas become moister and the surrounding non-convecting areas become drier. This is manifest as an increase in the spatial variance of $\hat{h}$ computed over a box surrounding the developing storm. Each of the terms on the right hand side of Equation (3) measures the contribution of a feedback to the increase in $\hat{h}$ variance; a positive feedback indicates that the processes amplifies $\hat{h}$ anomalies, such as enhanced surface fluxes in an area of already moister than average air. In idealized simulations, the moist static energy variance always increases as the TC forms and intensifies (Wing et al. 2016), but this does not necessarily have to generalize to more realistic simulations (or nature). We examine whether the moist static energy variance increases with TC intensification in the climate model simulations, but note that even if this relationship does not always strictly hold, it is still informative to examine how the different terms in the budget contribute to the variance tendency.

We calculate each term in the two budgets at each grid point in the box following the tracks of each simulated TC. We then composite over the simulated TCs in two different ways:

1. A life cycle composite, where all snapshots at the same time relative to the time of lifetime maximum intensity (LMI) of each TC are averaged together; and

2. An intensity-bin composite, where all snapshots in which the TC has a maximum near surface wind speed in a given range are averaged together.
In the life cycle composite, we examine times prior to the LMI in 6-hour increments, and go backwards in time until the composite contains less than 25% of the total TCs (the lifetime varies from storm to storm). This allows us to assess how different processes are contributing to the formation and intensification of the composite TC in each model as it moves through its life cycle, and can be compared to similar analysis for idealized TCs simulated with explicit convection (Wing et al. 2016). When comparing the different models, however, the average intensity may be quite different at the same life cycle stage, which may contribute to a feedback being stronger or weaker. This motivates the use of the intensity-bin composite, following Kim et al. (2018), in which the model-to-model comparison is made using TC snapshots at the same intensity (the maximum near surface wind at each TC snapshot, as determined by the tracking algorithm). Only TC snapshots up until the time of the LMI of a given storm are included in the composite. The intensity bins used for this composite analysis and the number of snapshots in each bin are given in Table 3.

4. Results

a. General characteristics of TC simulation

As an overview of the TC climatology in the six simulations we examine, the genesis positions for the tracked TCs in each model, and in the best-track observational data, is shown in Figure 1. While all models have reasonable spatial distributions and genesis frequency of TCs, there are large differences between them and clear biases compared to the observations. Many of the models struggle to accurately simulate the genesis distribution in the North Atlantic, for example. Overall, HiRAM and FLOR seem to form the most TCs, which is also true in the two years of data.

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1Tracks in the North Atlantic and eastern North Pacific are from the National Hurricane Center (Landsea and Franklin 2013) and tracks in other basins are from the Joint Typhoon Warning Center (Chu et al. 2002)
we analyze in detail (Table 2). Note that it is expected that CAM-SE generates few TCs outside of the Atlantic because the high resolution region is confined to only that basin.

The intensity distribution for the simulated TCs in each model is shown in Figure 2 (only for the two years that are analyzed - see Table 2 - and, for CAM-SE, only for TCs in the North Atlantic). CAM-SE has a greater likelihood of simulating storms at the high intensity tail of the distribution than CAM-FV, consistent with Reed et al. (2015), though the mean LMI is higher in CAM-FV. Overall, CAM-SE and CAM-FV simulate significantly stronger storms than the other four models, as expected due to their finer grid spacing. However, resolution is not the only source of inter-model spread in intensity. The TCs in HiRAM are noticeably stronger than those in AM2.5 and FLOR, despite those models having the same resolution and dynamical core. All the models have a low intensity bias compared to the best-track observations (dashed line in Figure 2a). Only a few of the models show evidence of the observed bimodal distribution of intensity, where the secondary peak in LMI is associated with storms that undergo rapid intensification (Lee et al. 2016).

The multiple tracking algorithms used across the simulations could contribute to these differences. Cursory analysis found minimal differences in TC statistics in the CAM-SE and CAM-FV simulations, limited to weaker storms, when applying both the Zhao et al. (2009) and Tempest-Extremes algorithms to the same dataset (not shown). We performed more in-depth analysis (repeating all calculations described in subsequent sections) for the case in which the GFDL tracking algorithm (used for AM2.5 and FLOR; Murakami et al. 2015; Harris et al. 2016) was also applied to HiRAM (cyan-curve in Figure 2, referred to as HiRAM-G). When applied to the HiRAM simulation, the GFDL algorithm yields weaker TCs than the HiRAM (Zhao et al. 2009) algorithm does (blue curve in Figure 2). We speculate that this is because the Murakami et al. (2015) implementation of the Harris et al. (2016) algorithm has less strict wind speed conditions for detecting TCs.
than does the HiRAM algorithm, allowing the GFDL algorithm to detect more weaker TCs, and to track those TCs for longer, which impacts the likelihood of observing any individual intensity (note that for an individual TC snapshot at the same time and location, the two algorithms yield the same intensity). Importantly, we find that the sensitivity to tracking algorithm does not cause any significant differences in the results of our moist static energy variance budget analysis. Some of the terms in the moist static energy variance budget have slightly smaller values in HiRAM-G than in HiRAM (not shown), but this does not change the comparison to the other models or any of our conclusions.

b. Moist static energy budget

We first examine the evolution of the moist static energy budget over the composite TC life cycle (Equation 2). Each term in the moist static energy budget composited 48 hours prior to the LMI of the simulated TCs is shown, for the CAM-FV simulation, in Figure 3. The signature of the TC can be easily seen in the spatial distribution of column moist static energy, which is larger near the TC center due to the warm, moist air there (Figure 3b). The moist static energy of the composite TC generally increases as it intensifies towards its LMI, as can been seen in an animation of the evolution of the moist static energy budget with time over the composite TC life cycle (found in the supplementary material), and in the positive tendency of $\hat{h}$ in the vicinity of the TC (Figure 3c). The column radiative flux convergence is generally negative (cooling) and thus a sink of moist static energy. At this particular time, however, it is actually slightly positive (indicating net column radiative heating) in the vicinity of the TC (Figure 3d), which reflects the influence of the moist air and thick cloud shield associated with the TC. The surface enthalpy fluxes are positive, and are therefore a source of moist static energy (Figure 3e). They are larger in the vicinity of the TC because of the larger surface winds there. The advection of moist static energy is generally
negative and downgradient, though since this term is calculated as a residual, we cannot be certain that it is entirely and only representing advection (Figure 3f). These relationships are also found in the other models; equivalent figures and animations for the other five models are provided in the supplementary material.

c. Moist static energy variance budget

As noted above, the moist static energy of the TC increases as the TC forms and intensifies, and in particular, it increases relative to the moist static energy of the surrounding environment. This should be reflected in an increase in the spatial variance of the moist static energy. To quantify the feedbacks that may contribute to a change in the spatial variability of \( \hat{h} \), we now examine the \( \hat{h} \) variance budget over the composite TC life cycle (Equation 3). Each term in the \( \hat{h} \) variance budget composited 48 hours prior to the LMI of the simulated TCs is shown, for the CAM-FV simulation, in Figure 4. As could be inferred from Figure 3, \( \hat{h} \) is anomalously high in the vicinity of the TC. The tendency of \( \hat{h}'^2 \) is noisy but positive near the TC center (Figure 4c). Both the radiative and surface flux feedbacks are positive, indicating that both of these processes contribute to the amplification of \( \hat{h} \) anomalies. The radiative feedback is positive throughout the domain, but largest near the center of the TC where the anomalously high \( \hat{h} \) is coincident with reduced column radiative cooling associated with thick cloud cover (Figure 4d). The surface flux feedback is most positive near the TC eyewall, where the largest surface winds (which enhance the surface fluxes) are found and where \( \hat{h} \) is large; it is near zero at the center of the TC because the winds are calmer there (Figure 4e). There are some areas in the environment away from the TC where the surface flux feedback is slightly negative (tending to damp \( \hat{h} \) anomalies). This is because surface enthalpy fluxes depend both on surface wind speed and air-sea enthalpy disequilibrium, and the two influences generally oppose each other (Wing et al. 2016). The advective term is negative,
indicating that advection of \( \hat{h} \) damps \( \hat{h} \) anomalies (Figure 4f). Equivalent figures and animations for the other five models are provided in the supplementary material.

Across all models, though to a lesser extent in FLOR and GEOS, the surface flux feedback is positive near the TC and becomes larger as the TC approaches the LMI (Figures 5, 6, 7, and 8). The radiative feedback is also positive across all models but, with the exception of GEOS, is smaller than the surface flux feedback. It also generally increases with intensification towards the LMI, though the relative rate of increase is slower than that of the surface flux feedback (Figures 5, 6, 7, and 8). The feedback terms generally increase with intensification because the anomalously high values of moist static energy, surface fluxes and cloud-induced reduction in radiative cooling increase as the TC develops and matures. While the structure of these feedback terms is similar across all models, there are notable differences in their strengths (e.g., Figure 7). The models that produce stronger storms, both overall and at the time of the composite, have stronger feedbacks (CAM-SE, CAM-FV, and HiRAM), especially with regard to the surface flux feedback. In the two models with the highest resolutions, CAM-SE and CAM-FV, and in GEOS, the surface flux feedback is near zero at the center of the TC, indicating a reduction of the winds near an eye-like feature. This is not as apparent in the other models.

One possible explanation for the differences in the magnitudes of feedbacks across the models is that they may simply have different absolute values of moist static energy and its variability. To adjust for this, we normalize the feedback terms by the value of the box average \( \hat{h} \) variance at a given time, then perform the composite. An example of this analysis, for the composite 48 hours prior to LMI, is shown in Figure 9 (other times are shown in the supplementary material). The differences between models remain, particularly in the surface flux feedback. There are minimal model-model differences in the radiative feedback, which indicates that the radiative feedback is
relatively more important in the models with weaker surface flux feedbacks and weaker storms (AM2.5, FLOR, and GEOS).

d. Box-average variance budget

The above analysis shows the contribution of different terms to the \( \hat{h} \) variance on a grid point-by-grid point basis, but it is also informative to examine the box-average budget. This is computed by, for each TC and track point, averaging the squared \( \hat{h} \) anomalies and each term in the variance budget over the box surrounding the TC, and then taking a composite over the same time relative to LMI. The composite box-average \( \hat{h} \) variance generally increases as the LMI is approached (Figure 10a-f), though individual TCs do not always have a monotonic increase in \( \hat{h} \) variance over their life cycle (in part because individual TCs do not always have a monotonic increase in intensity). We find that an increase in the box-average \( \hat{h} \) variance with TC formation and intensification is more robust in the stronger TCs. Therefore, for the calculation of the life cycle composite box-average \( \hat{h} \) variance budget, we restrict our analysis to the storms whose LMI is in the upper quartile of the LMI distribution (Figure 10).

The evolution of the terms in the box-average \( \hat{h} \) variance budget throughout the TC life cycle is qualitatively similar across the models and similar to the behavior of an idealized TC in cloud-resolving simulations (Wing et al. 2016). The surface flux and longwave radiative feedback are the two main contributors to increases in box-average \( \hat{h} \) variance. Early in the TC life cycle, the two have similar magnitudes, but as the TC intensifies towards its LMI, the surface flux feedback increases substantially (as a result of the increasing surface wind speed, which drives higher surface fluxes near the TC). This is apparent in the HiRAM, CAM-SE, and CAM-FV simulations (which have the strongest TCs) and consistent with the results of Wing et al. (2016). In the other models, the surface flux feedback increases only slightly, if at all. In FLOR and GEOS (which have the
weakest TCs), the box-average surface flux feedback is actually smaller than the longwave radiative feedback throughout the composite TC life cycle. These results indicate that, not only do the values of the feedback terms differ from model to model, but so does the relative importance of a given feedback compared to the other feedbacks. Across all models, the shortwave feedback is very small (so the radiative feedback is dominated by spatial variability in the longwave cooling) and the advection (residual) term is negative.

Whether measured by the maximum intensity produced by any storm in the simulation or the average LMI of all the TCs, the models that simulate more intense storms have larger box-average surface flux feedbacks (Figure 11; shown for the composite 48 hours prior to LMI, but the results are similar at other times). The box-average radiative feedback, on the other hand, does not vary much across models. It follows that the models with stronger storms have a higher ratio of composite mean box-average surface flux feedback to radiative feedback (Figure 11b). That is, while both surface flux and radiative feedbacks contribute to increased $\hat{h}$ variance and TC development in all models, the surface flux feedback contributes relatively more in the models with stronger storms. This points to the importance of spatially varying surface fluxes (primarily driven by wind speed variability) for the simulation of TCs.

We note in passing that one potential limitation of this analysis is that the same sized-box was used for all six models and for all TCs in each model. Unlike idealized simulations where there is one TC in a homogenous domain (Wing et al. 2016), in these realistic simulations, a box size must be chosen such that it is large enough to contain the TC as well as the environment surrounding it, but not so large that it contains other disturbances. A larger or smaller box may therefore be more appropriate for larger or smaller TCs (and the minimum TC size is limited by the grid resolution, which varies between models), but for the purposes of the present study we emphasize simplicity and consistency by using a fixed $10^\circ \times 10^\circ$ box size.
e. Composite over intensity bins

While the life cycle composite discussed in Sections 4b-d is useful for examining how different feedbacks contribute to the increase in $\hat{h}$ variance throughout the TC life cycle in each model, the difference in feedback magnitudes across the models could also be an artifact of the fact that, though the composite is taken at the same stage in the TC life cycle, the intensities at that time are different (see, for example, the first row of Figure 7). The surface flux feedback explicitly depends on the TC intensity because of the dependence of surface fluxes on surface wind speed. Therefore, we also analyze an intensity-bin composite, as described in Section 3.

Despite being compared at the same TC intensities, there are differences in the moist static energy and its sources and sinks across the models (see Figure 12 for the 24-27 ms$^{-1}$ bin; other bins are in the supplementary material). GEOS stands out by having noticeably smaller values of moist static energy overall and stronger radiative cooling (more negative) in the environment around the TC (Figures 12f and l). The other models look fairly similar to each other, with the biggest difference being in the strength of the surface fluxes near the center of the TC. CAM-SE has the strongest surface fluxes, followed by CAM-FV, HiRAM, AM2.5, GEOS, then FLOR (Figure 12). There are also slight differences in the radiative cooling; the reduced radiative cooling associated with thick cloud cover over the TC is spread over a larger area in HiRAM, AM2.5, and FLOR. This could be related to the coarser resolution of these models compared to CAM-SE and CAM-FV.

The different spatial structures of moist static energy, radiative cooling, and surface fluxes in Figure 12 are reflected in model-model differences in the feedback terms in the $\hat{h}$ variance budget, shown for three different intensity bins in Figures 13, 14, and 15. The structure of $\hat{h}^2$ and the feedback terms is similar across the intensity bins, but the magnitude generally increases with
intensity. One anomaly is the surface flux feedback in the CAM-SE simulation in the 15-18 ms$^{-1}$ bin (Figure 13m), which is likely due to the relative few samples included in that bin, some of which may have areas of land that are masked out. The main conclusion from Figures 13, 14, and 15 is that even when composited over the same intensities, there are notable differences in the strength of the surface flux feedback between models. The surface flux feedback near the center of the TC is strongest in CAM-SE and CAM-FV, which are the models that simulated the strongest TCs, followed by HiRAM, AM2.5, GEOS, and FLOR (Figures 14 and 15). The interpretation of this result is that, at a given intensity, certain models have a stronger surface flux feedback than others, which favors further amplification of $\hat{h}$ anomalies and further intensification of the TC, to the extent that $\hat{h}$ and surface winds are related. With the exception of GEOS, which has a notably strong radiative feedback, the radiative feedbacks are similar across the models. As in Section 4c, we also examine the intensity-bin composite where each term has been normalized by the box-mean $\hat{h}$ variance. The general result that the surface flux feedback differs across models is robust (see for example the 24-27 ms$^{-1}$ composite in Figure 16; other bins are shown in the supplementary material.)

The value of the intensity-bin composite is made clear in Figure 17, which shows the box-average $\hat{h}$ variance and surface flux and radiative feedbacks composited over each 3 ms$^{-1}$ intensity bin. There is a clear tendency for the $\hat{h}$ variance to be higher at higher wind speeds, though the absolute value of $\hat{h}$ variance differs across models, especially on GEOS (Figure 17a). There is a strong dependence of the surface flux feedback on the wind speeds over which it is composited, with the higher intensity bins having surface flux feedbacks that are 2-3 times stronger than lower intensity bins (Figure 17b). The radiative feedback, on the other hand, is only weakly dependent on the wind speed over which it is composited (Figure 17c). The surface flux feedback in CAM-SE and CAM-FV is similar across most intensity bins, while the radiative feedback in CAM-
FV becomes larger above the 30 m/s bin. This reflects the fact that the overall TC intensity distributions in CAM-SE and CAM-FV are similar; while CAM-FV has an LMI distribution that is shifted towards stronger storms (Figure 2a), CAM-SE has an overall higher probability of TC snapshots at higher intensities (Figure 2b). Between 20-35 m/s, AM2.5 has a notably stronger surface flux feedback than FLOR (Figure 17a) - recall that AM2.5 simulates more intense TCs than FLOR does (Figure 2). Above the 25 m/s bin, HiRAM has a significantly stronger surface flux feedback than AM2.5; suggesting that this allows the TCs in HiRAM to eventually become stronger than those in AM2.5. GEOS is a bit of an outlier; while the weak surface flux feedback is consistent with the fact that GEOS simulates weaker TCs, the radiative feedback and $\hat{h}$ variance itself are much stronger than in the other models.

These results are summarized in Figure 17d, which shows both the box-average surface flux and radiative feedbacks composited over the 24-27 m/s bin in each of the models. There is a clear tendency for the box-average surface flux feedback to be larger in the models that simulate TCs with higher mean LMI, while the radiative feedback does not vary much between models.

5. Discussion

There are several informative comparisons that can be made by comparing individual pairs of models in the set of six examined here. CAM-SE and CAM-FV differ primarily in their dynamical core, which has been shown to affect simulated TC intensity and frequency, with the spectral element core producing stronger TCs (Reed et al. 2015). In the simulations we examined, the distribution of LMI in CAM-SE was wider than that in CAM-FV, with a higher relative frequency of both weak and strong storms (Figure 2a). However, the comparison between CAM-SE and CAM-FV presented here is not an apples-to-apples comparison because the CAM-SE distribution includes only storms in the North Atlantic (which may have weaker storms than other basins, such
as the western North Pacific), includes different years than the CAM-FV simulation, and uses a
different tracking algorithm. When TCs in the North Atlantic in 1996-1997 are analyzed for both
CAM-SE and CAM-FV, the TCs in CAM-SE are found to reach higher intensity more frequently
(Moon et al. 2018), consistent with Reed et al. (2015). We showed that CAM-SE tends to have
a stronger surface flux feedback than CAM-FV near the center of the TC within 48 hours of the
time of LMI and that, when storms in the upper quartile of the LMI distribution are considered,
the box-average surface flux feedback is also larger in CAM-SE. The surface flux feedback was
also found to be slightly stronger in CAM-SE than CAM-FV when considering a composite at the
same intensity.

HiRAM and AM2.5 differ only in their choice of convection scheme, and HiRAM simulates
notably stronger TCs than AM2.5 (Figure 2). Kim et al. (2018) linked this to both larger surface
fluxes and greater rainfall amounts (and therefore diabatic heating) in the inner-core regions of
TCs in HiRAM compared to AM2.5. This is consistent with our analysis, in which the surface
flux feedback was notably stronger in HiRAM than in AM2.5, both at the same stage in the TC
life cycle and at the same intensity. The radiative feedback was found to be slightly stronger in
HiRAM, though the difference was small compared to the difference in surface fluxes.

AM2.5 and FLOR differ only in that FLOR is a coupled ocean-atmosphere model, while AM2.5
is an atmosphere-only model. AM2.5 simulates stronger TCs than FLOR (Figure 2), and this
too appears to be linked to a stronger surface flux feedback in in AM2.5. Ocean coupling is
known to reduce TC intensity, because the cold wake generated by TC-driven upwelling is a
negative feedback on the TC (e.g., Lloyd and Vecchi 2011; Zarzycki 2016; Zarzycki et al. 2016;
Scoccimarro et al. 2017). Here, we show explicitly that ocean coupling also reduces the surface
flux feedback, as defined in the $\hat{h}$ variance framework. This is significant because, in the context of
convective self-aggregation, these surface flux feedbacks have only been examined in simulations
with fixed SST (e.g., Wing and Emanuel 2014; Coppin and Bony 2015; Wing and Cronin 2016).

The reduction in the surface flux feedback with ocean coupling is consistent with studies that have found that ocean coupling delays self-aggregation (Hohenegger and Stevens 2016).

Why would the surface flux feedback differ across models? In general, the sign and magnitude of the surface flux feedback depends on the spatial co-variability of column-integrated moist static energy and surface fluxes. The spatial variability of surface fluxes in turn depends on the spatial variability in surface wind speed and air-sea enthalpy disequilibrium. Therefore, this feedback could be larger in a given model because of (i) higher moist static energy near the TC and/or lower moist static energy in the surrounding environment, (ii) larger values of surface fluxes near the center of the TC because of stronger winds or larger air-sea disequilibrium (though the latter is unlikely to be large near the center of the TC), or (iii) better alignment between the location of the high values of surface fluxes (usually near the strongest winds) and the location of highest moist static energy. Even when evaluated at the same intensity, the overall structure of the TC wind field may be different across different models. Differences in the representation of boundary layer processes or frequency of coupling to the surface could lead to different surface fluxes, and differences in the representation of moist convection could lead to different patterns of humidity.

With regards to CAM-SE and CAM-FV, Figure 12 indicates that the surface fluxes themselves are larger near the TC center in CAM-SE. Moon et al. (2018) found that this is mostly due to a difference in the latent heat flux, and that this was mostly due to a larger air-sea enthalpy disequilibrium in CAM-SE. It is not clear what about the different dynamical cores could cause this difference, but one possibility is a difference in how the physics-dynamics coupling is configured. More generally, differences in divergence damping have also been proposed as a reason for the sensitivity of TC simulation to dynamical core (Zhao et al. 2012).
GEOS, which has similar horizontal resolution as HiRAM, AM2.5, and FLOR, simulates the weakest storms and the weakest surface flux feedback compared to other models when compared at the same intensity. But, GEOS has a larger (more positive) radiative feedback than the other models, both when compared at the same intensity and at the same stage in the TC life cycle - which is a difference in the opposite direction of one that would explain the weaker storms. We speculate that the difference in radiative feedback originates from details in the convection and cloud schemes (such as cloud lifetimes and detrainment) or possible mean state differences, but an in-depth investigation is beyond the scope of this study. We also note that, when the 15.2 ms\(^{-1}\) threshold is applied, GEOS has much fewer storms than the other models (and observations). This is consistent with Lim et al. (2015), who found that realistic numbers of TCs were difficult to achieve with 0.5° grid spacing without modifying the values for TC detection.

The life cycle composites (Sections 4c-d) also indicate that, in TCs simulated by high-resolution GCMs, the radiative feedback is at least as important as the surface flux feedback in the early stages of TC development, and in some models, it remains as important throughout intensification to LMI. This result adds to a growing body of evidence on the importance of radiation in TC formation, intensification, and structure (Fovell et al. 2010; Bu et al. 2014; Melhauser and Zhang 2014; Nicholls 2015; Navarro and Hakim 2016; Tang and Zhang 2016; Fovell et al. 2016; Wing et al. 2016; O’Neill et al. 2017; Bu et al. 2017). It is consistent with the cloud-resolving model results of Wing et al. (2016), which found a similar role for the radiative feedback in the evolution of a spontaneously generated TC in radiative-convective equilibrium simulations, and that removal of radiative feedbacks inhibits or significantly delays the onset of genesis. The positive radiative feedbacks diagnosed in this study result from the direct effect of differential heating between the area of deep convection in the developing TC and the surrounding, drier environment, which acts to favor ascent and moistening in the already moist area. This promotes clustering of convection and
continued moistening of the atmosphere, both of which further the formation of a tropical cyclone. The differential heating can also indirectly favor TC formation by the generation of a circulation response (Nicholls 2015; Muller and Romps 2018), though this is not explicitly quantified by our $\hat{h}$ variance budget diagnostic. Our results indicate that it is specifically the variability in longwave radiation due to clouds (Figure 10) that drives the positive radiative feedback.

6. Conclusions

We have developed and applied process-oriented diagnostics utilizing budgets of column moist static energy and the spatial variance of column moist static energy to tropical cyclones in six high-resolution climate models. These diagnostics allow us to quantify different feedbacks related to how convection, moisture, clouds, and related processes are coupled.

We found that the general evolution of the moist static energy variance budget along the composite TC life cycle is qualitatively similar to that found in idealized cloud-resolving model simulations. The box-average moist static energy variance is higher at higher wind speeds, both in the life cycle and intensity-bin composites. Surface flux and radiative feedbacks both contribute positively, and fairly equally, to an increase in moist static energy variance in the early stages of TC formation and intensification. As the TC nears its lifetime maximum intensity, the surface flux feedback increases beyond the magnitude of the radiative feedback (which is dominated by longwave-cloud effects) in most, though not all models. At the same point in the TC life cycle, the models that simulate stronger storms have stronger surface flux feedbacks, while the radiative feedback is more consistent across models. This indicates that the radiative feedbacks are relatively more important to TC formation and intensification in models with weak storms. The difference in surface flux feedback across the models is robust even when we consider composites over the same intensity.
In particular, CAM-SE and CAM-FV simulate the strongest storms and have the strongest surface flux feedbacks, and are even slightly different from each other despite the only difference being the dynamical core. HiRAM has notably stronger storms and stronger surface flux feedbacks than do AM2.5 or FLOR, despite all three models being at the same resolution and using same dynamical core - indicating the importance of physics parameterizations, especially the convection scheme, as has also been noted by other studies. AM2.5 has stronger storms and a stronger surface flux feedback than FLOR, indicating that ocean coupling reduces the strength of the surface flux feedback. GEOS has the weakest storms and weakest surface flux feedback, but, curiously, a stronger than average radiative feedback.

The inter-model spread in surface flux feedbacks results from a difference in the spatial covariability in moist static energy, surface wind speed, air-sea disequilibrium, and surface enthalpy fluxes between the different models, which is linked to the model representation of the spatial structure of the TC wind and moisture field. Overall these results indicate that the representation of the interaction of spatially varying surface fluxes with the developing TC is partially responsible for inter-model spread in TC simulation, in which stronger variability of surface fluxes between the TC core and its surroundings leads to stronger TCs. Our results also indicate that the radiative feedback contributes to TC development across all models, especially at weaker intensities or in earlier stages of development.

These results show that the moist static energy variance budget is a useful tool for examining tropical cyclone formation and intensification in models, with links to the actual physical processes responsible for model simulation of TCs. However, while it is able to distinguish between models, there does not yet exist an observational “reference” version of this diagnostic, so it is unknown which models’ representation of surface flux and radiative feedbacks is “correct”. Creating a
reference diagnostic from observations of TCs, as well as applying this diagnostic to a broader range of models, will be the subject of future work.

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References


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<th>Resolution</th>
<th>Dynamical Core</th>
<th>Convection Scheme</th>
<th>Other Notes</th>
</tr>
</thead>
<tbody>
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<td>HiRAM</td>
<td>~ 50 km</td>
<td>Finite volume cubed sphere</td>
<td>Bretherton et al. (2004)</td>
<td>Other physics: GFDL AM2</td>
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<tr>
<td>AM2.5</td>
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<td>Relaxed Arakawa-Schubert</td>
<td>Other physics: GFDL AM2</td>
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<tr>
<td>FLOR</td>
<td>~ 50 km</td>
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<td>Relaxed Arakawa-Schubert</td>
<td>Coupled to 1° ocean, SST nudged to obs.</td>
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<td></td>
<td>~ 100 km global</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GEOS</td>
<td>~ 50 km</td>
<td>Finite volume cubed sphere</td>
<td>Relaxed Arakawa-Schubert</td>
<td>MERRA-2 AMIP</td>
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</table>

40
TABLE 2. Number of tropical cyclones (TCs) analyzed. Only TCs in the North Atlantic are analyzed in CAM-SE.

<table>
<thead>
<tr>
<th>Model</th>
<th>Years Analyzed</th>
<th>Number of TCs</th>
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<tr>
<td>AM2.5</td>
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<td>170</td>
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<tr>
<td>FLOR</td>
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<td>211</td>
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<td>CAM-FV</td>
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</tr>
<tr>
<td>GEOS</td>
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<td>Intensity Range (m s(^{-1}))</td>
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<td>---------------------------------</td>
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<td>9</td>
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Fig. 17. Box-average MSE variance (a) and surface flux (b) and radiative (c) feedback terms in the MSE variance budget composited over intensity bins. The x-axis indicates the mean wind speed in each bin, for each model. Panel (c) shows the box-average surface flux (asterisk) and radiative (open circle) feedback terms composited over the 24-27 ms$^{-1}$ bin (indicated by the dashed line in (b) and (c)) for each model, as a function of the mean LMI of simulated TCs in that model.
FIG. 1. Genesis positions for tropical cyclones in each model (a-f) and in the best-track observational data (g), for 1995-2000. For the models, the genesis position is the latitude and longitude of the first point in the track, as determined by the tracking algorithm.
FIG. 2. Probability density function of lifetime maximum intensity (LMI) (a) and of the maximum wind speed at each snapshot along the TC track up until the time of LMI (b), for the two years of TCs that are analyzed in each model, excluding snapshots poleward of 30° and, in CAM-SE, excluding storms outside of the North Atlantic. “HiRAM-G” (in cyan) indicates TCs in the HiRAM simulation that have been identified and tracked using the GFDL tracking algorithm (the same as used for AM2.5 and FLOR; Murakami et al. 2015). The black dashed line in (a) shows the observed distribution of LMI from the best-track data, for storms of at least tropical storm strength (LMI \( \geq 17 \) ms\(^{-1} \)) from 1995-2000, and equatorward of 30°. The PDF in (a) is smoothed while the PDF in (b) uses the un-smoothed 3 ms\(^{-1} \) bins from Table 3 (extended to 93 ms\(^{-1} \)).
FIG. 3. Composite 48 hours prior to LMI of moist static energy budget (MSE) of all TCs in CAM-FV. The composite mean TC intensity (blue line) and number of storms in the composite (red line) as a function of time relative to LMI is shown in (a); the star indicates the time at which the rest of the panels are valid. The column-integrated MSE (b), MSE tendency (c), column radiative flux convergence (d), surface enthalpy flux (SEF) (e) and MSE advection (f) are also shown as a function of latitude and longitude relative to the TC center.
FIG. 4. Composite 48 hours prior to LMI of moist static energy variance (MSE) budget in CAM-FV. The composite mean TC intensity (blue line) and number of storms in the composite (red line) as a function of time relative to LMI is shown in (a); the star indicates the time at which the rest of the panels are valid. The column-integrated MSE anomaly from the box mean (b), MSE variance tendency (c), radiative feedback (d), surface flux feedback (e) and advective feedback (f) are also shown as a function of latitude and longitude relative to the TC center.
FIG. 5. Composite 96 hours prior to LMI of radiative (g-l) and surface flux feedbacks (m-r) as a function of latitude and longitude relative to the TC center in the CAM-SE (a,g,m), CAM-FV (b,h,n), HiRAM (c,i,o), AM2.5 (d,j,p), FLOR (e,k,q), and GEOS (f,l,r) simulations. The composite mean TC intensity as a function of time relative to LMI is shown in the first row (a-f); the star indicates the time at which the rest of the panels are valid.
Fig. 6. As in Fig. 5 but for composite 72 hours prior to LMI.
Fig. 7. As in Fig. 5 but for composite 48 hours prior to LMI.
FIG. 8. As in Fig. 5 but for composite 24 hours prior to LMI.
FIG. 9. Composite 48 hours prior to LMI of normalized radiative (g-l) and surface flux feedbacks (m-r) as a function of latitude and longitude relative to the TC center in the CAM-SE (a,g,m), CAM-FV (b,h,n), HiRAM (c,i,o), AM2.5 (d,j,p), FLOR (e,k,q), and GEOS (f,l,r) simulations. The composite mean TC intensity as a function of time relative to LMI is shown in the first row (a-f); the star indicates the time at which the rest of the panels are valid.
FIG. 10. Composite of the box-average MSE variance budget in the CAM-SE (a,g), CAM-FV (b,h), HiRAM (c,i), AM2.5 (d,j), FLOR (e,k), and GEOS (f,l) simulations. The first row (a-f) shows, as a function of time relative to LMI, the composite mean TC intensity (red line, right axis) and the box-average MSE variance (blue line, left axis), scaled by $10^{14}$. The second row (g-l) shows, as a function of time relative to LMI, the surface flux (green line), longwave (blue line), shortwave (red line), and advective (pink line) feedbacks. The composite is over all TCs that have a LMI in the upper quartile of the LMI distribution.
FIG. 11. Panel (a) shows the composite of the box-average surface flux (asterisks) and longwave radiative feedback (open circles) at 48 hours prior to LMI for each model as a function of that models TC intensity. Panel (b) shows the ratio of the composite box-average surface flux and radiative feedbacks for each model. Simulated TC intensity is defined as the average LMI of all TCs that have LMI in the upper quartile of the LMI distribution. In all panels, the models are CAM-SE (red), CAM-FV (yellow), HiRAM (blue), AM2.5 (purple), FLOR (green) and GEOS (black). The composite is over all TCs that have a LMI in the upper quartile of the LMI distribution.
Fig. 12. Composite of MSE (J m$^{-2}$; a-f), column radiative flux convergence (g-l) and surface fluxes (m-r) as a function of latitude and longitude relative to the TC center in the 24-27 ms$^{-1}$ intensity bin, in CAM-SE (a,g,m), CAM-FV (b,h,n), HiRAM (c,i,o), AM2.5 (d,j,p), FLOR (e,k,q), and GEOS (f,l,r).
FIG. 13. Composite of MSE variance ($J^2 m^{-4}$; a-f), radiative (g-l) and surface flux feedbacks (m-r) as a function of latitude and longitude relative to the TC center in the 15-18 ms$^{-1}$ intensity bin, in CAM-SE (a,g,m), CAM-FV (b,h,n), HiRAM (c,i,o), AM2.5 (d,j,p), FLOR (e,k,q), and GEOS (f,l,r).
Fig. 14. As in Fig. 13 but for the 24-27 ms$^{-1}$ intensity bin.
Fig. 15. As in Fig. 13 but for the 33-35 ms$^{-1}$ intensity bin.
FIG. 16. Composite of normalized MSE variance (a-f), radiative (g-l) and surface flux feedbacks (m-r) as a function of latitude and longitude relative to the TC center in the 24-27 \text{ ms}^{-1} \text{ intensity bin, in CAM-SE (a,g,m), CAM-FV (b,h,n), HiRAM (c,i,o), AM2.5 (d,j,p), FLOR (e,k,q), and GEOS (f,l,r).}
FIG. 17. Box-average MSE variance (a) and surface flux (b) and radiative (c) feedback terms in the MSE variance budget composited over intensity bins. The x-axis indicates the mean wind speed in each bin, for each model. Panel (c) shows the box-average surface flux (asterisk) and radiative (open circle) feedback terms composited over the 24-27 ms$^{-1}$ bin (indicated by the dashed line in (b) and (c)) for each model, as a function of the mean LMI of simulated TCs in that model.