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The Role of Mesoscale Cloud Morphology in the Shortwave Cloud Feedback

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Key Points:

- Mesoscale cloud morphology albedo varies with fraction of optically thin cloud features
- Closed mesoscale cellular convection occurrence changes are predictable from environmental controls
- Environmentally driven cloud morphology changes in optical depth produce a shortwave feedback of 0.04–0.07 W m^{-2} K^{-1}

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract A supervised neural network algorithm is used to categorize near-global satellite retrievals into three mesoscale cellular convective (MCC) cloud morphology patterns. At constant cloud amount, morphology patterns differ in brightness associated with the amount of optically thin cloud features. Environmentally driven transitions from closed MCC to other morphology patterns, typically accompanied by more optically thin cloud features, are used as a framework to quantify the morphology contribution to the optical depth component of the shortwave cloud feedback. A marine heat wave is used as an out-of-sample test of closed MCC occurrence predictions. Morphology shifts in optical depth between 65°S and 65°N under projected environmental changes (i.e., from an abrupt quadrupling of CO_2) assuming constant cloud cover contributes between 0.04 and 0.07 W m^{-2} K^{-1} (aggregate of 0.06) to the global mean cloud feedback.

Plain Language Summary Marine boundary layer clouds are essential to the energy balance of Earth, reflecting sunlight back to space and covering a large percentage of the globe. These clouds can organize into open, closed, and disorganized cellular structures. Cloud morphology patterns differ in their ability to reflect sunlight back to space. Closed cellular clouds transition to open and disorganized clouds associated with changes in environmental factors (i.e., sea surface temperature and the stability of the lower atmosphere). This study examines how a shift in cloud morphology with climate change will change the amount of sunlight reflected back to space: a shortwave cloud feedback. We predict the frequency of occurrence of closed cellular clouds based on changes in environmental factors estimated from global climate model simulations under climate change scenarios. An observed marine heat wave is used to test occurrence predictions. The change in reflected sunlight due to the shift between morphology types at fixed fractional cloud cover produces a global feedback that ranges between 0.04 and 0.07 W m^{-2} K^{-1}.

1. Introduction

The response of low clouds to global warming is one of the largest uncertainties in projections of climate change. Low clouds strongly affect the amount of shortwave radiation reflected back to space from Earth, but do not affect outgoing longwave radiation substantially (e.g., Hartmann & Short, 1980). How clouds alter reflected shortwave radiation in response to warming is termed the shortwave cloud feedback. It is uncertain how low clouds will respond to changes in the atmosphere in a warming world and contribute to this feedback (e.g., Ceppi et al., 2017; Zelinka et al., 2012a, 2012b, 2016, 2020). This uncertainty drives spread in the climate sensitivity predicted by global climate models (GCMs) (e.g., Caldwell et al., 2016). Thus, improving our understanding of how low clouds will change in a warming world is critical to predicting 21st century warming (e.g., Bony et al., 2015; Sherwood et al., 2020).

At zeroth order, the mean optical thickness and extent of low cloud strongly affect global albedo (Engstrom et al., 2015b). However, low clouds encompass different morphology patterns with regionally varied mesoscale features (e.g., large-scale structures $O \sim 100$ km of clouds with typical cell sizes $O \sim 20$–80 km, Wood & Hartmann, 2006; Zhou et al., 2021; Stevens et al., 2019). For example, open and closed mesoscale cellular convective (MCC) organization that dominate subtropical stratocumulus (Sc) cloud decks and marine cold-air

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outbreaks (I. L. McCoy et al., 2017; Mohrmann et al., 2021; Muhlbauer et al., 2014) are distinctly different from the more disorganized cumulus (Cu) cloud structures in the tropical trade-winds (Stevens et al., 2019). The radiative properties of mesoscale morphology patterns differ even for the same cloud areal coverage (I. L. McCoy et al., 2017), indicating microphysical and macrophysical differences between organization structures (consistent with Bretherton et al. (2019), Kang et al. (2022), Muhlbauer et al. (2014), Painemal et al. (2010), Terai et al. (2014), Wood (2012), Watson-Parris et al. (2021), and Zhou et al. (2021)). The occurrence of cloud morphology patterns is strongly connected to environmental factors (e.g., Agee et al., 1973; Atkinson & Zhang, 1996; Bony et al., 2020; Eastman et al., 2021; I. L. McCoy et al., 2017; Mohrmann et al., 2021; Muhlbauer et al., 2014; Narenpitak et al., 2021; Schulz et al., 2021; Wood, 2012).

Past literature has used changes in cloud horizontal extent (detectable cloud amount termed cloud fraction, CF) in response to warming to constrain changes in albedo (e.g., Klein et al., 2017; Qu et al., 2015). Recent analyses have examined regional contributions based on large-scale meteorology (Cesana & Del Genio, 2021; Myers et al., 2021; Scott et al., 2020) and, following a radiative kernel framework, dissected the change in cloud radiative properties into a CF component and a combined optical thickness and altitude component (Myers et al., 2021; Scott et al., 2020). The amount and optical depth components of the cloud radiative effect are likely to encapsulate some of the variation in cloud morphology radiative properties.

State-of-the-art GCMs from phase 6 of the Coupled Model Intercomparison Project (CMIP6) do not capture the radiative properties of low clouds largely due to poorly representing cloud heterogeneity. GCMs' inability to simulate optically thin cloud features at lower CF is thought to be a contributor to this issue (Konsta et al., 2022). Optically thin features are observed across mesoscale cloud morphologies (Leahy et al., 2012; Mieslinger et al., 2021; O, Wood, & Bretherton, 2018; Wood et al., 2018) and are likely associated with precipitation processes during cloud morphology development and transition (O, Wood, & Tseng, 2018). In addition to the so-called "too few, too bright" bias (Bender et al., 2017; Engstrom et al., 2015a; Konsta et al., 2022; Nam et al., 2012), representation of morphology and generation of optically thin features may also effect GCM biases in cyclone cold sectors (Bodas-Salcedo et al., 2014; Williams & Bodas-Salcedo, 2017) and simulated mean-state sea surface temperature (SST) (e.g., coastal gradients, regional seasonal cycles) (Farneti et al., 2022; Hyder et al., 2018; Wang et al., 2022). These diagnosed model biases suggest that consideration of mesoscale cloud morphology will assist in improving mean-state cloud radiative properties and their subsequent environmental impacts in GCMs.

In this study, we use a process-driven morphology lens to gain insight into how low clouds will change under climate change and feedback on the climate system.

We calculate the optical depth component of the shortwave cloud feedback associated with shifting the partitioning of clouds between different morphologies in response to warming. We use a global, multi-year morphology identification data set for three cloud patterns (Wood & Hartmann, 2006): open, closed, and cellular but disorganized MCC (Section 2.1). We examine the underlying reason behind differences in MCC radiative properties (Section 3.1) and develop relationships between morphology occurrence and environmental controls (Section 3.2), analogous to cloud-controlling factor analysis (e.g., Heintzenberg et al., 2009; Klein et al., 2017; Qu et al., 2015; Scott et al., 2020; Stevens & Brenguier, 2009). We leverage this predictive relationship and cloud morphology radiative properties to quantify the morphology contribution to the shortwave cloud feedback (Section 3.3). We conclude with a discussion and summary of the results (Section 4, 5).

2. Materials and Methods

2.1. Mesoscale Cloud Morphology Classifications

Wood and Hartmann (2006) (hereafter WH6) developed a supervised neural network algorithm that is applied to liquid water path (LWP) retrievals from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) (King et al., 1997; Platnick et al., 2003). This method uses the magnitude and spatial distribution of LWP to identify three types of marine cloud morphology patterns: open, closed, and cellular but disorganized MCC. Each identification is for a 256×256 km^2 scene from a MODIS swath and each scene is overlapped by 128 km across and along the swath to maximize data usage (Figure 1a). Only scenes where clouds are majority liquid-topped (i.e., have a LWP retrieval), cloud top temperature is within 30 K of surface temperature (i.e., low clouds), and where SST is above 275 K (i.e., avoiding sea ice, equating to ~65°N–65°S) are used. We use an expanded, multi-year data set from applying WH6 to MODIS collection 6.1 (Platnick et al., 2015) for 2003–2018. This data set is referred to here as Morphology Identification Data Aggregated over the Satellite-era (MIDAS). WH6 has

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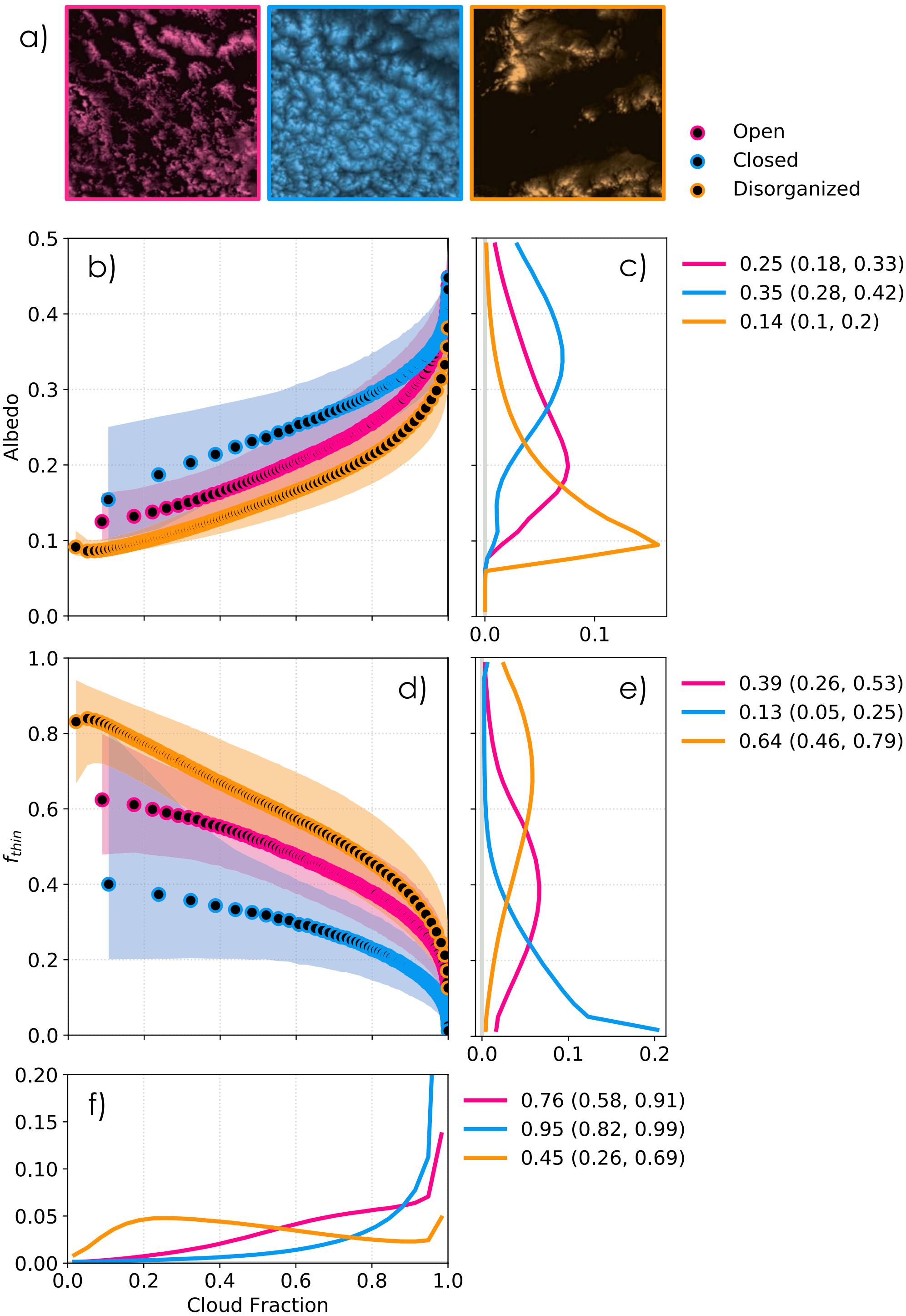

Figure 1. (a) Example identified scenes (256×256 km^2) show typical cloud morphology patterns within each Morphology Identifiation Data Aggregated over the Satellite-era (MIDAS) category. MIDAS scene cloud fraction, from MODIS cloud mask, versus (b) CERES albedo and (d) optically thin cloud feature fraction from MODIS optical depth, f_{thin}. Corresponding PDFs for (c) albedo, (e) f_{thin}, and (f) CF with legends detailing median and 25–75th percentiles. Morphology data is binned into 100 cloud fraction quantiles in (b and d) and their median (dots) and 25–75th percentiles (shading) shown while the standard error is too small to be visible.

maintained skill across satellite retrieval collections since a subset of these identifications (2007–2010) were confirmed to have the original 85%–90% success rate as WH6 in cloud type identifications (Eastman et al., 2021).

The distribution of cloud morphological types in MIDAS is consistent with previous MCC climatologies (Agee et al., 1973; Atkinson & Zhang, 1996; Muhlbauer et al., 2014) (Figure S1 in Supporting Information S1). Closed MCC contribute to the sub-tropical Sc decks (Klein & Hartmann, 1993) to the west of continents and to the high latitudes (Figure S1a in Supporting Information S1). Open MCC are the cloudy-edged cellular features seen downwind of the Sc decks and in the cold sectors of cyclones (or cold-air outbreaks) in the mid-latitudes (Figure S1b in Supporting Information S1). The remaining low clouds across the globe, including trade Cu downwind of subtropical closed and open MCC and most organizational structures in the tropics (Rasp et al., 2020), are classified in the third, expansive category of cellular but disorganized MCC (Figure S1c in Supporting Information S1).

2.2. Radiative Properties

We look at two aspects of MCC radiative properties in this study. Albedo is estimated for each MCC identified scene using Clouds and the Earth's Radiant Energy System (CERES) (Wielicki et al., 1996) Top of Atmosphere (TOA) upwelling shortwave fluxes and solar insolation from the Single Scanner Footprint (SSF) daily $1 \times 1°$ gridded product (NASA/LARC/SD/ASDC, 2015). Each mean scene albedo is computed for data within a 128 km radius circle centered on the MCC identification (I. L. McCoy et al., 2017).

We also examine the amount of optically thin cloud features that occur within each MCC identification scene. These features are approximately identified from MODIS Level 2 cloud optical depth retrievals (Platnick et al., 2015) using the observation-based optical depth criteria: $\tau < 3$ (O, Wood, & Tseng, 2018). For each identified scene, we generate a PDF of cloud optical depth and estimate the fraction of optically thin cloud (f_{thin}) as the proportion that satisfy this criteria.

Mean monthly incoming solar flux ($SW^{\downarrow}$) over 2003–2018 from edition 4.1 of the CERES Energy Balanced and Filled (EBAF) TOA product (NASA/LARC/SD/ASDC, 2019) is used to scale changes in shortwave reflection to energy units in Equations 5 and 6. We also compute a mean monthly low cloud fraction over 2003–2018 assuming low cloud is overlapped (as in Scott et al., 2020) and using the cloud mask from the daily Level-3 MODIS Atmosphere Global COSP $1 \times 1°$ gridded product (Pincus et al., 2020) (Figure S2c in Supporting Information S1).

2.3. Environmental Controls

SST and lower tropospheric stability (e.g., estimated inversion strength, EIS) are likely the dominant meteorological drivers of low cloud feedback (Bretherton, 2015; Ceppi & Nowack, 2021; Cesana & Del Genio, 2021; Klein et al., 2017; Myers et al., 2021; Qu et al., 2015; Scott et al., 2020). We use European Center for Mid-range Weather Forecasting ERA5 reanalysis data (Copernicus Climate Change Service, 2017) collocated to morphology identifications to capture the influence of these environmental controls on cloud morphology. In addition to SST, we use a measure of lower tropospheric stability with proved skill in predicting cloud morphology occurrence (I. L. McCoy et al., 2017), the marine cold-air outbreak index (Kolstad & Bracegirdle, 2008):

$$M = \theta_{SST} - \theta_{800hPa} \tag{1}$$

Because M is also a good predictor of boundary layer depth (Naud et al., 2018, 2020), using it as a predictor may implicitly factor in optically thin feature occurrence (O, Wood, & Tseng, 2018). M can also be formulated as a combined measure of EIS and surface forcing (I. L. McCoy et al., 2017). See Text S1 and S2 in Supporting Information S1 for details.

2.4. Global Climate Models

We use 11 GCMs participating in CMIP6 to estimate the changes in environmental controls under climate change using the idealized abrupt quadrupling of CO_2 experiment (which does not include changes in other forcers, e.g., aerosols): AWI-CM-1-1-MR, BCC-ESM1, CanESM5, CNRM-CM6-1, GFDL-CM4, GISS-E2-1-G, GISS-E2-1-H, HadGEM3-GC31-LL, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0. Changes in M and SST are estimated from the difference between piControl and abrupt4 × CO_2 simulations and reported per degree of global warming ($\Delta T = 4.69$ K, the area weighted global mean change in 2-m air temperature). We use the multi-model mean $\Delta SST/\Delta T$, $\Delta M/\Delta T$ (Figures S2a and S2b in Supporting Information S1) in our calculations (see Text S1 in Supporting Information S1) (Borchert et al., 2021; Carmo-Costa et al., 2022; Qu et al., 2014b).

3. Results

3.1. Radiative Impact of Cloud Morphologies

Open, closed, and disorganized MCC as identified by WH6 have distinct radiative (I. L. McCoy et al., 2017) and microphysical (Danker et al., 2022; Muhlbauer et al., 2014; Zhou et al., 2021) properties, consistent with other MCC studies (e.g., Bretherton et al., 2019; Kang et al., 2022; Painemal et al., 2010; Terai et al., 2014; Watson-Parris et al., 2021; Wood, 2012). We utilize the updated MIDAS data set and CF versus albedo diagrams (following earlier studies Bender et al., 2011; Bender et al., 2017; Engstrom et al., 2015b; Feingold et al., 2016; Feingold et al., 2017; I. L. McCoy et al., 2017) to isolate the cloud properties that contribute to distinction between morphologies. At constant CF, albedo differs significantly between cloud morphologies with closed MCC more effectively scattering sunlight than open (I. L. McCoy et al., 2017) and disorganized MCC (Figures 1b and 1c). The curvature of these relationships is consistent with Bender et al. (2017).

MIDAS classifications capture low clouds at different stages in their Lagrangian evolution, which gives us insight into the relationship between process-driven cloud evolution and radiative properties. Closed MCC (e.g., Sc) tend to transition into open MCC or more disorganized clouds (e.g., trade Cu) in the subtropics (e.g., Eastman et al., 2021, 2022; Wyant et al., 1997; Yamaguchi et al., 2017). Similar transitions, associated with even stronger surface forcing in cold-air outbreaks, occur in the mid-latitudes (e.g., Agee & Dowell, 1973; I. L. McCoy et al., 2017; Tornow et al., 2021). Boundary-layer deepening and increased precipitation are important in cloud morphology transitions in the mid-latitudes (and may be further modulated by mixed-phase processes, Danker et al., 2022; Tornow et al., 2021) and in the subtropics (Sarkar et al., 2019; Smalley et al., 2022; Wyant et al., 1997; Yamaguchi et al., 2017) although deeper boundary layers are not necessary (Eastman et al., 2022). In the subtropics, closed MCC tend to evolve to open MCC under heightened wind conditions, leading to increased boundary layer moisture and rain rates by increasing relative humidity or latent heat fluxes. In contrast, closed MCC tend to evolve to disorganized MCC under warmer SST conditions and increased entrainment of dry-air at cloud top (Eastman et al., 2022). *In situ* sampling in the northeast Pacific (NEP) Sc to Cu transition identified optically thin cloud features at the detraining edges of broken clouds in the deeper boundary layers at the end of the transition (Bretherton et al., 2019; O, Wood, & Bretherton, 2018; Wood et al., 2018). The relationship between optically thin features, precipitation removal of cloud droplets, and deeper boundary layers is robust globally (O, Wood, & Tseng, 2018). Disorganized MCC encompasses many types of cloud patterns, from NEP Cu to more varied trade-wind structures (Rasp et al., 2020; Stevens et al., 2019). In the trades, cloud reflectivity is described well by cloud amount (Bony et al., 2020) but optically thin features are also frequently observed (Leahy et al., 2012; Mieslinger et al., 2019, 2021). These include both small, suppressed clouds at the lifting condensation level (Delgadillo et al., 2018; Mieslinger et al., 2019, 2021) and detraining layers like in the NEP (Schulz et al., 2021) generated through deepening and moistening processes (Narenpitak et al., 2021; Vogel et al., 2021).

Variation in the amount of optically thin cloud features across mesoscale cloud morphologies contributes to the separation of their albedo curves. Optically thin features act to increase cloud cover without a commensurate increase in cloud albedo. Indeed, CF versus f_{thin} curves have the opposite descending order (disorganized, open, closed) from the albedo curves (closed, open, disorganized) (Figures 1d and 1e). Predictions of scene albedo using both CF and f_{thin} are more accurate than when only CF is used, showing the radiative importance of these features (Figure S7 in Supporting Information S1). We do not capture all of the variability in albedo with these two terms (Figure S7b in Supporting Information S1), as expected. For example, aerosols are not considered here which generally influence cloud radiative properties and specifically influence optically thin cloud feature development, often through modulating morphology transitions (e.g., Albrecht, 1989; Carslaw et al., 2013; Eastman et al., 2021; Eastman et al., 2022; I. L. McCoy et al., 2021; O, Wood, & Tseng, 2018; Twomey, 1977; Tornow et al., 2021; Wyant et al., 2022; Yamaguchi et al., 2017; Zuidema et al., 2008).

We hypothesize that variation in cloud evolution mechanisms lead to differences in the radiative properties of morphologies. Broadly, processes analogous to warming-deepening will support the transition to more disorganized cloud morphologies, possessing the largest f_{thin} of the three WH6 morphology types (e.g., Eastman et al., 2022; Narenpitak et al., 2021; Wyant et al., 1997). Processes analogous to precipitation-depletion will support the transition to morphologies with more detraining cloud features including open MCC, which has the second largest f_{thin} of the WH6 categories (e.g., Eastman et al., 2022; Sarkar et al., 2019; Smalley et al., 2022; Tornow et al., 2021; Vogel et al., 2021; Wyant et al., 1997; Yamaguchi et al., 2017).

The balance of different cloud controlling processes will likely change in an enhanced-CO_2 climate, potentially manifesting in different proportions of morphologies. This is because morphology occurrence is dependent on environmental conditions (e.g., shown for WH6 in Eastman et al. (2021, 2022); I. L. McCoy et al. (2017)). Utilizing our knowledge of present-day transitions between morphologies, we use the framework of transitions to/from closed MCC relative to open and disorganized MCC to predict how morphology will change associated with shifts in environmental controls under climate change. A climate-driven morphology occurrence shift will result in a change in optically thin cloud feature amount, creating dimmer or brighter cloud scenes even for the same detected cloud amount. We estimate the magnitude of this change and its influence on TOA radiation in the remaining sections.

3.2. Predicting Shifts in Cloud Morphology Occurrence From Changes in Environmental Controls

We examine the relative frequency of occurrence for all MIDAS MCC categories in a simple environmental phase space: M and SST (Section 2.3). We find that the relative frequency of closed MCC (f_{Closed}) has an approximately linear relationship with M and SST, both over a base period (2003–2012, Figure 2a) and the complete MIDAS period (2003–2018, Figure S8 in Supporting Information S1). The base period is separated to facilitate out-of-sample testing. There are two broad tendencies of morphology frequency shift across M-SST space. Below SST ≈ 290 K, more frequent open MCC (f_{Open}) occurs with increasing M (greater instability) (Figure 2b). Above SST ≈ 290 K, f_{Closed} tends toward more frequent disorganized cloud types ($f_{\text{Disorganized}}$, Figure 2c). These behaviors are consistent with closed MCC undergoing Lagrangian transitions to disorganized at warmer SSTs (Eastman et al., 2022).

Using the morphology transition framework proposed in Section 3.1, we focus on predicting f_{Closed}. Utilizing the f_{Closed} dependency in M-SST space, we use multiple linear regression to develop two predictive models from Figure 2a fitting all data together:

$$f_{\text{Closed}} = a_{\text{total}} \cdot M + b_{\text{total}} \cdot \text{SST} + c_{\text{total}} \tag{2}$$

and fitting SST > 290 K and SST ≤ 290 K data separately:

$$f_{\text{Closed}} = \begin{cases} a_{>290} \cdot M + b_{>290} \cdot \text{SST} + c_{>290} \ : \ \text{SST} > 290K \\ a_{\leq 290} \cdot M + b_{\leq 290} \cdot \text{SST} + c_{\leq 290} \ : \ \text{SST} \leq 290K \end{cases} \tag{3}$$

The latter formulation accounts for the more pronounced dependence (stronger gradient) of closed MCC on the environment over subtropical surface temperatures (SST > 290 K) (Figure 2a). As M and SST increase in this regime, closed MCC tend to shift more toward disorganized than open MCC (the reverse of the SST ≤ 290 K regime) (Figures 2b and 2c). Equation 3 captures more of this behavior than Equation 2, which is reflected in the closer correspondence between its prediction and observed f_{Closed} (the slope is closer to unity: $m = 0.95$ in Figure 2d compared to $m = 0.88$ in Figure S9 in Supporting Information S1). See Table S1 in Supporting Information S1 for coefficients and Text S2 in Supporting Information S1 for expanded fit discussion (Qu et al., 2015; D. T. McCoy et al., 2022).

Equation 3 captures the base period behavior well but will only be useful for our analysis if it can also reliably predict frequency changes under future climate scenarios (assuming it is robust under time-scale invariance, Klein et al., 2017). Following Myers et al. (2021), we utilize a subtropical marine heatwave (MHW) as an out-of-sample test of SST anomalies analogous to those associated with climate change. We examine a region of the NEP (15°–30°N, 140°–115°W, Figure S2c in Supporting Information S1) that was heavily influenced between November 2013 and January 2016 by a MHW (driven and maintained by cloud changes, Myers et al., 2018; Schmeisser et al., 2019). All three MCC types are prevalent in this region (Figure S1 in Supporting Information S1). Yearly regional anomalies are computed relative to the full MIDAS period (2003–2018). The MHW affected 2015 the most (e.g., Myers et al., 2021) and yielded a $\sim 2\sigma$ event in yearly regional SST anomaly (shading in Figure 2a, 2e, 2f). In response to the MHW SST anomaly, f_{Closed} was anomalously low while f_{Open} decreased slightly and $f_{\text{Disorganized}}$ increased significantly. Given the warm initial state of the region, the shift in relative occurrence frequency from

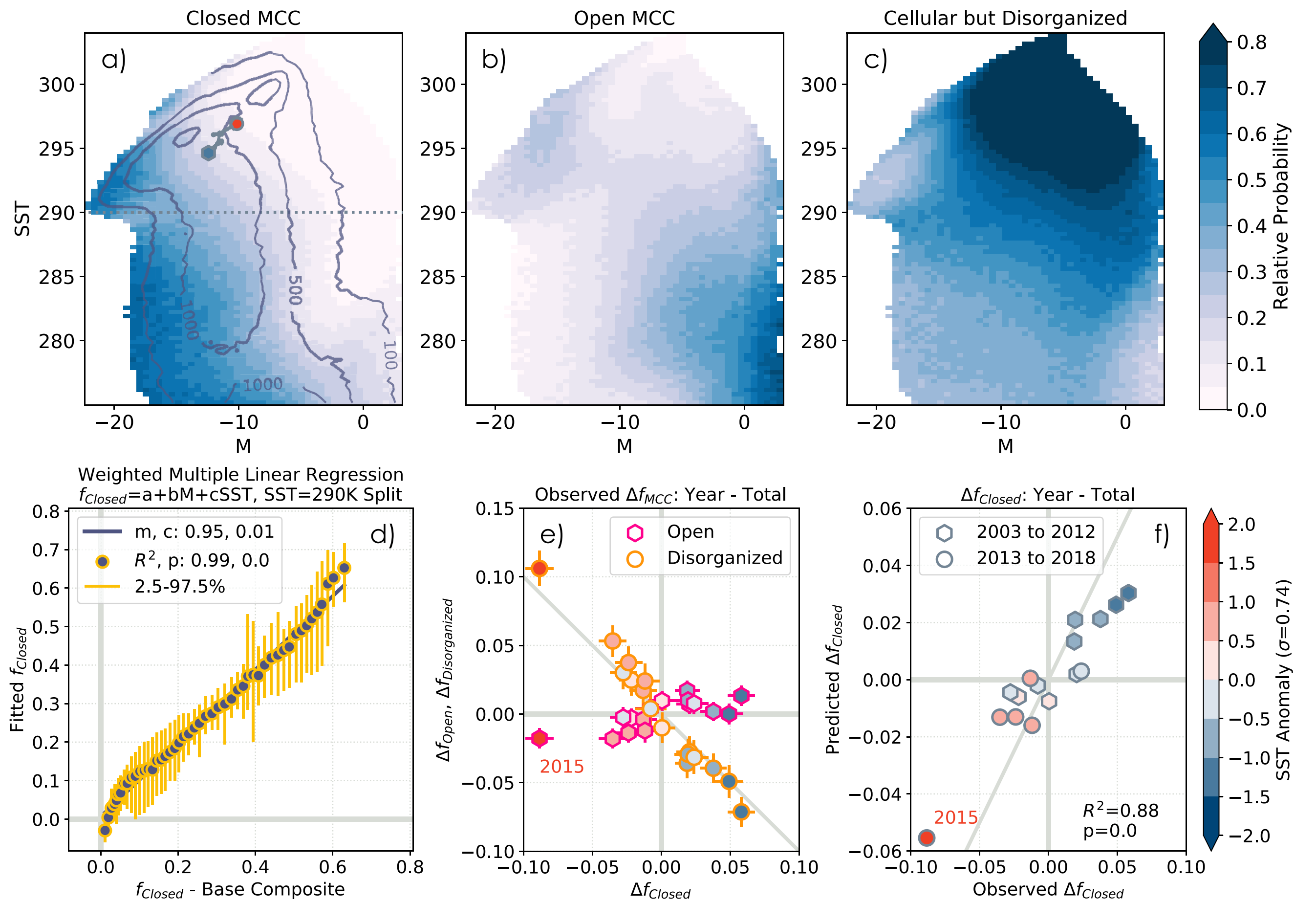

Figure 2. Morphology Identification Data Aggregated over the Satellite-era (MIDAS) relative occurrence frequency in the M-SST environmental phase space over a base period (2003–2012) for (a) closed, (b) open, and (c) cellular but disorganized mesoscale cellular convection (MCC) (see Figure S8 in Supporting Information S1 for total MIDAS period, 2003–2018). Lines for SST = 290 K (dashed) and closed MCC observation number (contours) are included in (a). Equation 3 is applied to the f_{Closed} composite in (a), see Text S2 in Supporting Information S1. (d) The resulting prediction is plotted versus the original f_{Closed} with mean (dots) and 95% confidence bounds (lines) for each of the 100 observational quantile bins. Quantile means are correlated with $R^2 = 0.99$ at 95% confidence and have a linear regression slope near unity ($m = 0.95$). Out-of-sample marine heatwave (MHW) (Figure S2c in Supporting Information S1) test results are shown in (a, e, and f). Yearly anomalies are relative to the total MIDAS period. Yearly mean M, sea surface temperature (SST) values for the MHW region (gray line, points) are plotted in (a) with maximum, minimum SST anomaly markers corresponding to symbols in (f). (e) Yearly mean morphology frequency anomalies for f_{Closed} versus f_{Open} and $f_{\text{Disorganized}}$ are shown with 2SE encompassing monthly, regional uncertainty. (f) Observed yearly f_{Closed} anomalies versus mean bootstrapped predictions from Equation 3. Years 2013–2018 (circles) are out-of-sample tests. Lines for 95% confidence (not visible) from the bootstrapped coefficients applied to the regional, monthly prediction and 1:1 (gray) are included.

f_{Closed} toward $f_{\text{Disorganized}}$ more than f_{Open} (Figure 2e) is consistent with expectations (Eastman et al., 2022) and the shift in mean regional, yearly M, SST values toward regions of higher $f_{\text{Disorganized}}$ with increasingly positive SST anomalies (Figure 2a). Equation 3 robustly predicts yearly regional f_{Closed} anomalies ($R^2 = 0.89$), increasing our confidence in its ability to infer changes in morphology in response to changes in dominant large-scale environmental factors. Larger SST anomalies are harder to predict (as in Myers et al., 2021) and there are slight over and under predictions of Δf_{Closed} above and below SST anomalies of $\approx\pm 1.5$ K.

3.3. Predicting the Morphology Feedback

Analogous to cloud-controlling factor analysis (e.g., Heintzenberg et al., 2009; Klein et al., 2017; Qu et al., 2015; Scott et al., 2020; Stevens & Brenguier, 2009), we develop a predictive equation for Δf_{Closed} to estimate the morphology feedback associated with changes in environmental controls under climate change:

$$\frac{\Delta f_{\text{Closed}}}{\Delta T} = a\frac{\Delta M}{\Delta T} + b\frac{\Delta \text{SST}}{\Delta T} \tag{4}$$

We utilize the coefficients from Equation 3, which were tested using a MHW in Section 3.2. Predictions using coefficients from Equation 2 are shown in Figure S10 in Supporting Information S1. See Section 2.4 for $\Delta M/\Delta T$ and $\Delta \mathrm{SST}/\Delta T$ estimation.

The respective patterns of $\Delta M/\Delta T$ and $\Delta \mathrm{SST}/\Delta T$ combine to produce the pattern of $\Delta f_{\mathrm{Closed}}/\Delta T$ shown in Figure 3a. There are decreases in present-day regions of closed MCC (i.e., subtropical cloud decks, high latitudes, Figure S1a in Supporting Information S1). Where closed MCC clouds persist $\Delta f_{\mathrm{Closed}} = 0$. f_{Closed} also increases in poleward regions adjacent to the Southeast Pacific, Southeast Atlantic, and Canarian cloud decks, and in the northern and eastern Atlantic. Increasing f_{Closed} corresponds to increasing stability (decreasing $\Delta M/\Delta T$) and small $\Delta \mathrm{SST}/\Delta T$ increases. Decreasing f_{Closed} occurs for the opposite conditions (increasing $\Delta M/\Delta T$, large $\Delta \mathrm{SST}/\Delta T$ increases). Increases in stability do not outweigh the influence of surface warming in all instances.

We estimate the optical depth component of the morphology feedback assuming that $\Delta f_{\mathrm{Closed}}$ shifts to a single cloud type, either Δf_{Open} or $\Delta f_{\mathrm{Disorganized}}$. In reality, shifts to/from closed MCC will likely be associated with a mixture of open MCC and disorganized clouds. However, we can use shifts to/from open MCC as a lower bound (smaller albedo difference from closed MCC at constant CF, Figure 1b) while shifts to/from disorganized will be an upper bound (larger albedo difference). To estimate the aggregate response, we calculate the feedback conditioning shifts based on the initial (i), mean state SST: closed to open MCC when $\mathrm{SST}_i \leq 290$ K, closed to disorganized when $\mathrm{SST}_i > 290$ K. In this study we are isolating the feedback associated with changes in the optical thickness of cloud due to morphology shifts. We hold boundary layer CF fixed. This is analogous to the calculation of the optical depth, amount, and altitude components of the cloud feedback while holding all other component changes constant (Zelinka et al., 2012a, 2012b, 2016). We formulate our feedback estimate per degree warming resulting from a shift between closed MCC and either open (Figure 3b) or disorganized MCC (Figure 3c):

$$FB_{C \leftrightarrow O} = SW^{\downarrow} \cdot (\alpha_O - \alpha_C) \cdot \frac{\Delta f_{\mathrm{Closed}}}{\Delta T} \quad (5)$$

$$FB_{C \leftrightarrow D} = SW^{\downarrow} \cdot (\alpha_D - \alpha_C) \cdot \frac{\Delta f_{\mathrm{Closed}}}{\Delta T} \quad (6)$$

Morphology albedos (α_C, α_O, α_D) are estimated in Equations 5 and 6 by applying their respective, global CF-albedo relationships (Figure 1b) to the monthly mean CF in each grid box (Section 2.2, Figure S2c in Supporting Information S1). We multiply by monthly, grid $\Delta f_{\mathrm{Closed}}/\Delta T$ and mean solar flux ($\mathrm{SW}^{\downarrow}$, Section 2.2) values before computing the final feedback as the mean over all seasons. The aggregate closed to open, disorganized feedback uses Equation 5 or Equation 6 conditional on SST_i in each grid box (Figure 3d).

The morphology feedback magnitude varies geographically, consistent with the geographic pattern of $\Delta f_{\mathrm{Closed}}/\Delta T$ (increasing, constant, or decreasing $\Delta f_{\mathrm{Closed}}/\Delta T$, Figure 3a, leads to negative, null, or positive feedback, b–d). The area-averaged morphology feedback contribution between 65°S and 65°N to the global mean shortwave cloud feedback is 0.04 W m^{-2} K^{-1} for closed to open MCC and 0.07 W m^{-2} K^{-1} for closed to disorganized MCC. The more realistic aggregate estimate of closed MCC to open and disorganized MCC conditional on initial SST is 0.06 W m^{-2} K^{-1}. Equation 2 estimates are similar (0.04, 0.08, and 0.06 W m^{-2} K^{-1}, respectively) with subtly different geographic distributions (Figure S10 in Supporting Information S1).

4. Discussion

The contribution of the optical depth component of the morphology feedback under abrupt CO_2 quadrupling (Figure 3) to the global mean shortwave cloud feedback is 0.04–0.07 W m^{-2} K^{-1} with an aggregate of 0.06 W m^{-2} K^{-1}. To place this in context, the aggregate morphology feedback is the same order of magnitude as recent assessments of several cloud feedback components (e.g., mid-latitude marine low cloud amount, land cloud amount) and ∼15% of total cloud feedback (Sherwood et al., 2020). A global shift from closed to open MCC (0.04 W m^{-2} K^{-1}, our lower bound) for one degree of global warming is four times larger (and the opposite sign) than the expected radiative perturbation from closing all pockets of open cells in closed MCC cloud decks in the present day (0.01 W m^{-2}) (Watson-Parris et al., 2021). This magnitude difference is likely due in part to the higher frequency of open clouds in MIDAS, which includes both pockets of open cells (as in Watson-Parris et al., 2021) and open cell regions that span large areas of ocean without closed cell presence. The aggregate is

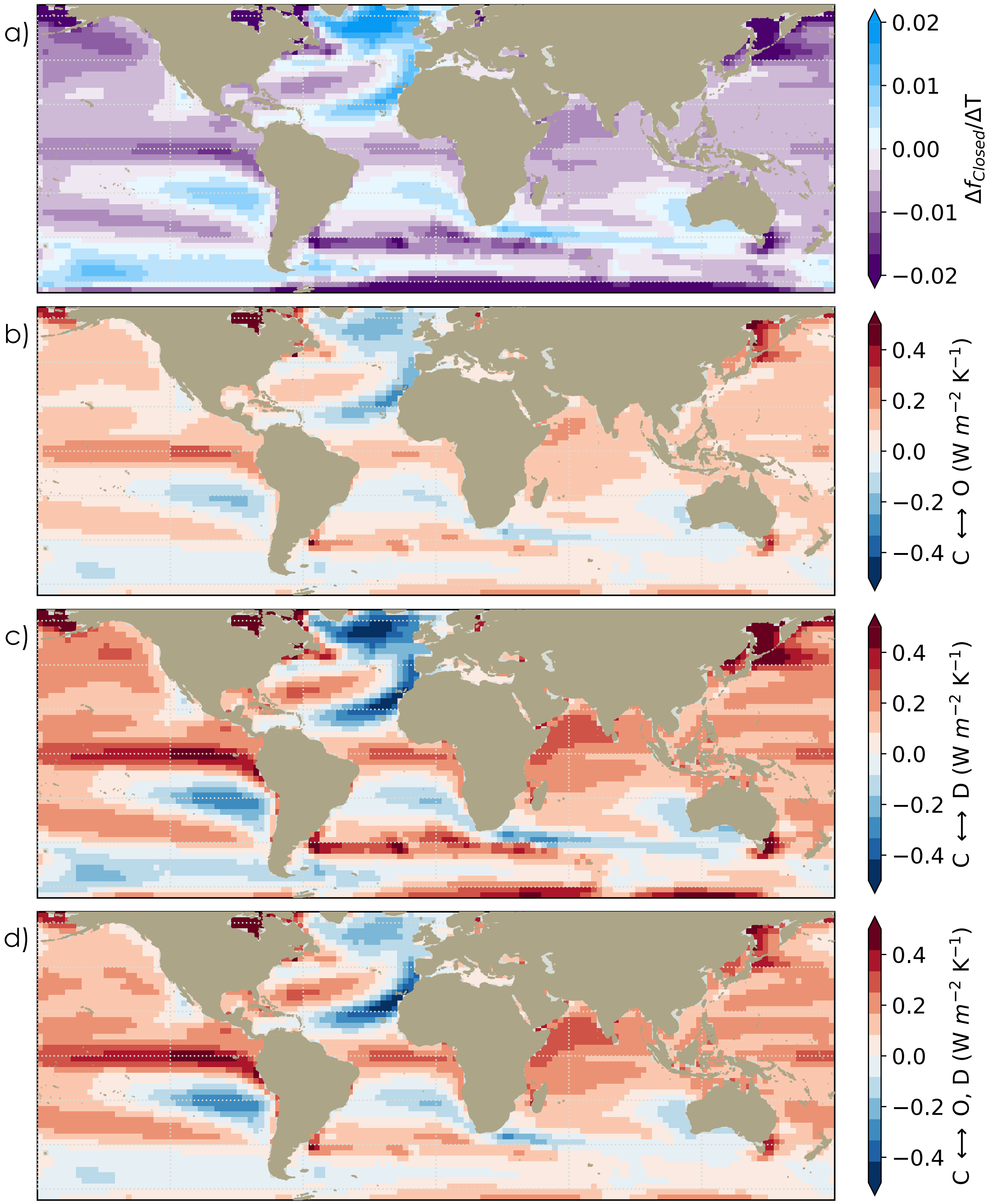

Figure 3. (a) Predicted $\Delta f_{\mathrm{Closed}}$ from the phase 6 Coupled Model Intercomparison Project (CMIP6) simulated multi-model mean $\Delta \mathrm{SST}/\Delta T$ (Figure S2a in Supporting Information S1) and $\Delta M/\Delta T$ (Figure S2b in Supporting Information S1) responses under an abrupt quadrupling of CO_2. The optical depth component of the morphology feedback per degree global temperature change is estimated assuming closed mesoscale cellular convection (MCC) shifts to (b) open MCC, (c) cellular but disorganized MCC, or (d) an aggregate of open and disorganized MCC dependent on initial Sea surface temperature. Figure S10 in Supporting Information S1 shows estimates using Equation 2 coefficients instead (Table S1 in Supporting Information S1).

also comparable with various feedback estimates in Cesana and Del Genio (2021): the Sc and Cu feedback under historic trends, Cu under abrupt4 × CO_2 and +4K, and low equilibrium climate sensitivity CMIP6 models. It is ~30% of Myers et al. (2021) near-global marine cloud feedback estimate (0.19 ± 0.12 W m^{-2} K^{-1}) and ~50% of the difference between CMIP5 (0.09 W m^{-2} K^{-1}) and CMIP6 (0.21) multi-model mean near-global net low cloud feedback that was associated with an increase in CMIP6 equilibrium climate sensitivity (Zelinka et al., 2020).

Consideration of changes in morphology occurrence under climate change may be helpful in predicting shortwave cloud feedback. Current models appear to poorly capture cloud heterogeneity and associated radiative effect (Konsta et al., 2022). The geographical pattern of the morphology feedback (Figures 3b–3d) contributes regions of positive and negative feedback that may be useful to consider in understanding patterns of radiative feedback. For example, in sub-tropical cloud decks the morphology feedback is largely negative, opposing positive cloud amount feedback (Qu et al., 2014a). MCC transitions may also contribute to observed variations in cloud optical depth as a function of temperature (Terai et al., 2016; Wall, Storelvmo, et al., 2022). Future work will seek to quantify remaining morphology feedback components (i.e., cloud amount and altitude), utilize observed morphology behaviors to constrain GCMs (e.g., Zelinka et al., 2022), and investigate aerosol influence separate from meteorological drivers (e.g., Wall, Norris, et al., 2022; Zhang & Feingold, 2022; Zhang et al., 2022) on morphology occurrence, transitions, and radiative properties.

Will sub-setting the broad "cellular but disorganized" WH6 morphology category (e.g., by contrasting MIDAS with other classification methods, Denby, 2020; Janssens et al., 2021; Rasp et al., 2020; Stevens et al., 2019; Yuan et al., 2020) help improve the morphology feedback estimate in regions that this category dominates (e.g., the tropics)? It is likely that the development and production of optically thin cloud features (and other characteristics impacting cloud radiative properties) varies across the sub-categories developed in these studies (e.g., Mohrmann et al., 2021; Narenpitak et al., 2021; Schulz et al., 2021; Vogel et al., 2021). While including more morphological types may only add variation around our central estimate of the morphology feedback, it could help to develop a clearer global picture of cloud morphology evolution and their sensitivities to climate change. Advances in process level understanding of cloud morphology evolution (e.g., in the "disorganized" trade winds through the EUREC^4*A*/ATOMIC field campaign, Stevens et al., 2021) will also assist in this effort.

5. Summary

Global cloud morphology patterns (large-scale structures $O \sim 100$ km of clouds with cell sizes $O \sim 10$–50 km, Figure 1a, Figure S1 in Supporting Information S1) identified by a supervised neural network algorithm based on their LWP characteristics (i.e., closed, open, and disorganized MCC, Wood & Hartmann, 2006) have distinct radiative properties over 65°N–65°S, 2003–2018 (Section 3.1). Closed MCC more effectively reflect sunlight than open and disorganized MCC for the same cloud coverage (Figure 1b). This is significantly influenced by differing preponderances of optically thin cloud features ($\tau < 3$) between morphologies (Figure 1d, Figure S7 in Supporting Information S1). Approximately, we can think of morphology transitions (i.e., from closed to open or disorganized MCC) as a shift in the fraction of optically thin cloud features, which both contributes to radiative differences between morphologies and are a diagnostic of the underlying processes driving morphological evolution. An implication of this is that accurate prediction of future climate may require understanding when and where different cloud morphologies occur.

We utilize knowledge of present-day cloud morphology transitions to develop a framework for estimating the optical depth component of the shortwave cloud feedback associated with shifts in morphology responding to environmental changes under climate change (Section 3.3). The morphology feedback is estimated as the shift from closed MCC to open and/or disorganized MCC in response to changes in environmental controls while cloud amount is held fixed at present-day regional mean values. This allows us to examine the contribution of morphology changes to cloud brightness separate from any accompanying cloud amount changes (i.e., capturing the influence of optically thin cloud features). This is analogous to the partitioning of cloud feedback between optical depth, amount, and altitude components in previous studies (e.g., Zelinka et al., 2012a). Shifts to open and disorganized MCC provide a lower and upper bound, respectively, while shifting to their aggregate provides a best estimate.

We develop a predictive model based on multiple linear regression (Equation 3) for the relative occurrence frequency of closed MCC (f_{Closed}) based on its dependence on SST and M, a measure of lower tropospheric stability (Section 3.2, Figures 2a and 2d). Model predictive ability is tested with an out-of-sample case (i.e., a subtropical MHW with SST anomalies analogous to climate change following Myers et al., 2021) (Figure 2f). Mean changes in SST and M in response to an abrupt quadrupling of CO_2 are estimated from 11 models participating in phase 6 of the CMIP6 and used to predict Δf_{Closed} under climate change (Figure 3a).

Predictions of Δf_{Closed} based on GCM predictions of ΔSST/ΔT and $\Delta M/\Delta T$ indicate that closed MCC occurrence will increase in the northern and eastern Atlantic, portions of southern hemisphere mid-latitudes, and poleward of southern hemisphere subtropical cloud decks. Using present day radiative properties (Figure 1b) and randomly overlapped cloud amount (Figure S2c in Supporting Information S1), we use Δf_{Closed} to estimate the morphology feedback resulting from a shift in morphology alone (Figures 3b–3d). The contribution to global mean feedback varies by predicted morphology transition: closed to open MCC (0.04), to disorganized (0.07), or to an aggregate of open and disorganized (0.06 W m^{-2} K^{-1}). Compared to other assessed cloud feedbacks (Sherwood et al., 2020), the optical depth component of the morphology feedback is non-trivial. Its geographic variations have the potential to modulate other feedback components. Our results emphasize the usefulness of applying a process-driven, morphological lens to interpretation and estimation of cloud feedback. This analysis also stresses the importance of developing an observational, process-based understanding of optically thin cloud feature development across different cloud morphologies in the present climate in order to accurately estimate their climate impact in the future.

Data Availability Statement

Manuscript supporting data is available at https://doi.org/10.5281/zenodo.7311993 (I. L. McCoy & Wood, 2022). CERES Single Scanner Footprint (SSF) daily 1deg product is available at https://asdc.larc.nasa.gov/project/CERES/CER_SSF1deg-Hour_Aqua-MODIS_Edition4A (NASA/LARC/SD/ASDC, 2015). CERES Energy Balanced and Filled (EBAF) Top of Atmosphere (TOA) Monthly means are available at https://asdc.larc.nasa.gov/project/CERES/CERES_EBAF-TOA_Edition4.1 (NASA/LARC/SD/ASDC, 2019). MODIS Collection 6.1 Level 2 data are available at https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/61/MYD06_L2/ (Platnick et al., 2015). MODIS (Aqua/Terra) Cloud Properties Level 3 daily, $1 \times 1°$ gridded data, including COSP cloud mask, is available at https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/62/MCD06COSP_D3_MODIS/ (Pincus et al., 2020). CMIP6 piControl and abrupt4 $\times$ CO_2 simulations used in this study are available at https://esgf-node.llnl.gov/projects/cmip6/. ECMWF ERA5 reanalysis products are available at https://confluence.ecmwf.int/display/CKB/ERA5%3A+data+documentation (Copernicus Climate Change Service, 2017).

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