# The Role of Mesoscale Cloud Morphology in the Shortwave Cloud Feedback

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December 7, 2022

#### 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  $65^{\circ}$ S -  $65^{\circ}$ N under projected environmental changes (i.e., from an abrupt quadrupling of CO2) assuming constant cloud cover contributes between 0.04-0.07 W/m2/K (aggregate of 0.06) to the global mean cloud feedback.

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Key Points:

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15	•	Mesoscale cloud morphology albedo varies with fraction of optically-thin cloud fea-
16		tures
17	•	Closed mesoscale cellular convection occurrence changes are predictable from en-
18		vironmental controls
10	•	Environmentally-driven cloud morphology changes in optical depth produce a short

• Environmentally-driven cloud morphology changes in optical depth produce a shortwave feedback of 0.04 - 0.07 W m<sup>-2</sup> K<sup>-1</sup>

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#### 21 Abstract

A supervised neural network algorithm is used to categorize near-global satellite retrievals 22 into three mesoscale cellular convective (MCC) cloud morphology patterns. At constant 23 cloud amount, morphology patterns differ in brightness associated with the amount of 24 optically-thin cloud features. Environmentally-driven transitions from closed MCC to 25 other morphology patterns, typically accompanied by more optically-thin cloud features, 26 are used as a framework to quantify the morphology contribution to the optical depth 27 component of the shortwave cloud feedback. A marine heat wave is used as an out-of-28 sample test of closed MCC occurrence predictions. Morphology shifts in optical depth 29 between  $65^{\circ}$ S -  $65^{\circ}$ N under projected environmental changes (i.e., from an abrupt qua-30 drupling of  $CO_2$ ) assuming constant cloud cover contributes between 0.04 - 0.07 W m<sup>-2</sup> K<sup>-1</sup> 31 (aggregate of 0.06) to the global mean cloud feedback. 32

#### <sup>33</sup> Plain Language Summary

Marine boundary layer clouds are essential to the energy balance of Earth, reflect-34 ing sunlight back to space and covering a large percentage of the globe. These clouds 35 can organize into open, closed, and disorganized cellular structures. Cloud morphology 36 patterns differ in their ability to reflect sunlight back to space. Closed cellular clouds tran-37 sition to open and disorganized clouds associated with changes in environmental factors 38 (i.e., sea surface temperature and the stability of the lower atmosphere). This study ex-39 amines how a shift in cloud morphology with climate change will change the amount of 40 sunlight reflected back to space: a shortwave cloud feedback. We predict the frequency 41 of occurrence of closed cellular clouds based on changes in environmental factors esti-42 mated from global climate model simulations under climate change scenarios. An ob-43 served marine heat wave is used to test occurrence predictions. The change in reflected 44 sunlight due to the shift between morphology types at fixed fractional cloud cover pro-45 duces a global feedback that ranges between  $0.04 - 0.07 \text{ W m}^{-2} \text{ K}^{-1}$ . 46

#### 47 **1** Introduction

The response of low clouds to global warming is one of the largest uncertainties in 48 projections of climate change. Low clouds strongly affect the amount of shortwave ra-49 diation reflected back to space from Earth, but do not affect outgoing longwave radia-50 tion substantially (e.g., Hartmann & Short, 1980). How clouds alter reflected shortwave 51 radiation in response to warming is termed the shortwave cloud feedback. It is uncer-52 tain how low clouds will respond to changes in the atmosphere in a warming world and 53 contribute to this feedback (e.g., Zelinka et al., 2012a, 2012b, 2016, 2020; Ceppi et al., 54 2017). This uncertainty drives spread in the climate sensitivity predicted by global cli-55 mate models (GCMs) (e.g., Caldwell et al., 2016). Thus, improving our understanding 56 of how low clouds will change in a warming world is critical to predicting 21st century 57 warming (e.g., Bony et al., 2015; Sherwood et al., 2020). 58

At zeroth order, the mean optical thickness and extent of low cloud strongly af-59 fect global albedo (Engstrom et al., 2015b). However, low clouds encompass different mor-60 phology patterns with regionally varied mesoscale features (e.g., large-scale structures 61  $O\sim100$  km of clouds with typical cell sizes  $O\sim20-80$  km, Wood & Hartmann, 2006; Zhou 62 et al., 2021; Stevens et al., 2019). For example, open and closed mesoscale cellular con-63 vective (MCC) organization that dominate subtropical stratocumulus (Sc) cloud decks 64 and marine cold-air outbreaks (Muhlbauer et al., 2014; I. L. McCoy et al., 2017; Mohrmann 65 et al., 2021) are distinctly different from the more disorganized cumulus (Cu) cloud struc-66 tures in the tropical trade-winds (Stevens et al., 2019). The radiative properties of mesoscale 67 morphology patterns differ even for the same cloud areal coverage (I. L. McCoy et al., 68 2017), indicating microphysical and macrophysical differences between organization struc-69 tures (consistent with Painemal et al., 2010; Wood, 2012; Terai et al., 2014; Muhlbauer 70

et al., 2014; Bretherton et al., 2019; Zhou et al., 2021; Watson-Parris et al., 2021; Kang
et al., 2022). The occurrence of cloud morphology patterns is strongly connected to environmental factors (e.g., Agee et al., 1973; Atkinson & Zhang, 1996; Wood, 2012; Muhlbauer
et al., 2014; I. L. McCoy et al., 2017; Bony et al., 2020; Schulz et al., 2021; Eastman et
al., 2021; Mohrmann et al., 2021; Narenpitak et al., 2021).

Past literature has used changes in cloud horizontal extent (detectable cloud amount 76 termed cloud fraction, CF) in response to warming to constrain changes in albedo (e.g., 77 Qu et al., 2015; Klein et al., 2017). Recent analyses have examined regional contribu-78 79 tions based on large-scale meteorology (Scott et al., 2020; Myers et al., 2021; Cesana & Del Genio, 2021) and, following a radiative kernel framework, dissected the change in 80 cloud radiative properties into a CF component and a combined optical thickness and 81 altitude component (Scott et al., 2020; Myers et al., 2021). The amount and optical depth 82 components of the cloud radiative effect are likely to encapsulate some of the variation 83 in cloud morphology radiative properties. 84

State-of-the-art GCMs from phase 6 of the Coupled Model Intercomparison Project 85 (CMIP6) do not capture the radiative properties of low clouds largely due to poorly rep-86 resenting cloud heterogeneity. GCMs' inability to simulate optically-thin cloud features 87 at lower CF is thought to be a contributor to this issue (Konsta et al., 2022). Optically-88 thin features are observed across mesoscale cloud morphologies (Leahy et al., 2012; Wood 89 et al., 2018; O, Wood, & Bretherton, 2018; Mieslinger et al., 2021) and are likely asso-90 ciated with precipitation processes during cloud morphology development and transition 91 (O, Wood, & Tseng, 2018). In addition to the so-called "too few, too bright" bias (Nam 92 et al., 2012; Engstrom et al., 2015a; Bender et al., 2017; Konsta et al., 2022), represen-93 tation of morphology and generation of optically-thin features may also effect GCM bi-94 ases in cyclone cold sectors (Bodas-Salcedo et al., 2014; Williams & Bodas-Salcedo, 2017) 95 and simulated mean-state SST (e.g., coastal gradients, regional seasonal cycles) (Farneti 96 et al., 2022; Hyder et al., 2018; Wang et al., 2022). These diagnosed model biases sug-97 gest that consideration of mesoscale cloud morphology will assist in improving mean-state 98 cloud radiative properties and their subsequent environmental impacts in GCMs. 99

In this study, we use a process-driven morphology lens to gain insight into how low 100 clouds will change under climate change and feedback on the climate system. We cal-101 culate the optical depth component of the shortwave cloud feedback associated with shift-102 ing the partitioning of clouds between different morphologies in response to warming. 103 We use a global, multi-year morphology identification dataset for three cloud patterns 104 (Wood & Hartmann, 2006): open, closed, and cellular but disorganized MCC (Section 2.1). 105 We examine the underlying reason behind differences in MCC radiative properties (Sec-106 tion 3.1) and develop relationships between morphology occurrence and environmental 107 controls (Section 3.2), analogous to cloud-controlling factor analysis (e.g., Stevens & Bren-108 guier, 2009; Heintzenberg et al., 2009; Qu et al., 2015; Klein et al., 2017; Scott et al., 2020). 109 We leverage this predictive relationship and cloud morphology radiative properties to 110 quantify the morphology contribution to the shortwave cloud feedback (Section 3.3). We 111 conclude with a discussion and summary of the results (Section 4, 5). 112

#### <sup>113</sup> 2 Materials and Methods

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#### 2.1 Mesoscale Cloud Morphology Classifications

<sup>115</sup> Wood and Hartmann (2006) (hereafter WH6) developed a supervised neural net-<sup>116</sup> work algorithm that is applied to liquid water path (LWP) retrievals from the NASA Mod-<sup>117</sup> erate Resolution Imaging Spectroradiometer (MODIS) (King et al., 1997; Platnick et al., <sup>118</sup> 2003). This method uses the magnitude and spatial distribution of LWP to identify three <sup>119</sup> types of marine cloud morphology patterns: open, closed, and cellular but disorganized <sup>120</sup> MCC. Each identification is for a  $256 \times 256 \text{ km}^2$  scene from a MODIS swath and each

scene is overlapped by 128 km across and along the swath to maximize data usage (Fig-121 ure 1a). Only scenes where clouds are majority liquid-topped (i.e., have a LWP retrieval). 122 cloud top temperature is within 30 K of surface temperature (i.e., low clouds), and where 123 sea surface temperature is above 275 K (i.e., avoiding sea ice, equating to  $\sim 65^{\circ}$ N- $65^{\circ}$ S) 124 are used. We use an expanded, multi-year dataset from applying WH6 to MODIS col-125 lection 6.1 (Platnick et al., 2015) for 2003-2018. This dataset is referred to here as Mor-126 phology Identification Data Aggregated over the Satellite-era (MIDAS). WH6 has main-127 tained skill across satellite retrieval collections since a subset of these identifications (2007-128 2010) were confirmed to have the original 85-90% success rate as WH6 in cloud type iden-129 tifications (Eastman et al., 2021). 130

The distribution of cloud morphological types in MIDAS is consistent with previ-131 ous MCC climatologies (Agee et al., 1973; Atkinson & Zhang, 1996; Muhlbauer et al., 132 2014) (Figure S1). Closed MCC contribute to the sub-tropical Sc decks (Klein & Hart-133 mann, 1993) to the west of continents and to the high latitudes (Figure S1a). Open MCC 134 are the cloudy-edged cellular features seen downwind of the Sc decks and in the cold sec-135 tors of cyclones (or cold-air outbreaks) in the mid-latitudes (Figure S1b). The remain-136 ing low clouds across the globe, including trade Cu downwind of subtropical closed and 137 open MCC and most organizational structures in the tropics (Rasp et al., 2020), are clas-138 sified in the third, expansive category of cellular but disorganized MCC (Figure S1c). 139

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#### 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 upwelling shortwave fluxes and
solar insolation from the Single Scanner Footprint (SSF) daily 1×1° 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).

<sup>147</sup> We also examine the amount of optically-thin cloud features that occur within each <sup>148</sup> MCC identification scene. These features are approximately identified from MODIS Level <sup>149</sup> 2 cloud optical depth retrievals (Platnick et al., 2015) using the observation-based op-<sup>150</sup> tical depth criteria:  $\tau < 3$  (O, Wood, & Tseng, 2018). For each identified scene, we gen-<sup>151</sup> erate a PDF of cloud optical depth and estimate the fraction of optically-thin cloud ( $f_{thin}$ ) <sup>152</sup> as the proportion that satisfy this criteria.

<sup>153</sup> Mean monthly incoming solar flux  $(SW^{\downarrow})$  over 2003-2018 from edition 4.1 of the <sup>154</sup> CERES Energy Balanced and Filled Top of Atmosphere product (NASA/LARC/SD/ASDC, <sup>155</sup> 2019) is used to scale changes in shortwave reflection to energy units in Equations 5, 6. <sup>156</sup> We also compute a mean monthly low cloud fraction over 2003-2018 assuming low cloud <sup>157</sup> is overlapped (as in Scott et al., 2020) and using the cloud mask from the daily Level-<sup>158</sup> 3 MODIS Atmosphere Global COSP  $1 \times 1^{\circ}$  gridded product (Pincus et al., 2020) (Fig-<sup>159</sup> ure S2c).

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#### 2.3 Environmental Controls

Sea surface temperature (SST) and lower tropospheric stability (e.g., estimated in-161 version strength, EIS) are likely the dominant meteorological drivers of low cloud feed-162 back (Qu et al., 2015; Bretherton, 2015; Klein et al., 2017; Scott et al., 2020; Myers et 163 al., 2021; Cesana & Del Genio, 2021; Ceppi & Nowack, 2021). We use European Cen-164 ter for Mid-range Weather Forecasting (ECMWF) ERA5 reanalysis data (Copernicus 165 Climate Change Service, 2017) collocated to morphology identifications to capture the 166 influence of these environmental controls on cloud morphology. In addition to SST, we 167 use a measure of lower tropospheric stability with proved skill in predicting cloud mor-168 phology occurrence (I. L. McCoy et al., 2017), the marine cold-air outbreak index (Kolstad 169

 $^{170}$  & 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, S2 for details.

#### 2.4 Global Climate Models

We use 11 GCMs participating in CMIP6 to estimate the changes in environmen-176 tal controls under climate change using the idealized abrupt quadrupling of  $CO_2$  exper-177 iment (which does not include changes in other forcers, e.g., aerosols): AWI-CM-1-1-MR, 178 BCC-ESM1, CanESM5, CNRM-CM6-1, GFDL-CM4, GISS-E2-1-G, GISS-E2-1-H, HadGEM3-179 GC31-LL, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0. Changes in M and SST are 180 estimated from the difference between piControl and  $abrupt4 \times CO_2$  simulations and 181 reported per degree of global warming ( $\Delta T$ =4.69 K, the area weighted global mean change 182 in 2-m air temperature). We use the multi-model mean  $\Delta SST/\Delta T$ ,  $\Delta M/\Delta T$  (Figure S2a, 183 b) in our calculations (see Text S1)(Qu et al., 2014b; Borchert et al., 2021; Carmo-Costa 184 et al., 2022). 185

#### 186 **3 Results**

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#### 3.1 Radiative Impact of Cloud Morphologies

Open, closed, and disorganized MCC as identified by WH6 have distinct radiative 188 (I. L. McCoy et al., 2017) and microphysical (Muhlbauer et al., 2014; Zhou et al., 2021; 189 Danker et al., 2022) properties, consistent with other MCC studies (e.g., Painemal et 190 al., 2010; Wood, 2012; Terai et al., 2014; Bretherton et al., 2019; Watson-Parris et al., 191 2021; Kang et al., 2022). We utilize the updated MIDAS dataset and CF vs. albedo di-192 agrams (following earlier studies Bender et al., 2011; Engstrom et al., 2015b; Feingold 193 et al., 2016; Bender et al., 2017; I. L. McCoy et al., 2017; Feingold et al., 2017) to iso-194 late the cloud properties that contribute to distinction between morphologies. At con-195 stant CF, albedo differs significantly between cloud morphologies with closed MCC more 196 effectively scattering sunlight than open (I. L. McCoy et al., 2017) and disorganized MCC 197 (Figure 1b, c). The curvature of these relationships is consistent with Bender et al. (2017). 198

MIDAS classifications capture low clouds at different stages in their Lagrangian 199 evolution, which gives us insight into the relationship between process-driven cloud evo-200 lution and radiative properties. Closed MCC (e.g., Sc) tend to transition into open MCC 201 or more disorganized clouds (e.g., trade Cu) in the subtropics (e.g., Wyant et al., 1997; 202 Yamaguchi et al., 2017; Eastman et al., 2021, 2022). Similar transitions, associated with 203 even stronger surface forcing in cold-air outbreaks, occur in the mid-latitudes (e.g., Agee 204 & Dowell, 1973; I. L. McCov et al., 2017; Tornow et al., 2021). Boundary-layer deepen-205 ing and increased precipitation are important in cloud morphology transitions in the mid-206 latitudes (and may be further modulated by mixed-phase processes, Tornow et al., 2021; 207 Danker et al., 2022) and in the subtropics (Wyant et al., 1997; Yamaguchi et al., 2017; 208 Sarkar et al., 2019; Smalley et al., 2022) although deeper boundary layers are not nec-209 essary (Eastman et al., 2022). In the subtropics, closed MCC tend to evolve to open MCC 210 under heightened wind conditions, leading to increased boundary layer moisture and rain 211 rates by increasing relative humidity or latent heat fluxes. In contrast, closed MCC tend 212 to evolve to disorganized MCC under warmer SST conditions and increased entrainment 213 of dry-air at cloud top (Eastman et al., 2022). In situ sampling in the northeast Pacific 214 (NEP) Sc to Cu transition identified optically-thin cloud features at the detraining edges 215 of broken clouds in the deeper boundary layers at the end of the transition (Wood et al., 216 2018; O. Wood, & Bretherton, 2018; Bretherton et al., 2019). The relationship between 217 optically-thin features, precipitation removal of cloud droplets, and deeper boundary lay-218



Figure 1. a) Example identified scenes  $(256 \times 256 \ km^2)$  show typical cloud morphology patterns within each MIDAS category. MIDAS scene cloud fraction, from MODIS cloud mask, vs. 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 25-75<sup>th</sup> percentiles. Morphology data is binned into 100 cloud fraction quantiles in b), d) and their median (dots) and 25-75<sup>th</sup> percentiles (shading) shown.

ers is robust globally (O, Wood, & Tseng, 2018). Disorganized MCC encompasses many 219 types of cloud patterns, from NEP Cu to more varied trade-wind structures (Stevens et 220 al., 2019; Rasp et al., 2020). In the trades, cloud reflectivity is described well by cloud 221 amount (Bony et al., 2020) but optically-thin features are also frequently observed (Leahy 222 et al., 2012; Mieslinger et al., 2019, 2021). These include both small, suppressed clouds 223 at the lifting condensation level (Mieslinger et al., 2019, 2021; Delgadillo et al., 2018) and 224 detraining layers like in the NEP (Schulz et al., 2021) generated through deepening and 225 moistening processes (Narenpitak et al., 2021; Vogel et al., 2021). 226

227 Variation in the amount of optically-thin cloud features across mesoscale cloud morphologies contributes to the separation of their albedo curves. Optically-thin features 228 act to increase cloud cover without a commensurate increase in cloud albedo. Indeed, 229 CF vs.  $f_{thin}$  curves have the opposite descending order (disorganized, open, closed) from 230 the albedo curves (closed, open, disorganized) (Figure 1d, e). Predictions of scene albedo 231 using both CF and  $f_{thin}$  are more accurate than when only CF is used, showing the ra-232 diative importance of these features (Figure S7). We do not capture all of the variabil-233 ity in albedo with these two terms (Figure S7b), as expected. For example, aerosols are 234 not considered here which generally influence cloud radiative properties and specifically 235 influence optically-thin cloud feature development, often through modulating morphol-236 ogy transitions (e.g., Twomey, 1977; Albrecht, 1989; Zuidema et al., 2008; Carslaw et 237 al., 2013; Yamaguchi et al., 2017; O, Wood, & Tseng, 2018; I. L. McCoy et al., 2021; East-238 man et al., 2021; Tornow et al., 2021; Wyant et al., 2022; Eastman et al., 2022). 239

We hypothesize that variation in cloud evolution mechanisms lead to differences 240 in the radiative properties of morphologies. Broadly, processes analogous to warming-241 deepening will support the transition to more disorganized cloud morphologies, possess-242 ing the largest  $f_{thin}$  of the three WH6 morphology types (e.g., Wyant et al., 1997; East-243 man et al., 2022; Narenpitak et al., 2021). Processes analogous to precipitation-depletion 244 will support the transition to morphologies with more detraining cloud features includ-245 ing open MCC, which has the second largest  $f_{thin}$  of the WH6 categories (e.g., Wyant 246 et al., 1997; Yamaguchi et al., 2017; Sarkar et al., 2019; Tornow et al., 2021; Vogel et al., 247 2021; Smalley et al., 2022; Eastman et al., 2022). 248

The balance of different cloud controlling processes will likely change in an enhanced-249  $CO_2$  climate, potentially manifesting in different proportions of morphologies. This is 250 because morphology occurrence is dependent on environmental conditions (e.g., shown 251 for WH6 in I. L. McCoy et al., 2017; Eastman et al., 2021, 2022). Utilizing our knowl-252 edge of present-day transitions between morphologies, we use the framework of transi-253 tions to/from closed MCC relative to open and disorganized MCC to predict how mor-254 phology will change associated with shifts in environmental controls under climate change. 255 A climate-driven morphology occurrence shift will result in a change in optically-thin 256 cloud feature amount, creating dimmer or brighter cloud scenes even for the same de-257 tected cloud amount. We estimate the magnitude of this change and its influence on top 258 of atmosphere radiation in the remaining sections. 259

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#### 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 262 in a simple environmental phase space: M and SST (Section 2.3). We find that the rel-263 ative frequency of closed MCC  $(f_{Closed})$  has an approximately linear relationship with 264 M and SST, both over a base period (2003-2012, Figure 2a) and the complete MIDAS 265 period (2003-2018, Figure S8). The base period is separated to facilitate out-of-sample 266 testing. There are two broad tendencies of morphology frequency shift across M-SST space. 267 Below SST  $\approx 290$  K, more frequent open MCC ( $f_{Open}$ ) occurs with increasing M (greater 268 instability) (Figure 2b). Above SST  $\approx 290$  K,  $f_{Closed}$  tends toward more frequent dis-269



Figure 2. 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 MCC (see Figure S8 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. d) The resulting prediction is plotted vs. 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 MHW (Figure S2c) test results are shown in a, e-f). Yearly anomalies are relative to the total MIDAS period. Yearly mean M, SST values for the MHW region (grey line, points) are plotted in a) with maximum, minimum SST anomaly markers corresponding to symbols in f). e) Yearly mean morphology frequency anomalies for  $f_{Closed}$  vs.  $f_{Open}$ and  $f_{Disorganized}$  are shown with 2SE encompassing monthly, regional uncertainty. f) Observed yearly  $f_{Closed}$  anomalies vs. 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 (grey) are included.

organized cloud types ( $f_{Disorganized}$ , 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:

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

and fitting SST > 290 K and  $SST \le 290$  K data separately:

$$f_{Closed} = \begin{cases} a_{>290} \cdot M + b_{>290} \cdot SST + c_{>290} : SST > 290K\\ a_{<290} \cdot M + b_{<290} \cdot SST + c_{<290} : SST \le 290K \end{cases}$$
(3)

The latter formulation accounts for the more pronounced dependence (stronger gradi-277 ent) of closed MCC on the environment over subtropical surface temperatures (SST >278 290 K) (Figure 2a). As M and SST increase in this regime, closed MCC tend to shift more 279 toward disorganized than open MCC (the reverse of the  $SST \leq 290$  K regime) (Figure 2b, 280 c). Equation 3 captures more of this behavior than Equation 2, which is reflected in the 281 closer correspondence between its prediction and observed  $f_{Closed}$  (the slope is closer to 282 unity: m = 0.95 in Figure 2d compared to m = 0.88 in Figure S9). See Table S1 for co-283 efficients and Text S2 for expanded fit discussion (Qu et al., 2015; D. T. McCoy et al., 284 2022).285

Equation 3 captures the base period behavior well but will only be useful for our 286 analysis if it can also reliably predict frequency changes under future climate scenarios 287 (assuming it is robust under time-scale invariance, Klein et al., 2017). Following Myers 288 et al. (2021), we utilize a subtropical marine heatwave (MHW) as an out-of-sample test 289 of SST anomalies analogous to those associated with climate change. We examine a re-290 gion of the NEP (15-30°N, 140-115°W, Figure S2c) that was heavily influenced between 291 November 2013-January 2016 by a MHW (driven and maintained by cloud changes, My-292 ers et al., 2018; Schmeisser et al., 2019). All three MCC types are prevalent in this re-293 gion (Figure S1). Yearly regional anomalies are computed relative to the full MIDAS pe-294 riod (2003-2018). The MHW affected 2015 the most (e.g., Myers et al., 2021) and yielded 295  $a \sim 2\sigma$  event in yearly regional SST anomaly (shading in Figure 2a, e-f). In response 296 to the MHW SST anomaly,  $f_{Closed}$  was anomalously low while  $f_{Open}$  decreased slightly 297 and  $f_{Disorganized}$  increased significantly. Given the warm initial state of the region, the 298 shift in relative occurrence frequency from  $f_{Closed}$  toward  $f_{Disorganized}$  more than  $f_{Open}$ 299 (Figure 2e) is consistent with expectations (Eastman et al., 2022) and the shift in mean 300 regional, yearly M, SST values toward regions of higher  $f_{Disorganized}$  with increasingly 301 positive SST anomalies (Figure 2a). Equation 3 robustly predicts yearly regional  $f_{Closed}$ 302 anomalies  $(R^2 = 0.89)$ , increasing our confidence in its ability to infer changes in mor-303 phology in response to changes in dominant large-scale environmental factors. Larger 304 SST anomalies are harder to predict (as in Myers et al., 2021) and there are slight over 305 and under predictions of  $\Delta f_{Closed}$  above and below SST anomalies of  $\approx \pm 1.5$  K. 306

#### 3.3 Predicting the Morphology Feedback

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

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

We utilize the coefficients from Equation 3, which were tested using a MHW in Section 313 3.2. Predictions using coefficients from Equation 2 are shown in Figure S10. See Section 2.4 314 for  $\Delta M/\Delta T$  and  $\Delta SST/\Delta T$  estimation.

The respective patterns of  $\Delta M/\Delta T$  and  $\Delta SST/\Delta T$  combine to produce the pat-315 tern of  $\Delta f_{Closed}/\Delta T$  shown in Figure 3a. There are decreases in present-day regions of 316 closed MCC (i.e., subtropical cloud decks, high latitudes, Figure S1a). Where closed MCC 317 clouds persist  $\Delta f_{Closed}=0$ .  $f_{Closed}$  also increases in poleward regions adjacent to the South-318 east Pacific, Southeast Atlantic, and Canarian cloud decks, and in the northern and east-319 ern Atlantic. Increasing  $f_{Closed}$  corresponds to increasing stability (decreasing  $\Delta M/\Delta T$ ) 320 and small  $\Delta SST/\Delta T$  increases. Decreasing  $f_{Closed}$  occurs for the opposite conditions 321 (increasing  $\Delta M/\Delta T$ , large  $\Delta SST/\Delta T$  increases). Increases in stability do not outweigh 322 the influence of surface warming in all instances. 323

We estimate the optical depth component of the morphology feedback assuming 324 that  $\Delta f_{Closed}$  shifts to a single cloud type, either  $\Delta f_{Open}$  or  $\Delta f_{Disorganized}$ . In reality, 325 shifts to/from closed MCC will likely be associated with a mixture of open MCC and 326 disorganized clouds. However, we can use shifts to/from open MCC as a lower bound 327 (smaller albedo difference from closed MCC at constant CF, Figure 1b) while shifts to/from 328 disorganized will be an upper bound (larger albedo difference). To estimate the aggre-329 gate response, we calculate the feedback conditioning shifts based on the initial (i), mean 330 state SST: closed to open MCC when  $SST_i \leq 290$  K, closed to disorganized when  $SST_i >$ 331 290 K. 332

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., 2012b, 2012a, 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):

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

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

Morphology albedos ( $\alpha_C$ ,  $\alpha_O$ ,  $\alpha_D$ ) are estimated in Equations 5, 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). We multiply by monthly, grid  $\Delta f_{Closed}/\Delta T$  and mean solar flux ( $SW^{\downarrow}$ , Section 2.2) values before computing the final feedback as the mean over all seasons. The aggregate closed to open, disorganized feedback uses Equations 5 or 6 conditional on  $SST_i$  in each grid box (Figure 3d).

The morphology feedback magnitude varies geographically, consistent with the ge-347 ographic pattern of  $\Delta f_{Closed}/\Delta T$  (increasing, constant, or decreasing  $\Delta f_{Closed}/\Delta T$ , Fig-348 ure 3a, leads to negative, null, or positive feedback, b-d). The area-averaged morphol-349 ogy feedback contribution between  $65^{\circ}S$  -  $65^{\circ}N$  to the global mean shortwave cloud feed-350 back is  $0.04 \text{ W m}^{-2} \text{ K}^{-1}$  for closed to open MCC and  $0.07 \text{ W m}^{-2} \text{ K}^{-1}$  for closed to dis-351 organized MCC. The more realistic aggregate estimate of closed MCC to open and dis-352 organized MCC conditional on initial SST is  $0.06 \text{ W m}^{-2} \text{ K}^{-1}$ . Equation 2 estimates are 353 similar (0.04, 0.08, and 0.06 W m<sup>-2</sup> K<sup>-1</sup>, respectively) with subtly different geographic 354 distributions (Figure S10). 355

#### **356 4 Discussion**

340

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  $0.04 - 0.07 \text{ W m}^{-2} \text{ K}^{-1}$  with an aggregate of  $0.06 \text{ W m}^{-2} \text{ K}^{-1}$ . 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



Figure 3. a) Predicted  $\Delta f_{Closed}$  from CMIP6 simulated multi-model mean  $\Delta SST/\Delta T$  (Figure S2a) and  $\Delta M/\Delta T$  (Figure S2b) 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 MCC shifts to b) open MCC, c) cellular but disorganized MCC, or d) an aggregate of open and disorganized MCC dependent on initial SST. Figure S10 shows estimates using Equation 2 coefficients instead (Table S1).

from closed to open MCC (0.04 W  $m^{-2}$  K<sup>-1</sup>, our lower bound) for one degree of global 363 warming is four times larger (and the opposite sign) than the expected radiative pertur-364 bation from closing all pockets of open cells in closed MCC cloud decks in the present 365 day  $(0.01 \text{ W m}^{-2})$  (Watson-Parris et al., 2021). This magnitude difference is likely due 366 in part to the higher frequency of open clouds in MIDAS, which includes both pockets 367 of open cells (as in Watson-Parris et al., 2021) and open cell regions that span large ar-368 eas of ocean without closed cell presence. The aggregate is also comparable with vari-369 ous feedback estimates in Cesana and Del Genio (2021): the Sc and Cu feedback under 370 historic trends, Cu under  $abrupt4 \times CO_2$  and +4K, and low equilibrium climate sen-371 sitivity CMIP6 models. It is  $\sim 30\%$  of Myers et al. (2021) near-global marine cloud feed-372 back estimate (0.19  $\pm$  0.12 W m<sup>-2</sup> K<sup>-1</sup>) and ~50% of the difference between CMIP5 373  $(0.09 \text{ W m}^{-2} \text{ K}^{-1})$  and CMIP6 (0.21) multi-model mean near-global net low cloud feed-374 back that was associated with an increase in CMIP6 equilibrium climate sensitivity (Zelinka 375 et al., 2020). 376

Consideration of changes in morphology occurrence under climate change may be 377 helpful in predicting shortwave cloud feedback. Current models appear to poorly cap-378 ture cloud heterogeneity and associated radiative effect (Konsta et al., 2022). The ge-379 ographical pattern of the morphology feedback (Figure 3b-d) contributes regions of pos-380 itive and negative feedback that may be useful to consider in understanding patterns of 381 radiative feedback. For example, in sub-tropical cloud decks the morphology feedback 382 is largely negative, opposing positive cloud amount feedback (Qu et al., 2014a). MCC 383 transitions may also contribute to observed variations in cloud optical depth as a func-384 tion of temperature (Terai et al., 2016; Wall, Storelvmo, et al., 2022). Future work will 385 seek to quantify remaining morphology feedback components (i.e., cloud amount and al-386 titude), utilize observed morphology behaviors to constrain GCMs (e.g., Zelinka et al., 387 2022), and investigate aerosol influence separate from meteorological drivers (e.g., Zhang 388 et al., 2022; Zhang & Feingold, 2022; Wall, Norris, et al., 2022) on morphology occur-389 rence, transitions, and radiative properties. 390

Will sub-setting the broad "cellular but disorganized" WH6 morphology category 391 (e.g., by contrasting MIDAS with other classification methods, Stevens et al., 2019; Rasp 392 et al., 2020; Denby, 2020; Yuan et al., 2020; Janssens et al., 2021) help improve the mor-393 phology feedback estimate in regions that this category dominates (e.g., the tropics)? 394 It is likely that the development and production of optically-thin cloud features (and other 395 characteristics impacting cloud radiative properties) varies across the sub-categories de-396 veloped in these studies (e.g., Mohrmann et al., 2021; Schulz et al., 2021; Narenpitak et 397 al., 2021; Vogel et al., 2021). While including more morphological types may only add 398 variation around our central estimate of the morphology feedback, it could help to de-399 velop a clearer global picture of cloud morphology evolution and their sensitivities to cli-400 mate change. Advances in process level understanding of cloud morphology evolution 401 (e.g., in the "disorganized" trade winds through the  $EUREC^4A/ATOMIC$  field cam-402 paign, Stevens et al., 2021) will also assist in this effort. 403

#### 404 5 Summary

Global cloud morphology patterns (large-scale structures  $O\sim100$  km of clouds with 405 cell sizes  $O \sim 10-50$  km, Figure 1a, S1) identified by a supervised neural network algorithm 406 based on their liquid water path characteristics (i.e., closed, open, and disorganized mesoscale 407 cellular convection (MCC), Wood & Hartmann, 2006) have distinct radiative properties 408 over 65°N-65°S, 2003-2018 (Section 3.1). Closed MCC more effectively reflect sunlight 409 than open and disorganized MCC for the same cloud coverage (Figure 1b). This is sig-410 nificantly influenced by differing preponderances of optically-thin cloud features ( $\tau <$ 411 3) between morphologies (Figure 1d, S7). Approximately, we can think of morphology 412 transitions (i.e., from closed to open or disorganized MCC) as a shift in the fraction of 413 optically-thin cloud features, which both contributes to radiative differences between mor-414

phologies and are a diagnostic of the underlying processes driving morphological evolu tion. An implication of this is that accurate prediction of future climate may require un derstanding when and where different cloud morphologies occur.

We utilize knowledge of present-day cloud morphology transitions to develop a frame-418 work for estimating the optical depth component of the shortwave cloud feedback asso-419 ciated with shifts in morphology responding to environmental changes under climate change 420 (Section 3.3). The morphology feedback is estimated as the shift from closed MCC to 421 open and/or disorganized MCC in response to changes in environmental controls while 422 423 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 ac-424 companying cloud amount changes (i.e., capturing the influence of optically-thin cloud 425 features). This is analogous to the partitioning of cloud feedback between optical depth, 426 amount, and altitude components in previous studies (e.g., Zelinka et al., 2012a). Shifts 427 to open and disorganized MCC provide a lower and upper bound, respectively, while shift-428 ing to their aggregate provides a best estimate. 429

We develop a predictive model based on multiple linear regression (Equation 3) for 430 the relative occurrence frequency of closed MCC ( $f_{Closed}$ ) based on its dependence on 431 sea surface temperature and M, a measure of lower tropospheric stability (Section 3.2, 432 Figure 2a, d). Model predictive ability is tested with an out-of-sample case (i.e., a sub-433 tropical marine heatwave with SST anomalies analogous to climate change following My-434 ers et al., 2021) (Figure 2f). Mean changes in SST and M in response to an abrupt qua-435 drupling of  $CO_2$  are estimated from 11 models participating in phase 6 of the Coupled 436 Model Intercomparison Project (CMIP6) and used to predict  $\Delta f_{Closed}$  under climate change 437 (Figure 3a). 438

Predictions of  $\Delta f_{Closed}$  based on GCM predictions of  $\Delta SST/\Delta T$  and  $\Delta M/\Delta T$  in-439 dicate that closed MCC occurrence will increase in the northern and eastern Atlantic, 440 portions of southern hemisphere mid-latitudes, and pole-ward of southern hemisphere 441 subtropical cloud decks. Using present day radiative properties (Figure 1b) and randomly 442 overlapped cloud amount (Figure S2c), we use  $\Delta f_{Closed}$  to estimate the morphology feed-443 back resulting from a shift in morphology alone (Figure 3b-d). The contribution to global 444 mean feedback varies by predicted morphology transition: closed to open MCC (0.04), 445 to disorganized (0.07), or to an aggregate of open and disorganized (0.06 W m<sup>-2</sup> K<sup>-1</sup>). 446 Compared to other assessed cloud feedbacks (Sherwood et al., 2020), the optical depth 447 component of the morphology feedback is non-trivial. Its geographic variations have the 448 potential to modulate other feedback components. Our results emphasize the usefulness 449 of applying a process-driven, morphological lens to interpretation and estimation of cloud 450 feedback. This analysis also stresses the importance of developing an observational, process-451 based understanding of optically-thin cloud feature development across different cloud 452 morphologies in the present climate in order to accurately estimate their climate impact 453 in the future. 454

#### 455 6 Open Research

Manuscript supporting data is available at https://doi.org/10.5281/zenodo.7311993 456 (I. L. McCoy & Wood, 2022). CERES Single Scanner Footprint (SSF) daily 1deg prod-457 uct is available at https://asdc.larc.nasa.gov/project/CERES/CER\_SSF1deg-Hour 458 \_Aqua-MODIS\_Edition4A (NASA/LARC/SD/ASDC, 2015). CERES Energy Balanced 459 and Filled (EBAF) Top of Atmosphere (TOA) Monthly means are available at https:// 460 asdc.larc.nasa.gov/project/CERES/CERES\_EBAF-TOA\_Edition4.1 (NASA/LARC/SD/ASDC, 461 2019). MODIS Collection 6.1 Level 2 data are available at https://ladsweb.modaps 462 .eosdis.nasa.gov/archive/allData/61/MYD06\_L2/ (Platnick et al., 2015). MODIS 463 (Aqua/Terra) Cloud Properties Level 3 daily, 1x1 degree gridded data, including COSP 464 cloud mask, is available at https://ladsweb.modaps.eosdis.nasa.gov/archive/allData/ 465

62/MCDO6COSP\_D3\_MODIS/ (Pincus et al., 2020). CMIP6 *piControl* and *abrupt*4×*CO*<sub>2</sub>
 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).

#### 471 Acknowledgments

We acknowledge the World Climate Research Programme and its Working Group on Cou-472 pled Modelling for coordinating CMIP6; the climate modeling groups involved for their 473 simulations; the Earth System Grid Federation (ESGF) for archiving and facilitating data 474 usage; and the multiple funding agencies who support CMIP and ESGF efforts. We thank 475 our editor, Hui Su, and two anonymous reviewers for their insights. Research by ILM 476 is supported by the NOAA Climate and Global Change Postdoctoral Fellowship Pro-477 gram, administered by UCAR's Cooperative Programs for the Advancement of Earth 478 System Science (CPAESS) under award NA18NWS4620043B. DTM acknowledges sup-479 port from the Process-Based Climate Simulation: Advances in High- Resolution Mod-480 elling and European Climate Risk Assessment (PRIMAVERA) project funded by the 481 European Union's Horizon 2020 program under Grant Agreement 641727, from NASA 482 PMM Grant 80NSSC22K0599, NASA MAP Grant 80NSSC21K2014, and DOE-ASR Grant 483 DE-SC002227. RW acknowledges support from the NASA MEASURES grant NASA0004-484 02 AM1 and NASA CloudSat and CALIPSO Science Team award 80NSSC19K1274. PZ 485 acknowledges support from NOAA CPO grant NA19OAR4310379. FAMB acknowledges 486 support from the Swedish Research Council, project 2018-04274, and the Swedish e-Science 487 Research Center (SeRC). 488

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## Supporting Information for The Role of Mesoscale Cloud Morphology

in the Shortwave Cloud Feedback

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1. Text S1 to S2  $\,$ 

2. Table S1

3. Figures S1 to S10

**Text S1.** We can examine the predicted changes in CMIP6 models (Figure S2, S3) in more detail to determine if the responses are i) consistent across models and ii) similar to the large-scale changes estimated in previous studies. Individual CMIP6 models behave similarly to each other (Figure S3, S4) with small multi-model standard deviations (Figure S5a, d) especially when scaled by their multi-model mean ( $O\sim0.5$ , Figure S5c, d). Small differences between model responses in  $\Delta M/\Delta T$  can be seen in regions where the details of ocean-atmosphere interactions likely vary between models (Figure S5d). Similarly,  $\Delta SST/\Delta T$  exhibits the largest model differences in the region of the North Atlantic subploar gyre (e.g., Borchert et al., 2021; Carmo-Costa et al., 2022) (Figure S5c).

We can particularly contrast the CMIP6 tendencies from this subset of GCMs with the CMIP5  $abrupt4 \times CO_2$  simulation results in Qu, Hall, Klein, and Caldwell (2014b). Comparing to their Figure 9, we can look at the typical behavior of temperature mediated (scaled by the change in tropical air temperature) estimated inversion strength (EIS) and surface temperature (SST) focusing on the early stage (first 30 years) which experiences the largest response. We can estimate EIS from M and  $\Delta T_{air-sea} = SST - T_{2m}$ using the  $M \approx \Delta T_{air-sea} - EIS + \text{constant relationship}$ from I. L. McCoy, Wood, and Fletcher (2017). In general, the global increase in  $\Delta EIS/\Delta T$  which is emphasized in sub-tropical decks (Figure S6a) and the global increase in  $\Delta SST/\Delta T$  with larger increases at the high-latitudes (Figure S2a) agrees with expected behavior under climate change (e.g., Qu et al., 2014b). The regionally varying although generally decreasing  $\Delta M / \Delta T$  follows from this, with the large North Atlantic decrease associated with strong weakening of marine cold air outbreaks consistent with expectations (e.g., Kolstad & Bracegirdle, 2008) (Figure S2b). We can also examine the expanded Klein-Hartmann boxes (Klein & Hartmann, 1993; Qu et al., 2014a, 2015) in more detail, which capture a range of MCC cloud morphologies in key sub-tropical regions (Figure S1, S6a). Multi-model changes are consistent in behavior with earlier studies (Qu et al., 2014b). Individual models agree in sign across regions and regional multi-model means are within 25-75% of each other (Figure Sb-e).

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In summary, these investigations into the CMIP6 predictions under  $abrupt4 \times CO_2$  simulations indicate that the changes in large-scale environment predicted by this set of 11 CMIP6 models are consistent with the behaviors expected by prior studies. The multi-model mean values of  $\Delta M/\Delta T$ and  $\Delta SST/\Delta T$  shown in Figure S2a, b are thus reasonable to use in our analysis.

Text S2. The multiple linear regressions used in Equations 2 and 3 of the main text are weighted by the number of observations in each bin. For reliability, only bins where there is a sufficient number of all MCC identifications  $(N_{Total} \ge 500)$  and closed MCC identifications  $(N_{Closed} \ge 100)$  are included in the fits. Because of the split-fit formulation in Equation 3, it was also necessary to apply bootstrapping for uncertainty estimation. Fits are bootstrapped with replacement ( $\times 5000$ ) from the original  $\Delta f_{Closed}$ -M-SST matrix from Figure 2a. The explained variance of both regressions is high ( $R^2$ =0.99). Mean and standard deviation of coefficients (calculated over all 5000 bootstrapped fits) for Equations 2, 3 are provided in Table S1. We additionally checked for collinearity between predic-

We additionally checked for collinearity between predictors (bins of M, SST where  $N_{Total} \geq 500$ ,  $N_{Closed} \geq 100$ ) and found that it was minimal as the correlation was very low. For all input data (Equation 2),  $R^2=0.034$ . For Equation 3,  $R^2=0.04$  for the data subset where SST > 290 k and 0.03 for  $SST \leq 290$  K. All of these correlations are well below the  $R^2=0.9$  threshold where predictor collinearity becomes an issue (Qu et al., 2015; D. T. McCoy et al., 2022).

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Table S1. Mean and Standard Deviations of Regression Coefficients for Equations 2 and  $3^{a,b}$ 

Fit	$a  ({\rm K}^{-1})$	$b  ({\rm K}^{-1})$	с
Total	$-0.0269 \pm 0.0003$	$-0.0161 \pm 0.0002$	$4.64 {\pm} 0.05$
SST > 290  K	$-0.0230 \pm 0.0004$	$-0.0145 \pm 0.0004$	$4.19{\pm}0.12$
$SST \le 290 \text{ K}$	$-0.0322 \pm 0.0002$	$-0.0165 {\pm} 0.0002$	$4.69{\pm}0.05$

<sup>a</sup> Fits of  $f_{Closed} - M - SST$  data (Figure 2a) generally take the form:  $f_{Closed} = a \cdot M + b \cdot SST + c$ .

 $^{\rm b}$  Equation 2 uses coefficients from row 1, Equation 3 uses coefficients from rows 2 and 3.



Figure S1. Annual mean MIDAS cloud morphology relative occurrence frequencies for 2003-2018: a) closed, b) open, and c) cellular but disorganized MCC.



Figure S2. CMIP6 simulated change from *piControl* to *abrupt4* ×  $CO_2$  in a) sea surface temperature (SST) and b) lower tropospheric stability (as measured by the marine cold air outbreak index, M) per degree of global warming (measured by area-weighted change in 2 m air temperature,  $\Delta T$ ). c) Annual mean estimate of randomoverlapped low cloud fraction from the MODIS cloud mask (Pincus et al., 2020), following Scott et al. (2020). The black box in c) shows the out-of-sample test region (15-30°N, 140-115°W) where a marine heatwave was influential between November 2013-January 2016 (Myers et al., 2018; Schmeisser et al., 2019; Myers et al., 2021).



Figure S3. Simulated  $\Delta SST/\Delta T$  for individual CMIP6 models contributing to the multi-model mean shown in Figure S2a.



Figure S4. Simulated  $\Delta M/\Delta T$  for individual CMIP6 models contributing to the multi-model mean shown in Figure S2b.



**Figure S5.** Standard deviation across individual CMIP6 model means for a)  $\Delta SST/\Delta T$  and c)  $\Delta M/\Delta T$ . Ratio of multi model standard deviation over multi-model mean for b)  $\Delta SST/\Delta T$  and d)  $\Delta M/\Delta T$ .



Figure S6. CMIP6 simulated changes for a) key subtropical regions in Qu et al. (2014a) for b)  $\Delta SST/\Delta T$ , c)  $\Delta M/\Delta T$ , d)  $\Delta T_{air-sea}/\Delta T$ , and e) an approximate estimate of  $\Delta EIS/\Delta T$  using  $M \approx \Delta T_{air-sea} - EIS +$ constant (I. L. McCoy et al., 2017). a) The multi-model mean of the approximate  $\Delta EIS/\Delta T$ , as in Figure S2. be) Individual model means (shapes) are shown with the multi-model mean (red circle), 5-95% (thin gray lines), and 25-75% (thick grey lines) for separate regional boxes in a) and the combined regional box behavior.



Figure S7. Predicting MIDAS identified scene albedo from Figure 1 using multiple linear regressions with a) CF and b) CF and  $f_{thin}$  as predictors. Fit predicted albedo is shown on the y-axis and the raw scene albedo is on the x-axis. Combined total (black), closed MCC (blue), open MCC (pink), and cellular but disorganized (orange) identifications are fit separately.  $R^2$  and p values are shown for the individual (Raw) points and for the mean fitted albedo within 25 x-axis quantile bins (Bin). Thick lines show 2SE and thin the 25-75% range within each quantile. Slope (m) and intercept (c) are shown for the linear fit applied to the quantile bins (line). A dashed 1:1 line is included for reference. Generally, the closer m is to one and c is to zero, the better the prediction with the regression model, suggesting b) captures more of albedo behavior than a).



Figure S8. As in Figure 2a-c but for the full MI-DAS period (2003-2018): the MIDAS relative occurrence frequency in the M-SST environmental phase space a) closed, b) open, and c) disorganized MCC.



Figure S9. As in Figure 2d but using Equation 2 to predict  $f_{Closed}$  from Figure 1a.



Figure S10. As in Figure 3 but predicted from Equation 4 using coefficients from the no-split model in Equation 2 instead of the split model in Equation 3. a)  $\Delta f_{Closed}/\Delta T$  with the optical depth component of the morphology feedback per  $\Delta T$  assuming closed MCC shift to b) open MCC, c) cellular but disorganized MCC, or d) an aggregate of open and disorganized MCC dependent on initial SST.