Linking Convective Self-Aggregation in Idealized Models
to Observed Moist Static Energy Variability near the
Equator

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Key Points:

• Moist static energy zonal spectral tendencies have similar signs and scale-selectivity
  in cloud-permitting models and observations.
• Radiation increases variance at long wavelengths while surface enthalpy fluxes and
  advection reduce variance.

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Abstract

Idealized cloud-permitting simulations of radiative-convective equilibrium have become a popular tool for understanding the physical processes leading to horizontal variability of tropical water vapor and rainfall. However, the applicability of idealized simulations to nature is still unclear given that important processes are typically neglected, such as lateral vapor advection by extratropical intrusions, or interactive ocean coupling. Here, we exploit an emerging spectral analysis technique that compactly summarizes the multiscale processes supporting convective aggregation. By applying this framework to high-resolution reanalysis data and satellite observations in addition to idealized simulations, we compare convective-aggregation mechanisms across horizontal scales and data sets. The results affirm the validity of the RCE simulations as an analogy to the real world. Column moist static energy spectral tendencies share similar signs and scale-selectivity in cloud-permitting models and observations: Radiation increases variance at wavelengths above 1,000km, while advection damps variance at all wavelengths, and surface enthalpy fluxes mostly reduce variance between wavelengths of 1,000km and 10,000km.

Plain Language Summary

Advances in computing have allowed computer models to simulate tropical weather systems spanning a few dozen kilometers at the same time as moist and dry regions spanning several thousand kilometers. To improve and validate computer models, we need to compare computer simulations to real-world observations, but we lack a compact way of simultaneously comparing them at scales close to 10km, 100km, 1,000km, and 10,000km. By breaking down water vapor variability near the Equator into contributions from these different length scales, we can identify the scales at which computer models agree with real-world observations and explain why. Surprisingly, even computer models that are run in a highly idealized configuration validate well against observations of the real world, despite the fact that nature never attains this idealized limit. We find that atmospheric radiation tends to intensify moist and dry regions of several thousand kilometers near the Equator, while lateral transport of energy and surface-atmosphere exchanges tend to smooth out these moist and dry regions.

1 Introduction

Tropical weather and climate are strongly shaped by the longitudinal variability of column water vapor, which dominates column-integrated moist static energy (MSE) variability due to weak horizontal variations in tropical atmospheric temperature. On meteorological timescales, the intensity of extreme precipitation events depends on the humidity and temperature of the surrounding environment, e.g., for isolated convective cells, mesoscale convective systems (LeMone et al., 1998) and tropical cyclones (Hill & Lackmann, 2009). On climatic timescales, the zonal variability of MSE is linked to the equator-to-pole energy transport (Trenberth et al., 2002) and to climate sensitivity through the link between the hydrological cycle and cloud and water vapor feedbacks (Feldl et al., 2014). Persistent regions of high and low MSE occur due to surface heterogeneities, including ocean currents, continents, and mountain ranges (Figure 1a), while transient anomalies in MSE near the Equator (e.g., Figure 1c) relate to a rich spectrum of tropical weather across a range of temporal and spatial scales. This includes isolated convective activity (~1 hour, ~10 km), mesoscale convective complexes (~10 hours, ~100 km) (e.g. review by Houze, 2004), tropical depressions (~10 days, ~1000 km) (e.g. review by Montgomery & Smith, 2017), the Madden-Julian Oscillation, and the Asian monsoon (~60 days, ~10000 km) (e.g. reviews by Zhang, 2005; Webster et al., 1998, respectively).

Advanced computing now allows simulation of planetary-scale domains (~10^4 km) with cloud-permitting models (CPM) of horizontal resolution ~1 km, which can resolve...
this entire spectrum of tropical weather. Explicit comparisons of tropical weather systems in observations and CPM, however, are rare because many CPM model configurations focus on idealized limits that neglect processes relevant to realistic tropical weather and climate. The goal of this paper is to use a spectral budget for sources and sinks of transient MSE variance as a step towards comparing tropical weather systems across observations and models of varying complexity.

Figure 1. (a) Instantaneous, (b) time-averaged, and (c) transient MSE in ERA from 10°S to 10°N. (d-i) Instantaneous transient MSE in each model of section 2. Transient MSE is normalized by the latent heat of vaporization of water $L_v$ to yield units kg m$^{-2}$: the length of the bottom colorbar corresponds to $\sim 60$ MJ m$^{-2}$. Panels (a-f) respect the original aspect ratio of the horizontal domain. While the length of the long-channel equals a third of the Equator’s length, its width has been multiplied by a factor 5 in panels (g-i) to facilitate visualization.

We use the column-integrated frozen moist static energy $H$ (units J m$^{-2}$):

$$H(x, y, t) \overset{\text{def}}{=} \int_0^{z_1} \bar{\rho} dz \left( L_v q - L_f q_i + c_p T + g z \right),$$

as a diagnostic because it is conserved by convection, and because previous studies in idealized CPM have successfully used its variance budget to assess processes that favor or disfavor convective aggregation. Here, $\bar{\rho}$ is the mean density profile, $L_v$ and $L_f$ are the latent heat of vaporization and fusion of water, respectively, $q$ and $q_i$ are water vapor and ice mixing ratios, respectively, $c_p$ is the specific heat capacity of dry air at constant pressure, $T$ is the absolute temperature, and $s$ is the dry static energy. The total
MSE field $H$ has spatial variability in its temporal mean $\overline{H}$, as well as spatiotemporal variability in the transient MSE anomaly $H'$, here defined by:

$$H(x, y, t) = \overline{H}(x, y) + H'(x, y, t)$$

(2)

Note that transient MSE variability may be modulated nonlinearly by the stationary MSE features, adding another level of complexity to MSE transients - but in this paper we will focus primarily on comparing transient MSE variability across models and observations without directly assessing this role of nonlinear modulation.

Previous work (e.g., Held et al., 1993; Muller & Bony, 2015) has consistently found that when CPMs are run on large enough domains, MSE self-organizes into moist and dry regions even in the absence of external forcing (such as planetary rotation, surface inhomogeneities or large-scale wind shear). This emergent property of moist convection, referred to as “convective self-aggregation” (e.g., review by Wing et al., 2017; Holloway et al., 2017), suggests that a significant fraction of transient MSE variability near the Equator might arise from internal self-organization rather than external processes such as surface characteristics, teleconnections with the mid-latitudes, or ocean coupling. The problem is that physical mechanisms of convective self-aggregation have been extensively studied in the context of idealized CPM with fixed surface temperatures, which ignore external processes, and thus provide an uncertain analogy to real-world settings.

This motivates the aim of our paper – quantitatively comparing convective-aggregation processes in idealized CPM and observations may deepen our understanding of (1) how transient MSE anomalies grow and decay and (2) how valid an analogy to the real world the RCE CPM limit represents. Idealized CPM have been compared to observations in the past, but mostly at coarse granularity by looking for similar correlations or distributions of variables. Using satellite data, Tobin et al. (2012) showed that $(10^\circ \times 10^\circ)$ longitude-latitude boxes with more convective organization also exhibited lower values of MSE and larger outgoing longwave radiation, consistent with idealized CPM experiments (Wing & Emanuel, 2014). Holloway et al. (2017) used data from the Nauru meteorological station and showed that the long-channel configuration of Wing & Cronin (2016) had more realistic distributions of MSE and vertical velocity than traditional square-domain CPM. Additionally, Stein et al. (2017) showed that for a given large-scale precipitation rate and vertical motion, anvil clouds decreased with the degree of aggregation in satellite data, while low clouds and precipitation efficiency increased with aggregation, consistent with CPM simulations (e.g., Figure 8 of Wing & Cronin, 2016). Recently, Holloway (2017) used the MSE spatial variance budget to show that interactive radiation maintained aggregation while MSE advection disaggregated convection in satellite data, as found in limited-domain CPM simulations.

While such correlations support the validity of the RCE analogy, they do not provide a very strong constraint on the underlying dynamics. Motivated by the recent availability of planetary-domain CPM and high-resolution reanalysis products, we proceed by comparing the observed transient MSE field (Figure 1c) to the transient MSE field from several idealized CPM experiments (Wing et al., 2017); Figures 1d-i) and ask:

How do the physical mechanisms that maintain observed moist static energy variance compare to the convective-aggregation mechanisms from idealized models at each horizontal scale?

The work below is organized as follows. After introducing the observational and model datasets in section 2, we investigate the zonal power spectra of transient MSE and how they evolve under the influence of radiation, surface enthalpy fluxes, and advection in section 3, before concluding in section 4.
2 Data

We use four datasets to compare convective aggregation in observations and idealized CPM: Meteorological reanalysis (ERA), satellite observations (CERES), a rotating near-global simulation (NG) and a non-rotating long-channel simulation (LC). A snapshot of the transient MSE field from each is shown in Figure 1, and each is described in more detail below.

2.1 Reanalysis observations: ERA

The European Centre for Medium-Range Weather Forecasts Re-Analysis (ERA) version 5 (Hersbach & H., 2016) was produced by assimilating observational data in version CY41R2 of the Integrated Forecast System. The new reanalysis dataset has a better hydrological cycle and sea surface temperatures in the Tropics and is calibrated for climate applications. Zonal and temporal resolutions are 27.5km × 1hour.

2.2 Satellite observations: CERES

The Clouds & Earth’s Radiant Energy Systems (CERES, Wielicki et al., 1996) “CERES SYN1deg Ed4A” dataset provides diurnally-complete top-of-atmosphere and surface radiative fluxes by using sixteen geostationary satellites as well as the National Aeronautics and Space Administration’s Moderate Resolution Imaging Spectroradiometer. Zonal and temporal resolutions are 110km × 1hour.

2.3 Cloud-Permitting Model (CPM) Simulations

The following experiments were conducted using the System for Atmospheric Modeling (SAM), a cloud-permitting model that is widely used for idealized studies, solves the anelastic equations of motion, and includes cloud microphysics and subgrid turbulence parameterizations (Khairoutdinov & Randall, 2003).

- **LC**: A suite of three idealized long-channel (LC) experiments with horizontal domain size 12, 288 × 192km$^2$ over a uniform ocean surface with temperature 300K, using SAM v6.8.2. These consist of a control simulation (LC CTRL, Figure 1g), described in Wing & Cronin (2016), a simulation with horizontally homogenized radiation (LC UNI-RAD, Figure 1h), and a simulation with horizontally homogenized surface enthalpy fluxes (LC UNI-SEF, Figure 1i) described in Beucler & Cronin (2018). Each experiment was run for 80 days to a statistically steady state and outputs were saved with zonal and temporal resolutions of 3km × 1hour.

- **NG**: Similar to LC, but for a much larger (near-global; NG, 40, 360 × 10, 000km$^2$) ocean-only domain with prescribed ocean surface temperatures that decrease away from the equator and a coriolis parameter that increases away from the equator, allowing for formation of extratropical eddies which intrude into the tropics. As with LC, three runs were conducted at 300K, consisting of NG CTRL (control experiment, Figure 1d), NG UNI-RAD (horizontally-uniform radiative heating, Figure 1c) and NG UNI-SEF (horizontally-uniform surface enthalpy fluxes, Figure 1f) in Khairoutdinov & Emanuel (2018). Each experiment was run for a year, using SAM v6.10.6. Outputs were saved with zonal and temporal resolutions of 156.25km × 1day.

At spatial scales below O(100km), most of the spatial variance comes from subdiurnal variability from isolated convective events (not shown). Hence, to make meaningful comparisons across datasets, we time-average the fields of ERA, CERES and LC over one-day blocks before calculating spatial co-spectra using the Fast Fourier Transform algorithm (Frigo & Johnson, 2005).
3 Zonal Spectral Budget of Transient Column Moist Static Energy

The following spectral method will allow us to (1) separate the zonal variability of MSE into contributions from different scales, in each dataset and (2) quantify the amount of variance created by radiation, surface enthalpy fluxes, and advection, separately at each zonal scale. Specifically, we measure zonal variability of transient MSE $H'$ at a given zonal wavelength $\lambda$ using the zonal power spectrum $\varphi_H$ of transient MSE, defined as:

$$\varphi_H (\lambda, y, t) \overset{\text{def}}{=} \widehat{H'}^* \widehat{H'},$$

where $t$ is time and $\widehat{H'}$ is the zonal Fourier transform of the transient MSE field $H'$:

$$\widehat{H'} (\lambda, y, t) \overset{\text{def}}{=} \frac{1}{\sqrt{2\pi}} \int_0^{L(y)} \exp \left( -\frac{2\pi i x}{\lambda} \right) H'(x, y, t) \, dx,$$

where $i$ is the unit imaginary number and $L(y)$ is the length of the latitude circles of ordinate $y$. From $\varphi_H$, one can calculate various aspects of the transient MSE zonal variability, including its spectral-mean wavelength (equation 2 of Beucler & Cronin (2018)) and its total (i.e. wavenumber-integrated) zonal variance.

3.1 Zonal Power Spectra

Figure 2a shows $\varphi_H$ for two LC experiments:

1. The control experiment CTRL (full lines): This experiment is initialized with a horizontally uniform sounding taken from small-domain RCE, but moist and dry regions of finite size ($\sim$ 2,000km) and MSE anomalies ($\sim$ 7kg m$^{-2}$ x $L_v$) spontaneously form after $\sim$ 1 month despite homogeneous boundary conditions (see Figure 1g for a snapshot at $t = 1$ month and Figure 1d of Beucler & Cronin (2018) for a Hovmoller plot of the full time evolution). Although the temporal variations of the transient MSE field appear complicated in physical space, Figure 2a reveals a simpler picture in spectral space: As convection self-aggregates (i.e. progressing from solid purple to yellow lines), MSE variance increases at wavelengths above $\lambda \sim$ 100km before equilibrating with a variance peak at $\lambda \sim$ 2,000km, explaining why anomalies of this scale are most visible in Figure 1g. Note that the y-axis of Figure 2a is logarithmic so the total variance in the aggregated state (solid yellow line) is dominated by the $\lambda \sim$ 2,000km variance peak.

2. The UNI-RAD experiment (dotted lines): Horizontally homogenizing radiative heating greatly weakens aggregation, as evidenced by reduced MSE perturbations ($\sim$ 2kg m$^{-2}$ x $L_v$). Unlike the CTRL experiment, MSE variance only grows at the longest wavelengths for the first 10 days before stabilizing around $1 - 2$ kg m$^{-4}$. Using UNI-RAD as our reference “non-aggregated” experiment$^1$, the effect of self-aggregation can then be quantified as the difference between the full and dotted yellow lines, and is only significant on scales larger than $\lambda \sim$ 1,000km.

Moving to the more realistic NG simulations in Figure 2b, the effect of self-aggregation is qualitatively similar to the LC case if measured by the difference between the full and dotted green lines. That is, removing the spatial variability of radiation (green dotted line) prevents the transient MSE field from developing variance at long wavelengths relative to the control (green solid line). In contrast, removing the spatial variability of surface enthalpy fluxes adds variance at long wavelengths (dashed lines) in both the LC and NG setups, because surface enthalpy fluxes damp developing MSE anomalies after the initial stages of aggregation, opposite to radiation (see Beucler & Cronin, 2018, for an extensive discussion on this topic).

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$^1$This experiment is very similar to the experiment in which both radiative heating and surface enthalpy fluxes are horizontally uniform (see Figures 1a and 1c of Beucler & Cronin (2018))
We now turn to our main goal of comparing idealized simulations against observational data. The black line in Figure 2 depicts the observational ERA spectrum, averaged from 10°S to 10°N and over 5 full years (January 1st 2010 - December 31st 2014). The zonal MSE variance is slightly larger in ERA than in the NG CTRL case, except over the range of wavelengths where the NG spectrum peaks (λ ∼ 500km − 2,500km). To assess the robustness of our observed spectrum, we recalculate the zonal MSE spectrum over the same latitude range and time period using satellite data (CERES, light blue line). The CERES and ERA spectra agree very well at all wavelengths, although this agreement breaks down at short wavelengths (λ < 1,000km) if we do not average the data over one-day blocks (not shown). Hourly ERA data exhibit more spatial variability at short wavelengths, suggesting that CERES data and one-day time-averaging in the NG case may smooth out the MSE variability at short wavelengths. Finally, although the observational MSE spectrum flattens progressively at long wavelengths, spectra from idealized CPM exhibit a local maximum in the MSE variance at wavelengths of ∼ 1,000 − 5,000km.

![Figure 2.](attachment:figure2.png)

(a) Zonal power spectrum of transient MSE in the LC CTRL experiment (full lines) and the LC UNI-RAD experiment (dotted lines), time-averaged over different stages of the simulation. (b) Zonal power spectrum of transient MSE of all datasets, time-averaged over 50d-80d for the LC experiments and over the entire time period for all other experiments. In both panels, spectra have been averaged over the y−dimension, divided by λ, and normalized to units kg² m⁻⁴ so that they integrate to the total variance in logarithmic λ−space.

3.2 Adapting a Spectral Budget for Model-Observations Intercomparison

We now derive a formal spectral decomposition of the transient MSE budget terms to quantitatively assess the respective roles of separate processes in maintaining the spectrum at each wavelength.
This begins with the transient MSE budget, building on standard approaches, but modified so as to help fairly compare our simulations with observations, thus forging new ground. The transient MSE field $H'$ evolves in response to the net MSE flux at the atmospheric column’s boundaries, with contributions from the net longwave flux $\dot{H}_{lw}$, the net shortwave flux $\dot{H}_{sw}$, the surface enthalpy fluxes $\dot{H}_{sf}$ and the advection of MSE through the column’s boundaries $\dot{H}_{adv}$. Separating the four MSE tendencies $\dot{H}_i$ into their temporal mean $\dot{H}_i$ and their transient component $\dot{H}'_i$ in the same spirit as equation 2, we can write the transient MSE budget as:

$$\frac{\partial H'}{\partial t} = \sum_{i=\text{lw,sw,sf,adv}} \dot{H}'_i. \quad (5)$$

Following Section 2.2 of Beucler & Cronin (2018), we take the Fourier transform of Equation 5 and multiply it by the complex conjugate $\hat{H}'^*$ of Equation 4 to derive a budget for the zonal spectrum $\varphi_H$ of transient MSE:

$$\frac{1}{2} \frac{\partial \varphi_H}{\partial t} = \sum_{i=\text{lw,sw,sf,adv}} \Re(\hat{H}'^* \hat{H}'_i), \quad (6)$$

where $\Re$ is the real part of a complex number. At each wavelength $\lambda$, MSE variance is created if a MSE tendency $\dot{H}_i$ increases MSE where the transient MSE anomaly $H'$ is positive, corresponding to a positive co-spectrum $\Re(\hat{H}'^* \hat{H}'_i)$. This framework generalizes the MSE variance framework of Bretherton et al. (2005) and Wing & Emanuel (2014), a particular case of Equation 6 that can be derived by integrating equation 6 across wavelengths before dividing it by the wavelength-integral of $\varphi_H$ (see Appendix B of Beucler & Cronin, 2018). To yield an equation for the rate at which MSE tendencies maintain the MSE spectrum at each wavelength (in units $s^{-1}$), we average equation 6 in time over a time-period $t_H$ and divide it by the time-mean MSE spectrum $\varphi_H$ at each wavelength:

$$\frac{1}{t_H} \frac{\Delta \varphi_H}{\varphi_H} = \sum_{i=\text{lw,sw,sf,adv}} \frac{2\Re(\hat{H}'^* \hat{H}'_i)}{\varphi_H}, \quad (7)$$

where $\Delta \varphi_H$ is the MSE spectrum difference between the beginning and the end of the time-average. We refer to the terms on the right-hand side of equation 7 as components of the spectral MSE variance tendency, or for brevity, as "variance rates".

Since Equation 7 is agnostic to the time-mean zonal structure of the MSE tendencies, we can make direct analogies between observations and zonally-symmetric RCE, which is a key theoretical result of this paper. The left-hand side of equation 7 is small when the initial and final spectra $\varphi_H$ are similar, or when the time-average is taken over a long time-period $t_H$. It respectively equals 17%, 1.3% and 0.1% of the longwave variance rate ($i = \text{lw}$) when the LC CTRL, NG CTRL and ERA datasets are time-averaged over 50–80d, 1year and Jan1, 2010 – Dec31, 2014, respectively. Therefore, the four components of spectral MSE variance tendency on the right-hand side of Equation 7 approximately balance.

### 3.3 Zonal Spectral Budget Intercomparison

The spectral rates of variance injection depicted in Figure 3 have similar signs and amplitude across models and observations. Surprisingly, even the LC spectral rates (yellow lines) have similar signs and amplitudes to the spectral rates from planetary-domain experiments, and are simply shifted to shorter wavelengths, despite the smaller zonal extent and 64:1 aspect ratio of the LC configuration. Therefore, we see the LC configuration as an idealized, reduced-size model to study the interaction between convection and
the large-scale circulation, which makes LC a promising yet relatively inexpensive framework to study the processes maintaining convective aggregation across climates (Wing et al., 2018).

Figure 3. Rate at which (a) longwave Radiation (b) shortwave Radiation (c) surface enthalpy fluxes and (d) MSE advection maintain the MSE power spectrum at each wavelength (in units day$^{-1}$) and for all datasets. The UNI-SEF rates of variance injection (dashed lines) have been divided by a factor of 5 because the denominator of equation 7, which is the time-averaged spectrum $\overline{\phi_H}$, is smaller for non-aggregated simulations.

First, since longwave cooling to space is systematically lower in moist regions of high MSE (e.g., Beucler & Cronin, 2016), longwave radiation injects MSE variance at all wavelengths (Figure 3a), with rates as high as 1/(2 weeks) at the planetary scale. Shortwave heating is larger in moister regions, mostly because of water vapor absorption (e.g., sub-section 3.3 of Wing et al., 2017), resulting in a shortwave injection of MSE variance at all wavelengths (Figure 3b). Surface enthalpy fluxes remove variance in observations and for idealized cases where convection has aggregated, while they unrealistically inject variance for the sensitivity tests (UNI-RAD) in which aggregation is artificially denied (Figure 3c) or in the early phases of convective self-aggregation (see Appendix D of Beucler & Cronin, 2018). The difference between the rate at which surface fluxes remove variance in the aggregated and non-aggregated cases can be explained by decomposing the surface enthalpy fluxes into a wind-driven component and a component driven by the near-surface enthalpy disequilibrium. Section 3.4 of Beucler & Cronin (2018) shows that while the wind-driven component favors convective aggregation (variance injection) because convective gustiness is higher in convectively-active regions, surface enthalpy disequilibrium is largest in dry regions, damping MSE variance (variance removal). As convection aggregates, MSE variance increases at long wavelengths and so does the surface enthalpy disequilibrium. In the real-world atmosphere, additional factors such as higher near-surface wind speeds, ocean heat transport and dry air intrusions further decrease
the aggregating effect of the wind-driven variability in surface enthalpy fluxes. This leads to larger surface flux damping at scales where radiation injects the most variance (Figure 3c), and could explain the absence of a peak in the ERA MSE spectrum (Figure 2b). MSE advection, calculated as a residual of equation 7, removes variance at all wavelengths with a maximum removal rate at the planetary scale (Figure 3d).

4 Conclusion

The multi-scale patterns of convective aggregation are directly connected to the hydrologic cycle in the Tropics (e.g., Kiranmayi & Maloney, 2011). While cloud-permitting models have provided insight into the physical processes controlling convective aggregation, it has been hard to meaningfully validate idealized simulations against observations. We have addressed this issue by applying a spectral technique that reveals scale-selective aggregation processes in meteorological reanalyses, satellite retrievals, and idealized cloud-permitting simulations of varying complexity.

The budget for the transient MSE spectrum exhibits scale-selective tendencies that hold across models and observations: longwave radiation injects variance at the longest wavelengths, shortwave radiation injects variance at long wavelengths, MSE advection removes variance across scales while surface enthalpy fluxes mostly remove variance between $\lambda \approx 1,000\text{km}$ and $\lambda \approx 10,000\text{km}$. We find a stronger damping effect of surface enthalpy fluxes in ERA reanalysis data relative to simulations that neglect ocean interaction and horizontal sea surface gradients. This finding is consistent with recent RCE simulations that have made surface flux feedbacks on aggregation more realistic by adding a meridional surface temperature gradient (e.g., Bretherton & Khairoutdinov, 2015) or increasing surface temperature variability by adding a slab ocean (e.g., Coppin & Bony, 2017) or soil (e.g., Hohenegger & Stevens, 2018), resulting in a damping of self-aggregation patterns.

Removing the interaction between radiation and water vapor in the simulations prevents convective self-aggregation, resulting in a loss of MSE variance at long wavelengths ($\lambda > 1,000\text{km}$), and corresponding disagreement with the observed MSE variance. This adds to the growing body of evidence that radiatively-driven self-aggregation is key to generating realistic tropical dynamics (e.g., Arnold & Randall, 2015).

Undoubtedly, aspects of the causality are still murky since vertically-resolved, lower-tropospheric specific humidity, whose variance dominates the column MSE variance, may not directly respond to the thermodynamical constraints governing column MSE. For instance, is the longwave variance production peak too high for LC in Figure 3a because cloud-radiation processes are represented incorrectly, or because vertical advection of water vapor amplifies variance too much at a specific length scale? In this context, spectral analysis of vertically-resolved water vapor and buoyancy budgets could be beneficial as the weakness of tropical buoyancy gradients offers conceptual simplifications; the framework introduced here generalizes to three-dimensional tracer variance budgets, and could be used to investigate the processes injecting zonal variance in the lower-tropospheric water vapor spectrum at long wavelengths.

Ultimately, we hope the tool summarized here can be deployed across the emerging hierarchy of global cloud resolving models (Satoh et al., 2019) to help clarify their intrinsic dynamics. While spatio-temporal spectra are familiar to tropical dynamicists (e.g., Wheeler & Kiladis, 1999; Yasunaga et al., 2019), formal spectral decomposition of underlying process budgets are not yet in widespread use. In this context, traditional diagnostic tools may fail to compactly analyze the underlying causes of multi-scale discrepancies across models. By quantifying the preferential scales of zonal thermodynamic variability, our spectral framework allows comparison between models and observational datasets across configurations, resolutions, and scales.
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