Environmental and internal controls on Lagrangian transitions from closed cell mesoscale

cellular convection over subtropical oceans

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Abstract

Classifications of mesoscale cellular convection (MCC) for marine boundary layer clouds are produced using a supervised neural network algorithm applied to MODIS daytime liquid water path data. The classifier, used in prior studies, distinguishes closed, open, and cellular, but disorganized MCC. This work uses trajectories in four eastern subtropical ocean basins to compare meteorological variables and the structures of boundary layers for trajectories that begin as closed cells, but evolve either into open cells, disorganized cells, or remain closed cells over one afternoon-afternoon cycle.

Results show contrasts between the trajectory sets: Trajectories for MCC that remain closed cells are more frequently observed nearer coasts, while trajectories that break into open and disorganized cells begin farther offshore. The frequency at which closed cells transition to open cells is seasonally invariant. The fraction of trajectories that stay as closed MCC varies throughout the year in opposition to those that break into disorganized cells, so that their annual cycles are 180° out of phase. Trajectories remain as closed cell more frequently in austral spring and boreal summer when the trade inversion is stronger.

The closed-disorganized MCC breakup is associated with weaker subsidence, a weaker inversion, a drier free troposphere, and enhanced nighttime boundary layer deepening, consistent with a warming-drying mechanism. The closed-open transition occurs in meteorological conditions similar to closed-closed trajectories. However, prior to the transition, the closed-open trajectories exhibit stronger surface winds, lower cloud droplet concentrations,
and rain more heavily overnight. Results suggest that multiple, independent mechanisms drive changes in cloud amount and morphology.
Low-altitude, optically thick marine clouds cool Earth’s oceans by reflecting sunlight and emitting infrared radiation to space (Hartmann et al. 1992, L’Ecuyer et al. 2019). Marine low clouds cover nearly 200 million square kilometers of ocean on average during the day (Hahn & Warren, 2007), while overcast marine cloud scenes are estimated to reflect 30-40% (Bender et al. 2016) of incoming solar radiation. Taken together, the extent and albedo of marine clouds has an effect equivalent to covering 60-80 million square kilometers of dark ocean with reflectors that scatter 100% of incoming radiation back out of the atmosphere. Variations in marine cloud brightness and cover can therefore have significant consequences for climate.

Attempts to understand the mechanics of marine cloud cover evolution have been made using a variety of approaches: Comparing long-term climatologies (yearly, seasonal, monthly) of cloud cover and environmental predictor variables shows correlations between variables (for example: Norris, 1998), though no single variable predicts a majority of cloud variability on subseasonal time scales (Klein, 1997). Further, relationships between variables are difficult to disentangle and causality cannot be attributed to predictors without a time dimension (Qu et al. 2015; Klein, 2017). In-situ studies using aircraft or ships can collect a large amount of data at a very high resolution, but they lack the longevity needed to build up statistical significance and typically lack the spatial extent needed to follow cloud scenes as they respond to their environment while advecting downstream. Studies using computer models capable of resolving circulations on the sub-cloud level can isolate predictors and assess causality, but are computationally expensive and exist at the mercy of parameterized model
physics (Guichard & Couvreux, 2017). Here we use a newer Lagrangian approach (introduced in Eastman & Wood 2016): Following thousands of cloudy parcels as they evolve in time and space while sampling cloud properties and environmental drivers twice-daily using sun-synchronous polar-orbiting satellites and reanalysis grids. This approach provides sample sizes large enough to attain statistical significance and control for confounding behaviors, while also assessing precursors to cloud changes with the introduction of a time dimension.

This work is concerned with the Lagrangian evolution of the cellular organization of stratiform clouds over the subtropical oceans (Agee 1987). In marine environments characterized by a strong temperature and humidity inversion (as is often observed in the eastern subtropical oceans), a cool and moist boundary layer is typically observed under a warm and dry free-troposphere. Here Stratocumulus (Sc) clouds tend to organize into broad, overcast, optically thick closed mesoscale cellular convective (MCC) clouds, whose cells are sustained by overturning driven by radiative cooling at cloud top (Wood 2012). Occasionally closed MCC clouds break into open MCC clouds, which are characterized by relatively narrow bands of optically thick clouds flanked by optically thin ‘veil clouds’ (Wood et al. 2018) with broad clear regions between the cloudy edges (Wood et al. 2008). As they advect equatorward and westward in the trade winds, subtropical closed and open cells eventually evolve into less tightly organized, more cumuliform structures (Muhlbauer et al., 2014) with sparsely distributed cloudy cells, sometimes surrounded by thin veil clouds and fields of shallow cumulus. These tropical trade wind cloud fields also frequently organize into distinct, quantifiable structures (Stevens et al. 2020), though for the purposes of this study they will be
characterized as “cellular, but disorganized” (shortened to “disorganized” here), since they lack the distinct repeating structures seen in closed and open MCC Sc clouds.

The drivers of transitions from closed to open cells versus closed to disorganized cells are the focus of this work. Prior research suggests that open cell formation from existing closed cells is triggered by precipitation processes (Wang and Feingold, 2009). Savic-Jovcic & Stevens (2008) use a Large Eddy Simulation to show how cool and moist perturbations in near-surface airmasses formed by evaporation of rain drops (cold pools) can shape and propagate convective elements in drizzling Sc. Terai & Wood (2013) state that cold pool processes do exert thermodynamic and dynamic forces on the PBL, but stop short of showing that they are responsible for any changes in cellular organization. Precipitation was tested as a possible driver of subtropical Sc breakup in Eastman and Wood (2016), but was found to be of little importance after controlling for the depth of the boundary layer, which covaries positively with rain rate. Instead, processes that warm and deepen the boundary layer appeared more important for Sc breakup. However, that work did not assess changes in cellular structure, and it is possible that evolution from closed to open cells is associated with different processes compared to evolution from closed to disorganized cells.

The Lagrangian evolution of overcast Sc clouds has recently been shown to be sensitive to the cloud droplet number concentration \(N_d\) and effective radius of cloud drops, which vary in opposition to one-another (Abel et al., 2020; Christensen et al., 2020). Christensen et al., (2020) used a Lagrangian framework with geostationary satellite data in the SE Atlantic to show that overcast Sc cloud decks are longer lived in stable marine conditions when \(N_d\) is higher. A Lagrangian study farther offshore in the SE Atlantic done by Abel et al., (2020) used aircraft and
geostationary satellite data to show that cloud drops were significantly larger (therefor fewer in
number) in a pocket of open cells (POC) compared to surrounding close cells. Their Lagrangian
analysis compares 24-hour back trajectories initialized within and outside the POC, showing
equivalent effective radii, cloud amount, and above-cloud aerosol concentrations 24-hours
before breakup. Abel et al. (2020) goes on to show that the open cells studied entrain less free
tropospheric air downward into the boundary layer compared to neighboring closed cells that
sit beneath a uniformly polluted troposphere. These recent results show that microphysical
processes can affect cloud evolution, and that cellular structure has a significant effect on
entrainment processes.

The cellular structure of marine clouds affects albedo in a few ways: Closed cells are
typically cloudier than open, which are in-turn cloudier than disorganized cells. Further
complicating the picture, closed cells have been shown to have a higher albedo for an
equivalent cloud amount versus open (McCoy et al. 2017), and disorganized cells (personal
communication, I. L. McCoy, 2020) indicating that cloud condensate and microphysical
properties are also likely important for setting scene albedo in addition to cloud cover. Watson-
Parris et al. (2021) shows that the existence of pockets of open cells within broader closed-cell
Sc does lead to an increase in solar radiation received at the surface, though the radiative effect
is small when only considering pockets of open cells. This necessitates further study of these
organizational structures in order to understand what meteorological conditions and internal
processes may be driving transitions in cellular organization. Climate models that use
parameterizations based on meteorology and thermodynamic structure to simulate cloud
properties will be improved if they can better simulate cloud cellular properties and the
conditions associated with them.

Cellular structures in clouds can now be detected and defined using high-resolution
satellite imagery and efficient machine-learning techniques (Wood & Hartmann 2006; Stevens
et al. 2020; Yuan et al. 2020; Denby, 2020). Identifications from the supervised neural network
algorithm developed in Wood and Hartman (2006) are combined with our aforementioned
Lagrangian analysis to study the evolution of cloud structures as they advect in the subtropical
trade winds, identifying key precursors of changes in cellular organization. The details of this
methodology are presented in the Methods and Data Sources section. In the Results section,
we examine the meteorology and internal cloud processes associated with MCC evolution. In
the Discussion section, we contrast our results with prior work, in which MCC classifications
were not identified, in an effort to more accurately represent distinct cloud processes.

Methods and Data Sources

a) MCC Classifier

The cellular organization of marine cloud cover is determined using a supervised neural
network algorithm developed in Wood and Hartmann (2006). The three-layer back propagation
neural network is used to classify 256x256 km² scenes of MODIS day-time only LWP (King et al.
2003) into one of three cloud types: “closed cells”, “open cells”, and “cellular, but
disorganized”. In this study, these titles are shortened to “closed”, “open”, and “disorganized”
respectively. A fourth classification category in the original algorithm for “homogeneous/no
organization” has been collapsed into “closed cells” due to its limited occurrence, as in Muhlbauer et al. (2014) and McCoy et al. (2017).

Two sources of information from each scene are used as inputs to the neural network: i) the LWP probability density function, and ii) the LWP power spectrum from a spatial fast Fourier transform. This ensures that the neural network is trained to classify cloud morphologies by considering both the quantity of liquid water in the scene and its spatial arrangement (i.e., level of cloud clustering), emphasizing the distinctions in cloud micro- and macrophysics between morphologies in addition to their cloud coverage. One thousand cloud scenes were hand identified by cloud type and used to train the neural network until an 85-90% accuracy rate was reached when tested (Wood and Hartmann, 2006). Scenes with overlying mid to high altitude clouds are removed from the dataset when the difference between cloud top temperature and sea surface temperature exceeds 30°C (McCoy et al. 2017). Centers of classified scenes are spaced 128 km apart, producing overlap between each classified box and increasing the number of scenes that can be classified from each MODIS swath.

Previously, this neural network has been applied to single years of MODIS Terra collection 4 (Wood and Hartmann, 2006) and Aqua collection 5.1 (Muhlbauer et al. 2014; McCoy et al. 2017). Here, this algorithm is newly applied to MODIS Aqua collection 6.1 for multiple years 2007-2010. An example of the classifier is shown in Figure 1, where classifier output is overlaid on a MODIS Aqua daytime cloud scene. Numbers represent MCC classifications, where 0 is open cells, 1 is closed cells, and 3 is disorganized.

Figure 1 shows a few MCC classifications that appear incorrect. In particular, there are a number of cells misclassified as ‘1’ on the western edge of the swath that are clearly open or
disorganized scenes. To evaluate whether the classifier produces results reliable enough for
study, we have visually inspected the MCC classifications on 20 images, 10 in the NE Pacific and
10 in the SE Pacific in June and October, respectively. This includes a total of 3,878
classifications in boxes spanning 10 degrees latitude and 25 degrees longitude. A visual
assessment counting classifications that could be considered ‘unambiguously wrong’, meaning
another classification is clearly correct to an observer (the first author, who had no part in
developing the algorithm), shows that open cells are misclassified ~16% of the time, closed cells
are misclassified ~12% of the time, and disorganized, but cellular scenes are misclassified ~7%
of the time they are observed. While we would prefer these numbers be 0%, this lends
legitimacy to the classification analysis, since the vast majority of scenes classified as an MCC
type are actually that type, at least ~84% of the time. This is consistent with the 85-90%
accuracy rate of the neural network algorithm when it was originally developed and tested.
In order to determine an MCC classification for scenes observed and tracked in our
Lagrangian system, a frequency distribution of all MCC box centers within 200km of each
Lagrangian sampling point is produced at each point. If any MCC classification occurs more than
50% of the time in the scene distribution, that scene is considered to be the dominant MCC
type. This analysis was repeated using two other approaches for classifying scenes, producing
qualitatively identical results: 1) assign the single MCC classification nearest to the trajectory
sample as the MCC type for that sample, and 2) assign the sample MCC type to the majority
MCC type in the frequency distribution, not requiring 50% or greater representation.

b) Lagrangian framework
Trajectories used in this Lagrangian study are identical to those used in Eastman et al., 2017 and Eastman and Wood, 2018. They are generated from isobaric ERA-Interim (Dee et al., 2011) wind fields at 925 hPa using the routine introduced in Bretherton et al. (2010).

Trajectories are initiated along the CloudSat/CALIPSO curtain, spaced 200 km apart in four subtropical ocean study regions, shown in Figure 2 and defined below, for years 2007-2010. In order to capture two diurnal cycles while advecting westward in the trade winds, trajectories are run for 54 hours. This extra time is necessary given that the westward advection of trajectories follows the arc of the sun overhead, slightly lengthening the time between sunrises.

In total, ~170,000 54-hour trajectories are used. Samples of cloud and meteorological data are taken concurrent with each A-Train flyover at times defined as T = 0, 12, 24, 36, and 48 trajectory hours. Note, however, that the timing in UTC hours between each sample time is, on average, slightly longer than 12 hours due to the westward advection. Sample points include all data within a 100km radius of each observation point. A 100km radius is chosen in order for each sample to contain several 1°x1° latitude/longitude L3 grid boxes in order to generate robust averages. Different sample radii were investigated in Eastman et al. (2016), which showed that Lagrangian tendencies were consistent between 100km radii and larger radii up to 1200km.

Here, we focus on 24-hour (13:30-13:30) Lagrangian transitions in MCC classifications, specifically looking at trajectories that begin as closed cell Sc. Our 54-hour trajectories are split into 24-hour segments. Each segment contains one day-to-day diurnal cycle. This segmenting is done by splitting 54-hour trajectories that begin during the day into two segments: one that...
spans 0-24 hours, and another that spans 24-48 hours. For trajectories initialized at night, only
the span from 12-36 hours is used. This creates just over 250,000 24-hour trajectory segments.

Trajectory segments, heretofore called ‘trajectories’ are composited into three sets
based on their 0-hour and 24-hour MCC classifications: Closed-closed, closed-open, and closed-
disorganized. Requiring our trajectories to all begin as closed cells allows for a greater “apples-
to-apples” comparison since retrieved cloud variables at 0-hours may otherwise be artificially
affected by different cellular structures. The afternoon-afternoon time period is constrained by
the MCC data, which are only collected during the daytime overpass of the Aqua satellite at
13:30 local time. Given this constraint, there is no bias in our results due to compositing of non-
matching diurnal cycles. Nighttime data are collected concurrent with the 1:30 local-time
overpass of the Aqua satellite. Plots of these trajectories, colored based on transition type, are
shown in Figure 2, which also highlights the geographic bounds of our study regions.

Study regions are chosen in four eastern subtropical ocean basins with similar
climatologies, chosen to capture Sc maxima near the west coasts of major continents and also
the declining cloud-cover gradients further offshore as the Sc transition into trade Cumulus
(Cu). These regions are identical to those in Eastman & Wood (2016, their Figure 1), and are
named: The Northeast Pacific, Southeast Pacific, Southeast Atlantic, and the East Indian
regions. These regions are also illustrated here in the maps in Figure 2. The East Indian region
was chosen instead of the also-relevant NE Atlantic after an analysis of trajectories showed a
greater amount of synoptic influence in the NE Atlantic, characterized by a significant fraction
of trajectories abruptly changing direction from westward to eastward. This synoptic behavior,
which can interfere with the cloud processes we hope to study here, was less frequent in the E Indian.

c) Cloud and meteorological data

This work will combine several data sources from polar orbiting satellites and model reanalysis fields. Satellite data come from several platforms orbiting in NASA’s Afternoon-Train (A-Train) constellation, including: The Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Microwave Scanning Radiometer for EOS (AMSR/E) both orbiting aboard the Aqua satellite, the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO), and the spaceborne cloud profiling radar aboard CloudSat. The A-Train satellites orbit together with equator crossing times at 1:30 and 13:30 local times, allowing for near-simultaneous sampling of atmospheric features by several different instruments.

Meteorological data come from the ERA5 reanalysis (Copernicus Climate Change Service, 2017). Reanalysis data fields are interpolated to match the observation times of the A-Train satellites. ERA5 meteorological variables used in this study are: Surface wind speed, subsidence at 700 hPa \(w_{700}\), sea surface temperature (SST), lower tropospheric stability (LTS, \(\theta_{700}-\theta_{1000}\)), and humidity at 700 hPa \(q_{700}\). These variables are referred to as “environmental” or “meteorological” variables, and are tested as drivers of MCC evolution. Lower tropospheric stability is chosen as our measure of inversion strength instead of estimated inversion strength (EIS) due to the strong correlation between EIS and \(q_{700}\), which is shown to be a strong cloud controlling variable in the Lagrangian realm (Eastman & Wood 2018). The use of LTS in lieu of
EIS should not negatively impact results, since this study takes place exclusively within the subtropics (Wood & Bretherton, 2006).

Cloud cover data retrieved along trajectories for day and night come from the mean cloud fraction values in the MODIS cloud mask dataset (Hubanks et al. 2008; Oreopoulos 2005). These are available twice daily on the uniform 1°x1° latitude/longitude (L3) grid. The MODIS swath is over 2000 km wide, requiring sensor viewing angles over 60° from nadir at the swath edge. Geometric issues arise when clouds are viewed from this oblique angle, causing a high bias in cloud amount at swath edge (Maddux et al. 2010). This Lagrangian project uses MODIS retrievals taken along trajectories that originate on the CloudSat/CALIPSO curtain at hour 0 for every 54-hour trajectory. This means that the sensor zenith at trajectory outset is always around 19°, but is usually wider at subsequent observation times. Because cloud amount is biased higher at wider angles, a correction is necessary to avoid a spurious increasing tendency in cloud amount driven by the changing view angle. This zenith angle bias is accounted for by subtracting the mean excess in cloud cover from each sample caused by that sample’s view angle (Eastman & Wood, 2016), which can be as high as 14% at swath edge. This is done for day and night using the mean sensor zenith angle for each sampled 1°x1° L3 grid box.

Day and night cloud liquid water path (LWP) retrieved along trajectories comes from the AMSR/E sensor (Wentz & Meissner, 2004) averaged to the 1°x1° L3 grid. AMSR/E provides total LWP, which includes clear and cloudy portions, so total LWP is divided by MODIS cloud fraction to estimate the LWP for cloudy portions only (CLWP). This AMSR/E product is different from the MODIS LWP used to classify the MCC, which is only available during daytime. We choose the AMSR/E LWP as a tracked variable due to the availability of nighttime data. For LWP values
below 0.18 kg/m², the AMSR/E algorithm does not distinguish between cloud water and rain
water, producing a high bias in cloud water path due to the inclusion of rain water. In Appendix
A, we use rain rates produced using the AMSR/E 89 GHz brightness temperatures (introduced
below) to create an adjusted LWP product with the estimated rain water contribution removed.
This study was done using both the adjusted and unadjusted CLWP product, with little
qualitative difference in results.

Cloud droplet number concentration \( N_d \) estimates come from three sources: Our
primary \( N_d \) dataset uses a combination of cloud droplet effective radius and liquid water path
detected by the MODIS collection 6 daytime-only optical properties dataset (King et al. 2003)
and the relationship developed by Boers et al. (2006) and Bennartz (2007) and shown as
Equation 1 in Possner et al. (2020). Two other \( N_d \) products are compared in section 3c: One was
developed by Grosvenor & Wood (2018), which uses the collection 5 MODIS optical properties
data and a different set of relationships. A third, independent, \( N_d \) data source is the Modern-Era
Retrospective Analysis for Research and Applications, Version 2 (MERRA-2, Galero et al. (2017),
which provides estimates of aerosol concentrations for a variety of different aerosol types and
sizes. These concentrations can be combined with the regression coefficients determined in
McCoy et al. (2017) to estimate \( N_d \). Due to the difficult-to-retrieve nature of \( N_d \) and the
possibilities of biases in the data associated with cloud edge retrievals, multiple \( N_d \) products are
compared here in order to substantiate results.

Day and night rain rate estimates come from the routine introduced in Eastman et al.
(2019), which uses the relationship between brightness temperature \( T_b \) observed by AMSR/E
at 89 GHz and rain rate as measured by the rain-profile dataset (Mitrescu et al. 2010; Lebskoc
and L’Ecuyer 2011) from the CloudSat cloud profiling radar. Rain rate estimation relies on the positive relationship between $T_b$ and rain rate (Miller and Yuter, 2013), where warm $T_b$ is associated with greater in-cloud LWP and heavier rain rates. The product is able to produce estimates of rain rate after controlling for three other variables that also drive $T_b$ variation: surface wind speed, column water vapor, and sea surface temperature. Column water vapor is measured by the AMSR/E (Wentz and Meissner, 2004). For the updated version of this precipitation dataset used here, SST and wind speed now come from the ERA5 reanalysis. Rain rates are resolved in 4x6 km grid boxes, which is of a sufficient resolution to see most individual cellular elements in Sc cloud decks.

The depth of the planetary boundary layer (PBL), assumed to be the same as the height of the trade inversion, is estimated using the difference between SST and cloud top temperature for a subset of clouds with tops assumed to be at the base of the trade inversion. The depth of this layer is determined using a parameterized lapse rate from Wood and Bretherton (2004). The temperature of the clouds at inversion top is estimated using the algorithm developed in Eastman et al. (2016 & 2018) which is tuned through a comparison between MODIS cloud top temperature histograms and CALIPSO vertical feature mask data (Vaughan et al. 2004).

**Results**

a) Climatological behavior of transitions
A geographic comparison between our trajectory sets is shown in Figure 3, where trajectories are composited by transition type within each region. Figure 3 also includes mean wind vectors at 925 hPa, the annual mean LTS, and a shaded contour showing the relative frequency of closed cell MCC compared to the other MCC types. The NE Pacific, SE Pacific, and SE Atlantic show similar results: Closed-closed trajectories are seen further upwind, in regions with a stronger inversion, while the closed-open and closed-disorganized transitions tend to occur farther offshore and are in comparable locations. In contrast, the closed-open trajectories in the East Indian region tend to occur farther upwind and farther north while the closed-disorganized and closed-closed mean trajectories begin farther offshore.

The seasonality of closed cell transitions is explored in Figures 4 and 5. Figure 4 shows the number of trajectories that begin as closed cells within a 100-day sampling window. A significant seasonal cycle is apparent in every region, with peaks in the early austral spring for the southern hemisphere regions, and in the early boreal summer for the NE Pacific.

In Figure 5 the fraction of closed cells that break into open (red), break into disorganized (black), or stay closed (blue) are compared between regions. Trajectories remain closed more often when trajectories beginning as closed cell are more frequent (from Figure 4). The fraction of closed cells that break into open cells is relatively stable throughout the year. In contrast, the fraction of closed cells that transition to disorganized is seasonally variable, corresponding with the opposing seasonality in the fraction of closed cells that remain closed. The lack of a seasonal cycle in the relative frequency of closed-open transitions is peculiar, given the strong seasonal cycles in most meteorological variables in these regions (Eastman et al. 2017, Their figure 7) and may suggest that the closed-open transition has less sensitivity to seasonally
varying meteorology. This contrasts with the significant seasonal cycle in the relative frequency of the closed-closed and closed-disorganized transitions, which implies they may be driven by varying meteorology. For example, LTS tends to be higher when closed-closed trajectories are most frequently observed in the NE Pacific, SE Pacific, and SE Atlantic (again from Eastman et al. 2017, their figure 7).

b) Composite analysis of cloud and predictor variables

Figures 6 and 7 show regional breakdowns of composited cloud and meteorological variables taken at 0, 12, and 24 hours for our three trajectory sets. Composites represent averages of all trajectories exhibiting that transition type with the transition type specified by color. The width (in the y-direction) of the plots represents the 2-sigma standard error, in order to compare means. Separation between the bounds indicates a greater than 95% confidence that the sample means are different. Cloud variables compared in Figure 6 show that cloud cover (6a, 6f, 6k, 6p) evolves similarly in each region, but differently for each set: Closed-closed trajectories stay overcast, closed-open trajectories experience some cloud reduction, and closed-disorganized trajectories experience the most cloud loss. The sets remain overcast at the 1:30 sampling time, indicating that the breakup into open and disorganized cells occurs between 1:30 and 13:30. This timing is consistent with the conclusions from the analysis of a much more limited set of closed-to-open cell MCC transition cases in Wood et al. (2008, JGR, their Fig. 10), which showed transitions peaking from 3-6 am local time. For our other cloud variables, the NE Pacific, SE Pacific, and SE Atlantic show similar behavior. In those three regions closed-closed trajectories begin and end with the most $N_d$ and the lightest rain rates, begin with
less CLWP and begin in shallower PBLs. Compared to the other trajectory sets, closed-open trajectories have significantly lower $N_d$, greater overnight rain rates, and higher 0-hour CLWP.

Closed-disorganized trajectories begin in deeper PBLs, have less overnight CLWP, lower rain rates, and middling $N_d$ compared to the other two sets. The E Indian ocean appears to be an outlier in Figure 6, with less distinction between sets. The most significant difference between sets in the E Indian is the stronger rain rate seen throughout the evolution of the closed-open trajectories, which is in agreement with the rain behavior in the other regions.

Figure 7 shows composites of meteorological variables in the same manner as Figure 6.

In all regions except the SE Pacific, $q_{700}$ is lowest for the closed-disorganized set. Wind speed is significantly higher for the closed-open set in all four regions. The sea surface is coolest and LTS is highest for the closed-closed sets in all four regions. Subsidence is lowest at 0 and 12 hours for the closed-disorganized sets in the SE Pacific, SE Atlantic, and NE Pacific.

To further verify results, we remove the effects of mean geographical, seasonal, and diurnal differences between the trajectory sets by producing anomalies relative to the 100-day running mean of each variable centered on each day for day and night separately. Figures 8 and 9 show anomalies of our cloud and meteorological variables composited for all regions, respectively. Results using anomalies reinforce the results from Figures 6 and 7 with stark contrasts present between the trajectory sets. Closed-open trajectories are associated with significantly stronger winds, reduced $N_d$, and heavier overnight rain. Closed-disorganized transitions are associated with reduced subsidence and LTS, a drier free troposphere, and warmer sea surface. This suggests that drivers of closed-open cell transitions are distinct from closed-disorganized transitions: Closed-open transitions are associated with internal
microphysical and precipitation processes along with stronger winds, while closed-disorganized transitions are driven by the surrounding meteorology.

A comparison of Figures 8 and 9 with the regional behaviors seen in Figures 6 and 7 shows that the evolution of MCC within each region may be driven by somewhat different processes. For instance, there is little evidence that $N_d$ is lower before the closed-open transition in the E Indian compared to the other transitions, but in the other three regions $N_d$ is much lower prior to the closed-open transition. Instead, the E Indian closed-open transition is associated with much higher rain rates compared to the other transition types there, or the other regions. Combining all regions in Figures 8 and 9 allows us to see these processes in aggregate, where differing dominant processes in different regions are combined. Looking into a single region, or excluding any regions, may cause a study to miss out on relevant mechanics.

Typically, subtropical Sc PBLs deepen at night due to the increased turbulence and entrainment driven by radiative cooling at cloud top. However, Figure 8d illustrates shallower PBL depth anomalies at night for closed-closed and closed-open trajectories compared with closed-disorganized. Further, Figures 6d, 6i, 6n, and 6s show closed-closed and closed-open sets have less change in PBL depth over 24 hours compared to closed-disorganized sets. This difference in cycles is likely due to differences in $q_{700}$, subsidence, and inversion strength seen between the trajectory sets in Figure 9. Taken together, these differences in meteorology for the closed-disorganized set drive: Increased cloud top cooling through a drier free troposphere, stronger entrainment across a weaker inversion, and more PBL deepening given the weaker compensating downward motion in the troposphere. All of these processes suggest that the clouds are experiencing warming and drying through entrainment of free tropospheric air. The
closed-open transition exhibits an enhanced diurnal cycle in precipitation and LWP. This suggests that overnight precipitation processes may drive the cloud evolution instead of the drying through PBL deepening and entrainment seen in the contrasting closed-disorganized cases. These results are summarized in Table 1, which shows the cloud and meteorological variables most strongly associated with the three MCC transitions examined in our study.

c) Untangling rain and $N_d$

Interpreting the evolution of rain rate and $N_d$ along Lagrangian trajectories requires more care as the calculations of these values are nuanced and entangled. This is in part because rain rate and $N_d$ tend to strongly covary. Cloud drops tend to be large and drop concentrations tend to be low when rain is present. Additionally, the routines and source data used to estimate $N_d$ from satellite observations may introduce biases due to the application of a single routine to distinct cloud regimes with distinct vertical variations of $N_d$ (Fu et al. 2019). Here, we attempt to untangle these issues by first comparing three different $N_d$ products in our compositing routine. Then, we further subset trajectories into groups where either precipitation or $N_d$ is held somewhat constant while the other variable is unconstrained, allowing for the effects of one to be tested while the other is controlled.

The $N_d$ analysis from Figure 6 (b, g, l, q) is repeated for all regions combined using three separate $N_d$ datasets: our default $N_d$ (Figure 10 a), the $N_d$ from Grosvenor and Wood (2018, hereafter “Grosvenor $N_d$”, Figure 10 b), and, as an entirely independent data source, the $N_d$ derived from MERRA aerosol reanalysis using the regression established by McCoy et al. (2017) (their Figure 10 c). The default $N_d$ dataset relies on MODIS C6 data, while the Grosvenor uses
MODIS C5, creating some degree of independence, though they are both derived from the
same sensor. The Grosvenor $N_d$ is specifically suited to single layer, mostly overcast Sc, making
it best suited for the comparison at 0 hours when all trajectories are closed cell, but less suited
for the later observations where clouds have broken up.

The separation of groups in all three frames of Figure 10 supports our result, showing
that closed-open transitions are associated with fewer $N_d$ at the outset and closed-closed
trajectories have higher $N_d$. The Grosvenor $N_d$ shows a higher mean and increasing tendency for
the closed-disorganized set, which is at odds with the other two products, although this
tendency is only based on two data points. This increase in Grosvenor $N_d$ is likely due to the
increasingly broken clouds over time in the closed-disorganized transition. The Grosvenor $N_d$ is
calculated for clouds that are primarily overcast, so the subset of observations we show that
are disorganized and also mostly overcast here represents a very small, and somewhat peculiar
slice of our data. A closer look shows that there are 838 closed-disorganized transitions
sampled for the Grosvenor $N_d$, while the other two products have over 4800. This makes the
Grosvenor $N_d$ less robust for this set and is likely why the mean and tendency is in
disagreement with the other products. However, again, it is unwise inferring much from slopes
derived from two data points.

In Figure 11 we attempt to untangle the covarying effects of rain and $N_d$. Here, our
trajectory sets are grouped into quantiles based on 0-hour precipitation probability or $N_d$.
Composites for the covarying variable from our three trajectory sets (closed-closed, closed-
open, closed-disorganized) are compared to see whether their behavior is different when their
covarying variable is constrained. Results from 11a-d show that reduced 0-hour $N_d$ is associated
with the closed-open transition regardless of whether rain is likely at 0 hours. This was 
repeated for overnight (12-hour) rain observations and results were qualitatively identical, 
indicating that N$_d$ may influence the closed-open transition independently of rain. Frames 11e-h 
show that rainfall appears significantly associated with the closed-open transition for three of 
the four sets. The rainfall signal was present, but not significant when N$_d$ was very low (below 
27 cm$^3$, from the default C6 product). Frames 11e-h indicate, as above, that rain may influence 
the closed-open transition independently of N$_d$. These results suggest that either rain and N$_d$
may be associated with separate mechanisms driving the closed-open transition, or they may 
be a symptom of another mechanism that drives the transition while also modifying both N$_d$
and rain rate.

Discussion

Prior work has shown a positive connection between heavier precipitation, depleted N$_d$, 
and the appearance of open MCC clouds using observations (Rosenfeld et al. 2006, Wood et al. 
Here, we substantiate these findings using a larger, more statistically robust dataset comprising 
tens of thousands of observations. We also analyze a time dimension showing that negative N$_d$
anomalies and positive precipitation anomalies precede the transition from closed to open MCC 
clouds. In addition to the established microphysical and precipitation connections, this work 
shows that faster surface wind speeds are associated with the closed-open transition. 

In comparing the closed-open transition with transitions from closed to disorganized 
MCC, we show that the former is physically distinct from the latter. Transitions from closed-
open MCC occur in PBLs that are environmentally similar to PBLs where MCC remain closed cell. However, different internal microphysical and precipitation properties are present in the closed-open transition, as suggested by Wood and Hartmann (2006). Thus, open cells can be considered a special expression of the Sc boundary layer. In contrast, the closed-disorganized MCC transition is driven by meteorology surrounding the PBL, where processes act to warm and dry the cloud deck.

Christensen et al. (2020) shows that high $N_d$ prolongs Sc lifetime. Using this Lagrangian analysis coupled with MCC classifications, we show that Sc that remain as closed cell prefer high $N_d$ environments. This result suggests that the Christensen et al. (2020) result may be in-part driven by fewer closed-open transitions when $N_d$ is high. This is also in agreement with the results from Rosenfeld et al. (2006), which shows that closed cells remain in ship tracks through fields of open cell MCC, and concludes that cellular transitions from closed to open are highly sensitive to cloud droplet concentrations.

Results here are limited to the large-scale meteorological variables and cloud deck conditions associated with MCC transitions seen by our trajectories. We have identified three of our tested variables as being associated with closed-open transitions, either prior to the transition in the case of reduced $N_d$ and stronger wind speed, or concurrent with the overnight transition in the case of heavier rain. These results can aid in predicting the likelihood of closed-open transitions or in establishing more realistic boundary conditions in models that study the transition, but they do not directly reveal an exact mechanism for the closed-open transition. The overnight PBL deepening and entrainment drying hypothesis for the closed-disorganized transitions appears well-supported by the data. The closed-disorganized transition usually
occurs further downstream, closer to the equatorial edge, with a warmer sea surface and weaker stability. A corresponding mechanism for the closed-open transition is less clear, but is likely associated with the high overnight rain rates and likely aided by increased wind speed and low N_d.

Future work may focus specifically on the closed-open transition, which occurs in similar boundary layers with similar meteorology to the unchanged closed-closed trajectories, but with stronger surface winds and different microphysics and rainfall characteristics. Some questions motivated by our results are: Is wind speed a driver of the closed-open transition; does wind speed have a strong effect on microphysics and/or precipitation; are synoptic differences apparent between longer back trajectories; and what drives the higher LWP and reduced N_d that tends to precede closed-open transitions? Prior observational work in pristine marine Cu appears to show that stronger wind is associated with more cloud drops (Colón-Robles et al. 2006), though that focuses on different geographical regimes (and perhaps different cloud processes) than we do here. Kazil et al. (2016) modelled non-precipitating Sc for a variety of wind speeds and show a stronger LWP diurnal cycle, and higher LWP on average when wind is stronger. This is due to enhanced surface moisture fluxes and increased production of turbulent kinetic energy (TKE) in buoyant updrafts, which could be part of the mechanism driving the closed-open transition, though a study including precipitation would be beneficial. A higher latent heat flux associated with stronger winds would lead to greater condensation and stronger buoyant production of TKE (as explained in Bretherton and Wyant 1997). Scott et al. (2020) go on to show that stronger winds in subtropical Sc regions are associated with enhanced cloud amount, but decreasing optical thickness, which could hint at changes in
cellular structure. The positive connection between surface wind speed and open cells was mentioned in Wood et al. (2008), however a detailed analysis is lacking. Bony et al. (2020) also see that patterns of mesoscale cloud organization are well separated by wind speed in the tropics. It is possible that other characteristics associated with stronger winds are mechanically responsible for the transition: convergence/divergence, shear within the PBL or across the inversion, or additional turbulence within the PBL. Future work concerning the closed-open transition will incorporate longer trajectories to study the boundary layer for several days prior to transition to see whether microphysical anomalies are organized around perturbations in the flow, or whether flow perturbations could be influenced by precipitation or microphysical processes in the clouds. Higher temporal sampling resolution of reanalysis variables is also a priority moving forward.

The analysis in section c of our results begins to untangle rain and Nd, suggesting that heavy rain and reduced Nd are independently associated with trajectories that transition from closed-open MCC. A limitation of this analysis is that we only observe precipitation at 12-hour intervals, with only one overnight observation at 01:30 local time. Rainfall may be present before or after this observation, making it possible that all transitions are associated with rain, but not all of the rain is observed. Studies using geostationary satellite data, large-eddy-simulating models, or higher-resolution in-situ studies (such as Abel et al. 2020) could aid in determining whether separate mechanisms exist for the closed-open transition, or whether a single mechanism explains the differences in rain, Nd, and wind speed.

The geographic limitation of this study raises questions as to whether the nature of the transitions seen in the subtropical Eastern ocean regions is common to other regions. Future
work should study transitions in MCC in a range of climatological regions, which may better elucidate a set of mechanisms associated with transitions. Transitions in remote mid-latITUDE oceans may be free of Nd-altering pollution near the coasts and may also occur where wind speeds are more variable, offering a wider sampling of wind conditions and perhaps better constraints on Nd. Further, midlatitude transitions are more likely to be synoptically driven, so understanding these meteorological mechanics will create a clearer, more robust understanding of MCC types and transitions.

In Eastman & Wood (2016) it was shown that rainfall had little effect on Lagrangian changes in Sc cloud amount. Now that cellular structure can be assessed alongside cloud amount, that result can be clarified: Rainfall does appear associated with the Lagrangian closed-open cell transition, but less-so for the closed-disorganized transition. The closed-disorganized MCC transition is over twice as common as the closed-open transition, and is associated with a greater decline in cloud amount. Therefore, it is likely that the closed-disorganized signal obscured the weaker, less frequent closed-open signal in that work. The new results presented here show that it is imperative that cloud cellular structure be assessed alongside cloud amount if the goal is to properly capture cloud processes.

Conclusions

Mesoscale cellular convection (MCC) is classified into three groups using a machine learning algorithm: Closed cell, open cell, and cellular but disorganized. Classifications of MCC type are sampled along 24-hour trajectory segments, beginning and ending at 13:30, and
sampled every 12 hours by A-Train satellites and ERA-Interim reanalysis fields. Three trajectory sets are analyzed, all of which begin as closed cells and either stay closed, transition into open cells, or transition into disorganized cells.

A geographical comparison of the mean locations of transition types in our four subtropical ocean study regions shows similar mean behaviors in the NE Pacific, SE Pacific, and SE Atlantic regions. In those three regions closed-closed trajectories tend to exist closer to the coasts where LTS is climatologically greater, while closed-open and closed-disorganized transitions occur farther offshore. The E Indian region behaves in the opposite way, with closed-open occurring closest to shore and closed-closed farthest offshore. These geographic distributions may be in-part due to the geographic distributions in the training dataset, which could influence the output of the algorithm.

A seasonal analysis shows that trajectories that begin as closed cells are more common in the spring in our southern-hemisphere regions, and in summer in the NE Pacific. A seasonal breakdown of the fraction of trajectories that stay closed as opposed to breaking into open or disorganized shows a strong trade-off between closed-closed and closed-disorganized MCC, while the fraction of trajectories that transition to open remains more constant throughout the year. The trade-off between closed-closed and closed-disorganized transitions hints at meteorological forcing driving the closed-disorganized transition. Specifically, the seasonal cycle of closed-closed/closed-disorganized MCC appears synchronized with LTS, which is highest when closed cells tend to remain closed.

A comparison of meteorological and cloud variables as drivers of MCC change shows significantly different conditions associated with closed-disorganized versus closed-open
transitions (Table 1). Transitions to disorganized cells are associated with a stronger diurnal cycle of PBL depth, showing a greater amount of overnight deepening. This is likely driven by the accompanying weaker subsidence, weaker inversion, and drier free troposphere, which allows for enhanced entrainment of dry air into the cloud deck, causing drying and breakup. This contrasts significantly with the closed-open transition, which is associated with reduced $N_d$, stronger surface winds, and enhanced overnight precipitation in PBLs that begin as meteorologically comparable to the closed-closed set. A cursory analysis suggests that low $N_d$ and heavier overnight rain may independently lead to the closed-open transition. Follow-on analyses are strongly motivated to untangle the effects of wind speed, $N_d$, and rain on the closed-open transition, with the goal of discovering mechanism(s) that drive this transition.

Appendix A

By design, the AMSR/E passive microwave LWP product fails to distinguish between cloud water and rain water until LWP exceeds 0.18 kg/m$^2$. At that threshold, a partitioning is imposed, assuming that cloud liquid water is a function of rain rate and the depth of the rain column. The inclusion of drizzle and rain in the calculation of $C_{LWP}$ for values below 0.18 km/m$^2$ introduces a high bias in $C_{LWP}$ compared to other products, such as the daytime-only MODIS $C_{LWP}$, which is based on cloud top optical properties and not passive microwave retrievals. This is shown in Greenwald et al. (2018, their Figure 3) where AMSR/E $C_{LWP}$ and MODIS $C_{LWP}$ calculated from the 3.7 $\mu$m channel are plotted as a function of AMSR/E Total Liquid Water Path (TLWP). In that plot, the mean AMSR/E $C_{LWP}$ is higher than MODIS $C_{LWP}$ for TLWP values above $\sim$0.03 kg/m$^2$. This high bias is likely due to the inclusion of drizzle in the
AMSR/E CLWP, so the separation of the curves for TLWP values below 0.18 kg/m\(^2\) may be in large part due to the unaccounted-for presence of drizzle and rain drops.

Now with the availability of a semi-independent rain-rate product, the CloudSat and AMSR/E 89 GHz rain rate estimates used in this work, we can recreate this plot (Greenwald et al., 2018, fig. 3) for values of CLWP as a function of rain rate for averages in 1\(^\circ\) L3 grid boxes, shown in Figure A1. We use the coarse L3 grid boxes to mitigate the effects of rainfall in neighboring AMSR/E pixels, which also have an effect on AMSR/E CLWP. The gray area between the two curves represents the high bias in AMSR/E CLWP compared to MODIS. It is likely that this high bias is caused by the inclusion of rain and drizzle drops in the AMSR/E Product. This bias begins to affect AMSR/E CLWP values for rain rates above 0.03 mm/hr.

The high bias in AMSR/E is approximated as a function of rain rate and can be accounted for. The difference between the two curves in Figure A1 is shown in Figure A2, where a polynomial is fit to the data points for rain rates below 1 mm/hr. The removal of the effects of rain water is done by estimating the CLWP bias in AMSR/E as a function of 89 GHz rain rate (using the polynomial from Figure 2) for all drizzling L3 grid boxes, then subtracting this estimated bias from the AMSR/E CLWP values, leaving an adjusted CLWP with the effects of precipitation reduced. This adjusted value is used here. For rain rates above 1 mm/hr, there are too few data points to extend the curve, so those values are eliminated. This removes less than 0.008% of our grid boxes.
Acknowledgments: This work was supported by NASA grant 80NSSC19K1274. Research by ILM is supported by the NOAA Climate and Global Change Postdoctoral Fellowship Program, administered by UCAR's Cooperative Programs for the Advancement of Earth System Science (CPAESS) under award #NA18NWS4620043B. The authors would also like to thank Johannes Mohrmann for helpful discussion.

Data Availability

ERA Interim data used here are available at: https://doi.org/10.1002/qj.828. As in Dee et al. 2011.

ERA5 data (DOI: 10.5065/D6X34W69) used are available at: https://apps.ecmwf.int/data-catalogues/era5/?class=ea

MODIS collection 6 L3 data are available at: dx.doi.org/10.5067/MODIS/MYD08_D3.006

MODIS collection 6 L2 data are available at: dx.doi.org/10.5067/MODIS/MYD06_L2.006

AMSR/E L3 gridded day and night averages from Wentz et al. 2014 are available at: www.remss.com/missions/amsr

AMSR/E 89 GHz Brightness temperatures from Ashcroft and Wentz (2006) are available at: https://doi.org/10.5067/YL62FUZLAJUT

CloudSat Rain-Profile (Lebsock and L’Ecuyer, 2011) Data are made available here: http://www.cloudsat.cira.colostate.edu/data-products/level-2c/2c-rain-profile

CALIPSO Vertical Feature Mask data are available: https://eosweb.larc.nasa.gov/project/calipso/lidar_l2_vfm_table

The observed PBL and rain rate estimate data are processed using the above datasets and are also available from the author upon request.


# Tables

<table>
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<th>Closed-Closed</th>
<th>Closed-Open</th>
<th>Closed-Disorganized</th>
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<tbody>
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<td>Deep PBL</td>
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<tr>
<td>High Nd</td>
<td>Low Nd</td>
<td>-</td>
</tr>
<tr>
<td>Low Rain Rate</td>
<td>Heavier overnight drizzle</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>Weak Subsidence</td>
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Table 1. The environmental and cloud variables most strongly associated with our three 24-hour MCC transitions.
Figure 1. Mesoscale Cellular Convection (MCC) classifications overlaid on the corresponding MODIS Aqua image of clouds in the SE Pacific on September 28, 2007. Classifiers are defined: 0 – open cells, 1 – closed cells, 3 – disorganized cells. Trajectories only originate from areas where the majority of cells are labeled as ‘1’.
Figure 2. Examples of 24-hour trajectories used in this study (1 in 20 shown) in our four study regions: a) NE Pacific, b) SE Pacific, c) SE Atlantic, and d) E Indian. All trajectories begin as closed. Blue trajectories remain closed, red trajectories transition to open cells, and black trajectories transition to cellular, but disorganized cells after 24-hours.
Figure 3. Thick lines: The mean locations of composited 24-hour trajectories for all three possible MCC transition types within each study region. Annual mean wind directions and relative speeds at 925 hPa are shown by the arrows. The colored line contours show the annual mean LTS. The shading shows the frequency of closed cell MCC relative to all classifications, with whiter shading indicating more closed cells.
Figure 4. The number of all available 24-hour trajectories per 100-day sampling window that start as closed cells for years 2007-2010, showing a strong yearly cycle of closed cells. Y-axis ranges differ between each region.
Figure 5. The fraction of 24-hour trajectories that begin as closed cells per 100-day sampling window that shows a specific transition in MCC classification for each study region.
Figure 6. Composited 24-hour evolution of cloud variables for trajectories that begin as closed, but evolve into open (red) cells, disorganized cells (black), or stay closed (blue). Broken down by
study region. Variables shown are: Cloud cover (a, f, k, p), cloud droplet number concentration (b, g, l, q), rain rate (c, g, m, r), planetary boundary layer depth (d, h, n, s), and cloud liquid water path (e, i, o, t). Plot width represents the 2σ standard error. The y-axis range is identical for the NE Pacific, SE Pacific, and SE Atlantic, but different for the E Indian region.
Figure 7. Composited 24-hour evolution of environmental variables for trajectories that begin as closed, but evolve into open (red) cells, disorganized cells (black), or stay closed (blue).
Broken down by region. Variables shown are: 700 hPa specific humidity (a, f, k, p), 10-meter wind speed (b, g, l, q), Lower tropospheric stability ($\Theta_{700}-\Theta_{1000}$, c, g, m, r), sea surface temperature (d, h, n, s), and 700 hPa subsidence (e, i, o, t). Plot width represents the 2σ standard error. The y-axis range is identical for the NE Pacific, SE Pacific, and SE Atlantic, but different for the E Indian region.
Figure 8. Composited 24-hour evolution of anomalies of cloud variables for trajectories that begin as closed, but evolve into open (red) cells, disorganized cells (black), or stay closed (blue).
Cloud variables include: a) Cloud cover, b) Cloud droplet number concentration, c) Rain rate, d) Planetary boundary layer depth, and e) In-cloud liquid water path. Anomalies are calculated by removing the 100-day running mean centered on each day in each 1°x1° grid box for day and night separately. Plot width represents the 2σ standard error.
Figure 9. Composited 24-hour evolution of anomalies of environmental variables for trajectories that begin as closed, but evolve into open (red) cells, disorganized cells (black), or
Environmental variables include: a) 700 hPa specific humidity, b) 10-meter wind speed, c) Lower tropospheric stability ($\theta_{700}$-$\theta_{1000}$), d) Sea surface temperature, and e) 700 hPa subsidence. Anomalies are calculated by removing the 100-day running mean centered on each day in each 1°x1° grid box for day and night separately. Plot width represents the 2σ standard error.
Figure 10. The 24-hour evolution of $N_d$ composited for our three trajectory sets (blue: closed-closed, red: closed-open, black: closed-disorganized) for three different $N_d$ products: (a) our default product, (b) Grosvenor 2018 $N_d$ from MODIS c5, (c) McCoy et al. (2017) MERRA aerosol regression $N_d$. Plot width represents the 2σ standard error. Droplet concentration values must be present at both 0 and 24 hours for a trajectory to contribute to the composite.
Figure 11. A closer look at composited trajectories showing the 24-hour changes of \( N_d \) and average precipitation probability for sets of trajectories beginning as closed cells. Trajectories are divided into quantiles based on 0-hour values of precipitation probability (a-d) and \( N_d \) (e-h) to show how one evolves while the other is constrained in quantile bins. The precipitation spike at 12 hours is associated with the diurnal cycle of stratocumulus drizzle, which peaks at night more strongly for trajectories that transition from closed-open. Plot width represents the 2\( \sigma \) standard error.
Figure A1. MODIS 3.7 μm (red) and AMSR/E (blue) CLWP as a function of CloudSat & AMSR/E 89 GHz rain rates. The gray area represents the high bias in AMSR/E CLWP that is likely caused by rain water, and is plotted in Figure A2 as a function of rain rate.
Figure A2. The difference between AMSR/E and MODIS CLWP as a function of rain rate (black dots) with a 7th-degree polynomial fit to the points (red line).