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Organized Trade Cumulus Clouds Suppressed by Climate Change

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Key Points:

- Trade cumulus mesoscale organization enhances the cloud response to climate change.
- The primary cause is down-welling long-wave radiation from increased greenhouse gas concentrations.
- The cumulus-valve mechanism does not universally stabilize trade cumulus clouds against climate change.

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Abstract

We present a first study showing that organization of trade cumulus (Tc) clouds can significantly enhance Tc response to climate change. Among four recently identified states of Tc organization, the “Flower” state has the highest and the “Sugar” state the lowest cloud fraction and cloud radiative effect. Using large-eddy simulations, we show that the organized “Flower” Tc state is strongly suppressed at the end of the 21st century, unlike the less organized “Sugar” Tc state and Tc studied previously. The primary cause of the suppression is down-welling long-wave radiation from increased greenhouse gas concentrations, which weakens the mesoscale circulation that organizes clouds into the “Flower” Tc state. The cumulus-valve mechanism, which is thought to limit Tc response to climate change, does not prevent this response. Our work unravels an unrecognized role of cloud organization in the cloud response to climate change.

Plain Language Summary

Trade cumulus clouds cover large swaths of the oceans and cool the planet. Climate models struggle to capture these clouds, leading to uncertainty in climate projections. We show that among four recently identified organized types of trade cumulus clouds, the type of organization with the highest cooling effect will be strongly suppressed at the end of the 21st century, unlike less organized trade cumulus clouds with a lower cooling effect. The strong suppression is a direct consequence of cloud organization. Down-welling long-wave radiation from rising greenhouse gases is the primary cause. The role of cloud organization and the underlying physical mechanisms we identify may contribute to improving the representation of trade cumulus clouds in climate models.

1 Introduction

Low clouds cool the Earth by reflecting sunlight back to space. The cooling effect depends on the response of clouds to the climate system, and in turn affects Earth's climate. This cloud-climate feedback determines climate sensitivity, the Earth's temperature response to rising levels of greenhouse gases (GHG). The latest generation of climate models predicts a high climate sensitivity due to strong low cloud feedbacks (Zelinka et al., 2020). Observations, however, indicate a moderate climate sensitivity due to low clouds (Cesana & Del Genio, 2021; Myers et al., 2021). The discrepancy is caused in part by trade cumulus (Tc) clouds, a key source of uncertainty in climate projections (Bony & Dufresne, 2005; Vial et al., 2013; Medeiros et al., 2015). Tc feedbacks in climate models are governed by changes in cloud fraction near cloud base (Brient et al., 2016; Vial et al., 2016). Climate models with a high climate sensitivity suggest a strong decrease in Tc cloud base cloudiness owing to increased lower-tropospheric mixing and cloud base evaporation (Sherwood et al., 2014; Brient et al., 2016; Vial et al., 2016). Vogel et al. (2022) refuted this mixing-desiccation hypothesis observationally, and found that a weak Tc feedback is more plausible than a strong one, providing an important line of evidence against high climate sensitivity. Observations (Nuijens et al., 2015) and large-eddy simulations (Rieck et al., 2012; Blossey et al., 2013; Vogel et al., 2016; Tan et al., 2017) suggest that Tc are remarkably stable against climate change, and exhibit a weak positive feedback (Vial et al., 2017). The leading hypothesis for a broad stability of Tc against climate change is the cumulus-valve mechanism (Neggers et al., 2006). This hypothesis postulates a negative feedback between the cloud base cloud fraction and the mixed layer height via the cloud mass flux.

Four new manifestations of Tc organization called Sugar, Gravel, Fish, and Flowers have been identified by Stevens et al. (2020). These cloud states cool the Earth to different extents: the Sugar Tc state has the lowest and the Flower Tc state the highest cloud fraction and cloud radiative effect (Bony et al., 2020). This diversity suggests an uncharted landscape of Tc responses to climate change involving potentially unrecognized mechanisms. We explore the role of organization of the Flower and Sugar Tc states to anthropogenic climate change from present-day (PD) to end-of-21st-century (EC) conditions. 21st century climate change is represented using the RCP8.5 scenario, which is the best match out to midcentury under current and stated policies, with still highly plausible levels of CO₂ emissions in 2100 (Schwalm et al., 2020). CO₂ approximately dou-

72 bles, and in the region considered here, sea surface temperature (SST) increases by 1.8 K
 73 from PD to EC. We divide climate change into effects from SST and large scale mete-
 74 orology (LSM), and effects from GHG down-welling long-wave (LW) radiation. LSM con-
 75 sists of atmospheric temperature, water vapor, zonal and meridional wind speed, and sub-
 76 sidence.

77 We use Lagrangian large eddy simulations (Kazil et al., 2021; Narenpitak et al.,
 78 2021) that track Tc evolution along two trajectories east of Barbados (Fig. SF1). Along
 79 a northern trajectory, three simulations (\mathcal{F}_{PD} , $\mathcal{F}_{\text{EC}}^-$, \mathcal{F}_{EC}) simulate the Flower Tc state
 80 but differ in their forcings. \mathcal{F}_{PD} uses SST_{PD} , LSM_{PD} , and GHG_{PD} . $\mathcal{F}_{\text{EC}}^-$ uses SST_{EC} ,
 81 LSM_{EC} , but GHG_{PD} . \mathcal{F}_{EC} uses SST_{EC} , LSM_{EC} , and GHG_{EC} . Simulations of the Sugar
 82 Tc state (\mathcal{S}_{PD} , \mathcal{S}_{EC}) are constructed from the Flower simulations along the northern tra-
 83 jectory by holding the subsidence profile constant starting from 8 h into the simulations
 84 (Fig. SF5). This suppresses large scale upward motion and keeps the cloud field in the
 85 Sugar Tc state until sunset. The role of large scale vertical motion for the evolution of
 86 the Flower Tc state is discussed by Narenpitak et al. (2021). The simulation \mathcal{S}_{PD} uses
 87 SST_{PD} , LSM_{PD} , and GHG_{PD} , simulation \mathcal{S}_{EC} uses SST_{EC} , LSM_{EC} , and GHG_{EC} . We
 88 quantify the response of the Flower Tc state to the change from PD to EC in SST and
 89 LSM, and down-welling LW from GHG. We identify the underlying physical mechanisms,
 90 and compare the response of the Flower Tc state to that of the Sugar Tc state and to
 91 Tc studied previously. Along a southern trajectory, the simulations $\mathcal{F}_{\text{PD}}^*$, $\mathcal{F}_{\text{EC}}^*$ explore
 92 the response to the change from PD to EC of the Flower Tc state in different conditions,
 93 and the simulations $\mathcal{F}_{\text{PD}}^{**}$, and $\mathcal{F}_{\text{EC}}^{**}$ test the sensitivity of the results to resolution.

94 We use the System for Atmospheric Modeling (SAM, Khairoutdinov & Randall,
 95 2003). The SST, LSM, and GHG forcing of our simulations is constructed from the ERA5
 96 reanalysis (Hersbach et al., 2020) along the simulation trajectories, and from CMIP5 (Taylor
 97 et al., 2012) simulations under the RCP8.5 scenario with CESM1(WACCM) (Marsh et
 98 al., 2013). The model, trajectories, PD and EC forcings, and simulations are described
 99 in the *Supporting Information (SI)*.

2 Results

2.1 Flowers

Figure 1 displays the simulated Tc evolution. The cloud field at sunrise (09h47m UTC) is in the Sugar Tc state across the simulations, without discernible organization. In the Flower simulations \mathcal{F}_{PD} , $\mathcal{F}_{\text{EC}}^-$, and \mathcal{F}_{EC} the cumulus clouds first cluster and then aggregate into Flowers as the day progresses, with characteristic stratiform patches from cloud top outflows (Stevens et al., 2020; Bony et al., 2020; Narenpitak et al., 2021; Schulz et al., 2021). The Flowers produce surface precipitation and a first generation of cold pools by sunset (21h18m UTC). The effect of SST increase and LSM change (\mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$) and of increased GHG levels ($\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC}) imprints itself by weakening cumulus clustering, aggregation, and Flower formation, and reduces the number and size of cold pools (Fig. 1a-c). The effect is subdued from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ and conspicuous from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} : \mathcal{F}_{EC} exhibits a much reduced number and size of Flowers and cold pools.

Figure 2a-c shows the time series of cloud fraction (CF), liquid water path (LWP), and short-wave cloud radiative effect (SWCRE) in the simulations. In the Flower simulations, as the Flower state evolves, the response of CF, LWP, and SWCRE to climate warming strengthens. Table 1 gives the change in CF, LWP, and SWCRE between the simulations, mean values for each simulation are given in Table ST1. Warming due to the changes in SST and LSM (\mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$) drives less of a response than the increase in GHG ($\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC}): CF and LWP fall by a smaller amount from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$, and by a larger amount from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} . Consequently, SWCRE is less sensitive to change in SST and LSM, and more sensitive to increased GHG: SWCRE weakens from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ by 0.5 Wm^{-2} and from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} by 0.7 Wm^{-2} .

We now identify the mechanisms by which climate warming suppresses the Flower Tc state. Figure 3 shows the change in mean profiles from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ (Fig. 3a-d) and from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} (Fig. 3e-h). We focus on the period until sunset, around which intermittent precipitation (Fig. SF9i, SF10) contributes a stochastic component whose elimination would require averaging over ensembles. From \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$, which differ in SST and LSM, warmer air takes up more moisture from the ocean. This causes a stronger vertical moisture flux in the sub-cloud layer and across cloud base, but not up to the inversion (Fig. 3a). This pattern shapes the response of liquid water; it is enhanced at cloud base and in the lower part of the cloud layer, but reduced around the inversion (Fig. 3b).

132 Why does boundary layer circulation not carry the enhanced moisture flux all the way
 133 to the inversion in $\mathcal{F}_{\text{EC}}^-$? The cause is the lapse rate reduction from PD to EC (Fig. SF4f),
 134 which results in greater atmospheric stability above the mixed layer in the simulations
 135 (Fig. SF7). To maintain intensity of circulation in the more stable EC conditions, tur-
 136 bulence kinetic energy (TKE) production would need to increase. TKE production does
 137 increase from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ in the lower part of the cloud layer (Fig. 3c) due to enhanced
 138 latent heat release from higher vertical moisture transport (Fig. 3a). In the upper part
 139 of the cloud layer and around the inversion, however, TKE production decreases from
 140 \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$. This decrease is caused by stronger radiative heating around the inversion
 141 (Fig. 3d). Decomposition of the radiative heating rate change into short-wave (SW) and
 142 LW components shows that it is stronger LW heating that is responsible for the over-
 143 all stronger heating around the inversion (Fig. SF14). At the inversion, down-welling LW
 144 increases more than up-welling LW from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$, by approximately 2 Wm^{-2} (Fig. SF15).
 145 The increase in radiative heating around the inversion is hence primarily caused by down-
 146 welling LW from the warmer atmosphere above, which is also a consequence of the lapse
 147 rate reduction from PD to EC. The stronger heating causes an enhanced temperature
 148 increase around the inversion from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ (Fig. SF14d), which stabilizes the air
 149 and suppresses TKE production.

150 From $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} , which differ in GHG levels, the vertical moisture flux and liq-
 151 uid water content decrease, most strongly around the inversion (Fig. 3e, f). TKE pro-
 152 duction is reduced as well, primarily below the inversion and in the upper part of the
 153 cloud layer (Fig. 3g). Here too, the cause is an increase in radiative heating at and around
 154 the inversion (Fig. 3h). Decomposition of the radiative heating rate into SW and LW
 155 components shows that it is stronger LW heating that is responsible for the overall stronger
 156 heating around the inversion (Fig. SF16). Down-welling LW increases more than up-welling
 157 LW from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} at the inversion, by approximately 7 Wm^{-2} (Fig. SF17). The in-
 158 crease in radiative heating around the inversion is hence caused by down-welling LW from
 159 increased GHG levels. The stronger heating causes an enhanced temperature increase
 160 around the inversion from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} (Fig. SF16d), which stabilizes the air and sup-
 161 presses TKE production.

162 Both from \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ and from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} , the Flower Tc state is suppressed.
 163 From \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$, which captures the effect of end-of-century SST and LSM, offsetting
 164 mechanisms are at play: the warmer atmosphere takes up more moisture from the ocean,

165 which results in a stronger moisture supply to the cloud layer, and a stronger TKE pro-
 166 duction in its lower portion, both mechanisms that strengthen cloudiness. Concurrently,
 167 a reduced lapse rate opposes moisture transport to the inversion and strengthens down-
 168 welling LW radiation from the free troposphere, which warms the air around the inver-
 169 sion and suppresses TKE production. In combination, these mechanisms weakly suppress
 170 the Flower Tc state. In contrast, from \mathcal{F}_{EC}^- to \mathcal{F}_{EC} , which captures the effect of increased
 171 GHG levels via LW radiation, there are no such offsetting mechanisms, and the increase
 172 in down-welling LW at the inversion is stronger compared to the step \mathcal{F}_{PD} to \mathcal{F}_{EC}^- . The
 173 result is a strong suppression of the Flower Tc state.

174 2.2 Sugar

175 In the simulations \mathcal{S}_{PD} and \mathcal{S}_{EC} , the Sugar Tc state persists throughout the day,
 176 with some clustering (Fig. 1d, e). Flowers begin to form only at sunset. The response
 177 to climate change of the Sugar Tc state (\mathcal{S}_{PD} to \mathcal{S}_{EC}) differs from the response of the
 178 Flower Tc state (\mathcal{F}_{PD} to \mathcal{F}_{EC}). During daytime, CF, LWP, and SWCRE change only
 179 imperceptibly from \mathcal{S}_{PD} to \mathcal{S}_{EC} compared to the change from \mathcal{F}_{PD} to \mathcal{F}_{EC} (Fig. 2a-c).
 180 The response becomes more discernible around sunset, when Flowers emerge in \mathcal{S}_{PD} and
 181 \mathcal{S}_{EC} (Fig. 1d, e, 21h18m UTC). We quantify the sensitivity of the two cloud states with
 182 the relative change of CF, LWP, and SWCRE from PD to EC, expressed per K of SST
 183 change. This reveals that the Flower Tc state is twice as sensitive as the Sugar Tc state
 184 to climate warming (Tab. 1). The Flower Tc state is also approximately twice as sen-
 185 sitive to climate warming in terms of SWCRE compared to the cumulus clouds studied
 186 by Blossey et al. (2013), which was found to be insensitive to GHG levels, and hence to
 187 down-welling LW radiation (Bretherton et al., 2013).

188 2.3 The Role of Organization

189 Fig. 2d-f shows spectra of TKE production, water vapor, and SWCRE at 18h00m UTC,
 190 when Flowers are present \mathcal{F}_{PD} , \mathcal{F}_{EC}^- , and \mathcal{F}_{EC} , but not in \mathcal{S}_{PD} and \mathcal{S}_{EC} (Fig. 1). In the
 191 Flower simulations, the spectra have a strong mesoscale peak at 48 km. The TKE pro-
 192 duction peak (Fig. 2d) drives circulation that aggregates moisture (Fig. 2e), creating mesoscale
 193 moist patches (Bretherton & Blossey, 2017) where Flower clouds form (Narenpitak et
 194 al., 2021). The result is a prominent SWCRE mesoscale peak (Fig. 2f). In contrast to
 195 the Flower Tc state, the Sugar Tc state exhibits smaller mesoscale peaks. These reflect

196 clustering of individual cumulus clouds in the Sugar Tc state (Fig. 1d, e). The mesoscale
 197 peaks in the spectra experience a stronger response from PD to EC in the Flower Tc state
 198 compared to the Sugar Tc state (Fig. 2d-f). In particular, the spectral response of SWCRE
 199 from PD to EC is much stronger in the Flower Tc state compared to the Sugar Tc state,
 200 and confined to the mesoscale (Fig. 2f). Hence the suppression of the Flower Tc state
 201 by climate warming, by the mechanisms identified above, arises from selective weaken-
 202 ing of mesoscale circulation that generates the Flower Tc state.

203 2.4 Cumulus-Valve Mechanism

204 The higher sensitivity to climate warming of the Flower Tc state compared to the
 205 Sugar Tc state appears in the vertical profiles of cloud mass flux and CF (Fig. SF13).
 206 From PD to EC, the cloud mass flux, and in particular CF, display a stronger decrease
 207 in the cloud top region of the Flower Tc state compared to the Sugar Tc state. The de-
 208 crease in CF near cloud top of the Flower Tc state reflects a reduction of the stratiform
 209 cloud patches that form from cloud top outflows. At cloud base, cloud mass flux and CF
 210 remain unchanged from PD to EC (Fig. SF9d, e; SF11d, e) prior to onset of drizzle and
 211 precipitation (Fig. SF9h, i; SF11h, i). This stability is consistent with the cumulus-valve
 212 hypothesis. Yet, this does not prevent the response of the Flower Tc state, which arises
 213 from the suppression of mesoscale circulation in the cloud layer.

214 2.5 Sensitivity Tests

215 To test the response of the Flower Tc state in different conditions, \mathcal{F}_{PD}^* and \mathcal{F}_{EC}^*
 216 simulate the Flower Tc state along the southern trajectory (Fig. SF1). The southern tra-
 217 jectory has a warmer SST, a lower estimated inversion strength, and an initially faster
 218 wind speed (Fig. SF2), all of which favor cloud development. Visual inspection reveals
 219 that Flower clouds form earlier in \mathcal{F}_{PD}^* and \mathcal{F}_{EC}^* (Fig. SF18a, b) compared to \mathcal{F}_{PD} and
 220 \mathcal{F}_{EC} (Fig. 1a, b). Daytime CF and LWP are elevated in \mathcal{F}_{PD}^* and \mathcal{F}_{EC}^* (Fig. SF19a, b)
 221 compared to \mathcal{F}_{PD} and \mathcal{F}_{EC} (Fig. 2a, b). Moving from PD to EC conditions (\mathcal{F}_{PD}^* to \mathcal{F}_{EC}^*),
 222 Flower formation is delayed (Fig. SF18a, b). CF, LWP, and SWCRE are more strongly
 223 reduced from \mathcal{F}_{PD}^* to \mathcal{F}_{EC}^* compared to from \mathcal{F}_{PD} to \mathcal{F}_{EC} (Tab. 1). The stronger sup-
 224 pression of SWCRE from \mathcal{F}_{PD}^* to \mathcal{F}_{EC}^* arises from the overall stronger reduction in CF
 225 and LWP, but also because CF and LWP peak closer to noon in \mathcal{F}_{PD}^* , and later in \mathcal{F}_{EC}^*
 226 (Fig. SF19a, b). This delay exposes the CF and LWP peaks in \mathcal{F}_{PD}^* to stronger and in

227 $\mathcal{F}_{\text{EC}}^*$ to weaker insolation, which adds to a reduced SWCRE (Fig. SF19c). The simula-
 228 tions along the southern trajectory, with a stronger suppression of the Flower Tc state
 229 compared to the northern trajectory from PD to EC conditions, suggest that the sup-
 230 pression of the Flower Tc state by climate change is a systematic phenomenon.

231 Our analysis has found that the sensitivity of CF of the Flower Tc state from PD
 232 to EC conditions is confined to the cloud top region. This raises the question whether
 233 the finite vertical resolution in the simulations may cause spurious mixing and cloud evap-
 234 oration that renders the top region and the stratiform patches of Flower clouds overly
 235 sensitive to the change in conditions from PD to EC. Simulation $\mathcal{F}_{\text{PD}}^{**}$ and $\mathcal{F}_{\text{EC}}^{**}$ use a ver-
 236 tical grid spacing that is refined relative to $\mathcal{F}_{\text{PD}}^*$ and $\mathcal{F}_{\text{EC}}^*$ from 50 to 25 m across the cloud
 237 layer (Tab. ST3). In PD conditions, $\mathcal{F}_{\text{PD}}^{**}$ produces visibly larger and denser stratiform
 238 Flower cloud patches (Fig. SF18c) compared to $\mathcal{F}_{\text{PD}}^*$ (Fig. SF18a). In EC conditions, in
 239 $\mathcal{F}_{\text{EC}}^{**}$ relative to $\mathcal{F}_{\text{EC}}^*$, the effect is more subtle (Fig. SF18d and SF18b). Averaged over
 240 the simulations, the vertical grid refinement strengthens CF, LWP, and SWCRE more
 241 in PD conditions compared to EC conditions (Tab. ST1), resulting in their stronger re-
 242 duction from PD to EC (Tab. 1). Spurious effects from a finite vertical resolution hence
 243 lead to a stronger underestimation of cloud top cloudiness of the Flower Tc state when
 244 it is more widespread, in PD conditions. This implies that the simulations underestimate
 245 the response of the Flower Tc state from PD to EC conditions.

246 **3 Discussion and Conclusions**

247 We present a first study of the response to climate change of two recently identi-
 248 fied manifestations of Tc organization, the organized Flower Tc state and the less or-
 249 ganized Sugar Tc state (Stevens et al., 2020; Bony et al., 2020). Using Lagrangian large
 250 eddy simulations forced by reanalysis meteorology and change in large scale conditions
 251 from climate simulations over the 21st century, we demonstrate that organization enhances
 252 the response of the Flower Tc state to climate change. Anthropogenic climate warming
 253 at the end of the 21st century strongly suppresses the organized Flower Tc state, result-
 254 ing in smaller Flower-type clouds. The response is primarily caused by stronger down-
 255 welling LW radiation from increased GHG levels, and secondarily by the change in SST
 256 and LSM over the course of the 21st century. The stronger down-welling LW radiation
 257 warms and stabilizes air near the trade inversion and weakens the mesoscale circulation
 258 which organizes clouds into the Flower Tc state. This renders the Flower Tc state twice

259 as sensitive in terms of SWCRE response to climate warming compared to the Sugar Tc
260 state, and compared to Tc studied previously (Blossey et al., 2013). Stability against cli-
261 mate warming of Tc identified in previous research is thought to be caused by the cumulus-
262 valve mechanism (Neggers et al., 2006). Both the Flower and Sugar Tc state in our sim-
263 ulations exhibit a stable cloud base cloud fraction and mass flux, consistent with the cumulus-
264 valve mechanism. However, we find that this does not prevent the strong response of the
265 Flower Tc state to climate warming, because the response arises from mesoscale circu-
266 lation in the cloud layer. Hence the cumulus-valve mechanism does not stabilize all Tc
267 against climate change.

268 Our simulations cover a limited range of conditions and Flower Tc state evolutions.
269 More comprehensive studies are needed to assess the prevalence of the phenomenon and
270 to quantify its role for cloud feedbacks on a global scale. Such studies could reveal a role
271 of mesoscale circulation and organization for cloud-climate feedbacks in the Gravel and
272 Fish Tc states, and in the Tc aggregates that resulted in the discovery of mesoscale mois-
273 ture aggregation as an organizing mechanism of Tc clouds (Bretherton & Blossey, 2017).
274 A diverse response of Tc to climate change and a role of cloud state organization would
275 present a more complex challenge in representing Tc feedbacks in climate simulations.
276 Climate models do not differentiate between individual Tc states, and therefore do not
277 capture cloud feedback associated with the expected change in their occurrence as the
278 Earth warms (Bony et al., 2020; Schulz et al., 2021). Climate models also do not resolve
279 the response and feedback of the individual Tc states to climate change, including a re-
280 sponse of mesoscale circulation to stronger down-welling LW radiation at future GHG
281 levels. The issue is compounded because observational studies (Denby, 2020; Scott et
282 al., 2020; Cesana & Del Genio, 2021; Myers et al., 2021; Schulz et al., 2021) do not de-
283 tect the effect of down-welling LW from increasing GHG on clouds and their spatial or-
284 ganization, and do not constrain the associated cloud-climate feedbacks.

285 This highlights the need for better understanding of cloud organization for Tc feed-
286 backs and improved approaches for Tc representation in climate models, in order to re-
287 duce uncertainty of climate projections. High resolution simulations and large-eddy sim-
288 ulations (LES) can provide the physical understanding of the various Tc states and their
289 behavior in response to climate change, and help formulate improved representations of
290 Tc in climate models that account for cloud organization. Still, constraints of Tc fee-
291 backs from simulations, which need to connect large scale dynamics, mesoscale organ-

292 ization, boundary layer dynamics, and cloud processes, may remain encumbered by lim-
293 ited resolution, as in the case of climate models, or limited spatial and temporal extent,
294 as in the case of high resolution simulations and LES. The promise of an independent
295 approach to constrain Tc feedbacks might be found in the application of machine learn-
296 ing methods trained on observational data and reanalysis products (Denby, 2020) to cli-
297 mate simulations to identify individual cloud states, in combination with an emulator-
298 based quantification of the cloud radiative effect based on LES (Feingold et al., 2016).
299 Thus, more than one approach to constraining the Tc feedback to climate is emerging
300 on the horizon, not only as an opportunity to improve understanding and quantification
301 of cloud-climate interactions, but also as checks and balances on one another.

302 **Open Research Section**

303 The System for Atmospheric Modeling (SAM, Khairoutdinov & Randall, 2003) is
304 available from <http://rossby.msrc.sunysb.edu/~marat/SAM.html>. The fifth gener-
305 ation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmo-
306 spheric reanalysis (ERA5, Hersbach et al., 2020) is available through the Copernicus Cli-
307 mate Change Service (<https://doi.org/10.24381/cds.bd0915c6>). CESM1(WACCM)
308 model output for the RCP8.5 scenario (National Science Foundation; US Department
309 of Energy; National Center for Atmospheric Research, 2017) is available from [https://](https://catalogue.ceda.ac.uk/uuid/beb9587bd78f4e959869d5c9dbd8a4ce)
310 catalogue.ceda.ac.uk/uuid/beb9587bd78f4e959869d5c9dbd8a4ce. The Hybrid Sin-
311 gle Particle Lagrangian Integrated Trajectory Model (HYSPLIT, Stein et al., 2015) is
312 available from <https://www.arl.noaa.gov/hysplit>. Simulation forcings and results
313 are available at [https://csl.noaa.gov/groups/cs19/datasets/data/cloud_phys/](https://csl.noaa.gov/groups/cs19/datasets/data/cloud_phys/2023a-Kazil-et-al)
314 [2023a-Kazil-et-al](https://csl.noaa.gov/groups/cs19/datasets/data/cloud_phys/2023a-Kazil-et-al).

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Table 1. Absolute change between simulations, and relative change per change in SST from PD to EC, of the 24 h mean of cloud fraction (CF), liquid water path (LWP), and short-wave cloud radiative effect (SWCRE). The final row gives the change from simulation CTL to P2S of cumulus clouds under idealized climate change in the multimodel ensemble of Blossey et al. (2013).

	ΔCF	ΔLWP	ΔSWCRE	$\frac{\Delta\text{CF}}{\text{CF}\Delta\text{SST}}$	$\frac{\Delta\text{LWP}}{\text{LWP}\Delta\text{SST}}$	$\frac{\Delta\text{SWCRE}}{\text{SWCRE}\Delta\text{SST}}$
	(g m^{-2})	(W m^{-2})	($\% \text{ K}^{-1}$)	($\% \text{ K}^{-1}$)	($\% \text{ K}^{-1}$)	($\% \text{ K}^{-1}$)
$\mathcal{F}_{\text{PD}} \rightarrow \mathcal{F}_{\text{EC}}^-$	-0.002	-0.8	0.5			
$\mathcal{F}_{\text{EC}}^- \rightarrow \mathcal{F}_{\text{EC}}$	-0.004	-1.9	0.7			
$\mathcal{F}_{\text{PD}} \rightarrow \mathcal{F}_{\text{EC}}$	-0.007	-2.7	1.3	-4.3	-12.8	-4.7
$\mathcal{S}_{\text{PD}} \rightarrow \mathcal{S}_{\text{EC}}$	-0.004	-1.0	0.4	-2.7	-6.3	-2.2
$\mathcal{F}_{\text{PD}}^* \rightarrow \mathcal{F}_{\text{EC}}^*$	-0.009	-4.2	1.7	-5.4	-12.2	-6.1
$\mathcal{F}_{\text{PD}}^{**} \rightarrow \mathcal{F}_{\text{EC}}^{**}$	-0.011	-5.7	3.1	-6.2	-13.5	-9.9
CTL \rightarrow PS2	-0.011	0.6	1.1	-3.1	1.0	-2.5

Figure 1. Trade cumulus evolution in the simulations: (a) \mathcal{F}_{PD} , (b) $\mathcal{F}_{\text{EC}}^-$, (c) \mathcal{F}_{EC} , (d) \mathcal{S}_{PD} , and (e) \mathcal{S}_{EC} . Sunrise (first column) is at 09h47m UTC (fractional day of year $d = 32.41$), sunset (last column) at 21h18m UTC (fractional day of year $d = 32.89$).

Figure 2. Time series from the simulation \mathcal{F}_{PD} (blue), $\mathcal{F}_{\text{EC}}^-$ (cyan) and \mathcal{F}_{EC} (red), \mathcal{S}_{PD} (light green), and \mathcal{S}_{EC} (dark green) of (a) cloud fraction, (b) liquid water path, and (c) short-wave cloud radiative effect (shading indicates nighttime), and spectra at 18h00m UTC ($d = 32.75$) of (d) TKE production due to buoyancy in the cumulus layer, (e) variance of water vapor in the cumulus layer, and (f) variance of the short-wave cloud radiative effect.

Figure 3. Change from simulation \mathcal{F}_{PD} to $\mathcal{F}_{\text{EC}}^-$ (a-d) and from $\mathcal{F}_{\text{EC}}^-$ to \mathcal{F}_{EC} (e-h) in total water flux (a, e), liquid water (b, f), TKE production due to buoyancy (c, g), and radiative heating (d, h). The base of active cloud convection (dashed, SI) and the inversion (solid) from $\mathcal{F}_{\text{EC}}^-$ (a-d) and \mathcal{F}_{EC} (e-h) are shown. An open triangle marks sunrise, a solid triangle sunset.

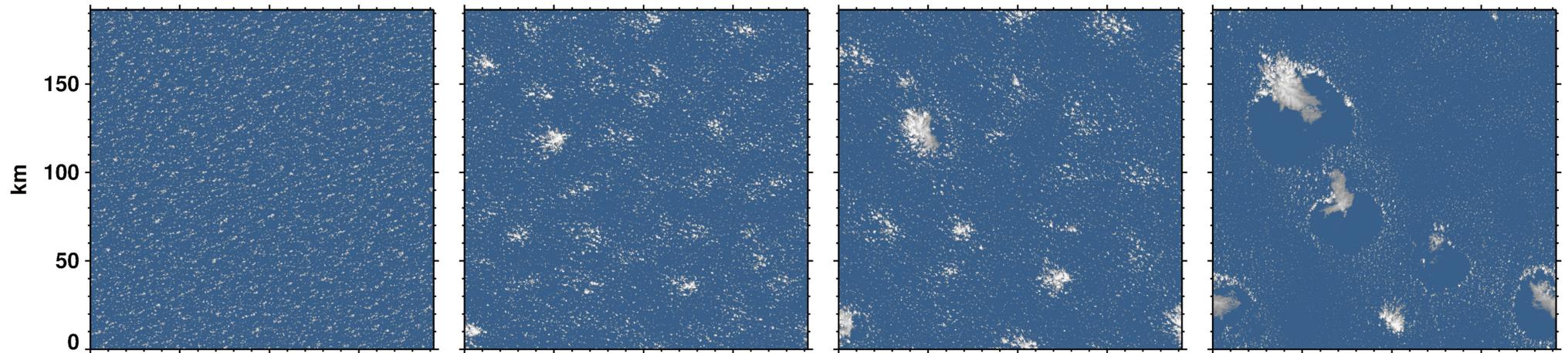
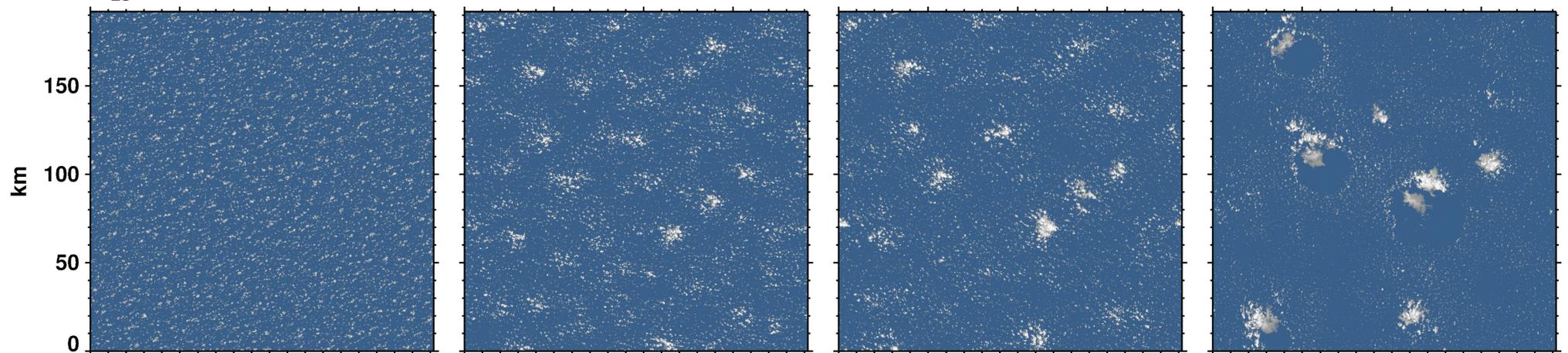
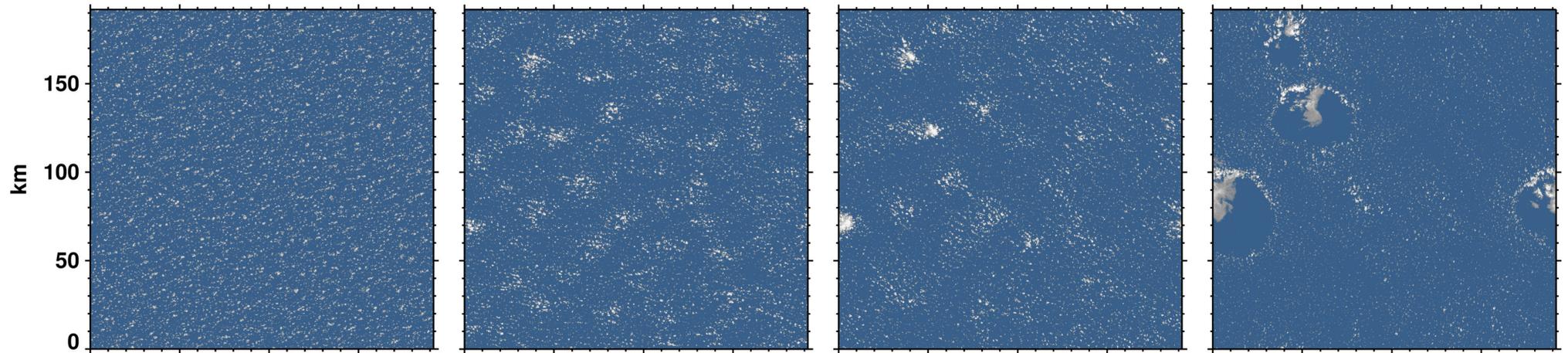
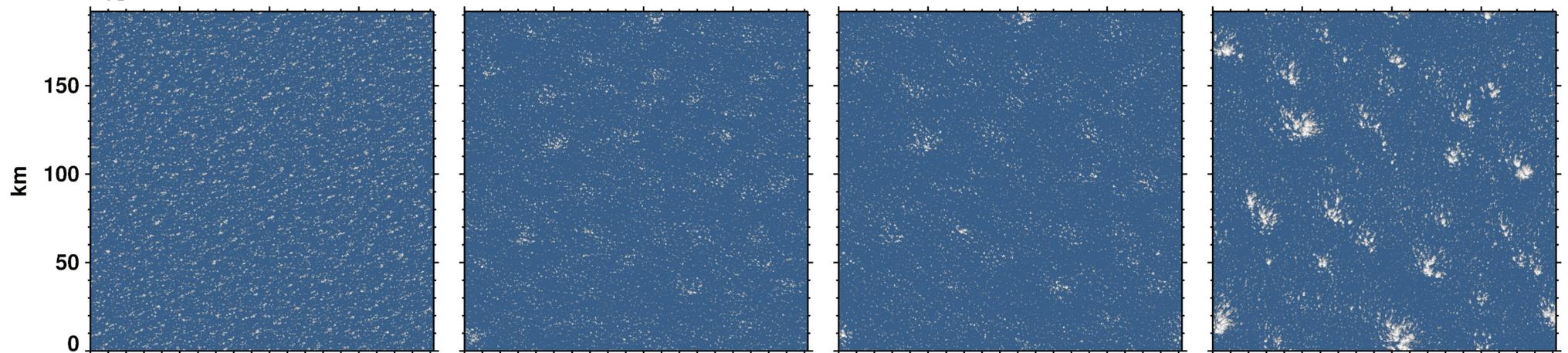
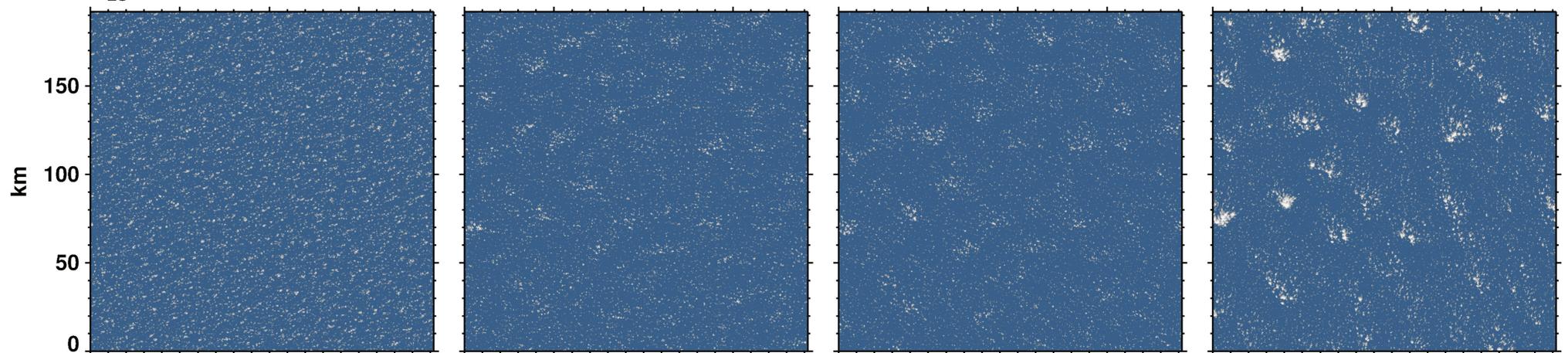
Figure 1.

09h47m UTC (d = 32.41)

16h00m UTC (d = 32.67)

18h00m UTC (d = 32.75)

21h18m UTC (d = 32.89)

a F_{PD} **b** F_{EC} **c** F_{EC} **d** S_{PD} **e** S_{EC} 

0 50 100 150 km 0 50 100 150 km 0 50 100 150 km 0 50 100 150 km



0 0.1 0.5 1 2 4 6 8 10 12 15 20 25 30 40 50 60 80 100

Optical depth

Figure 2.

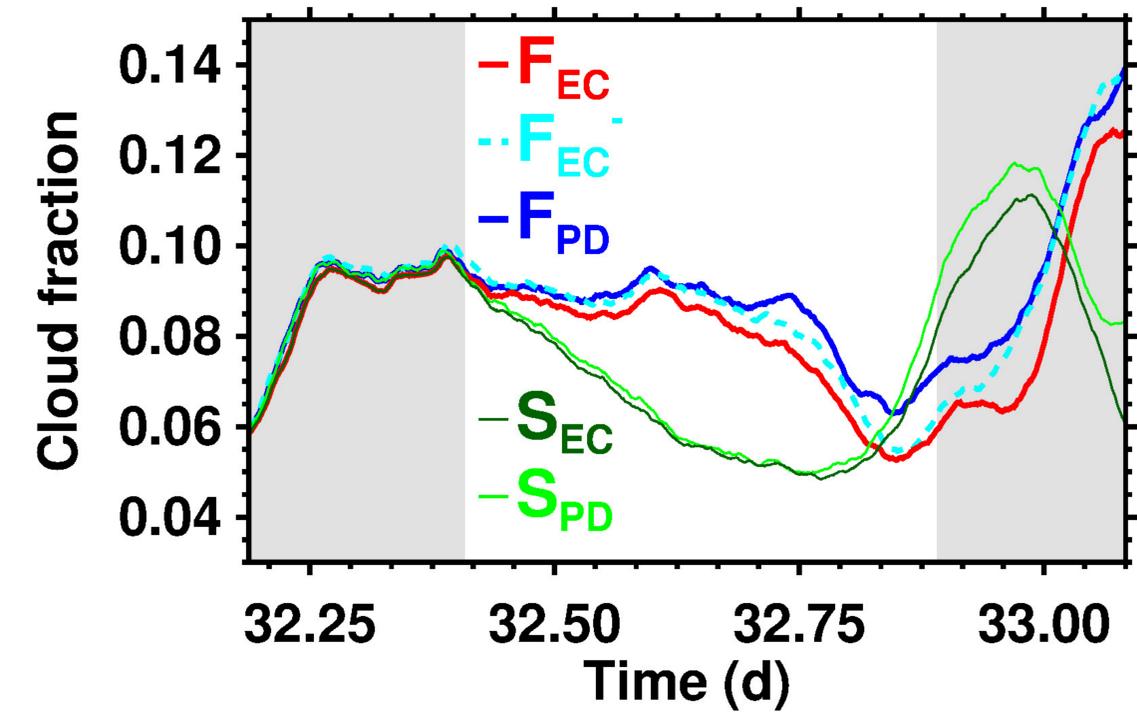
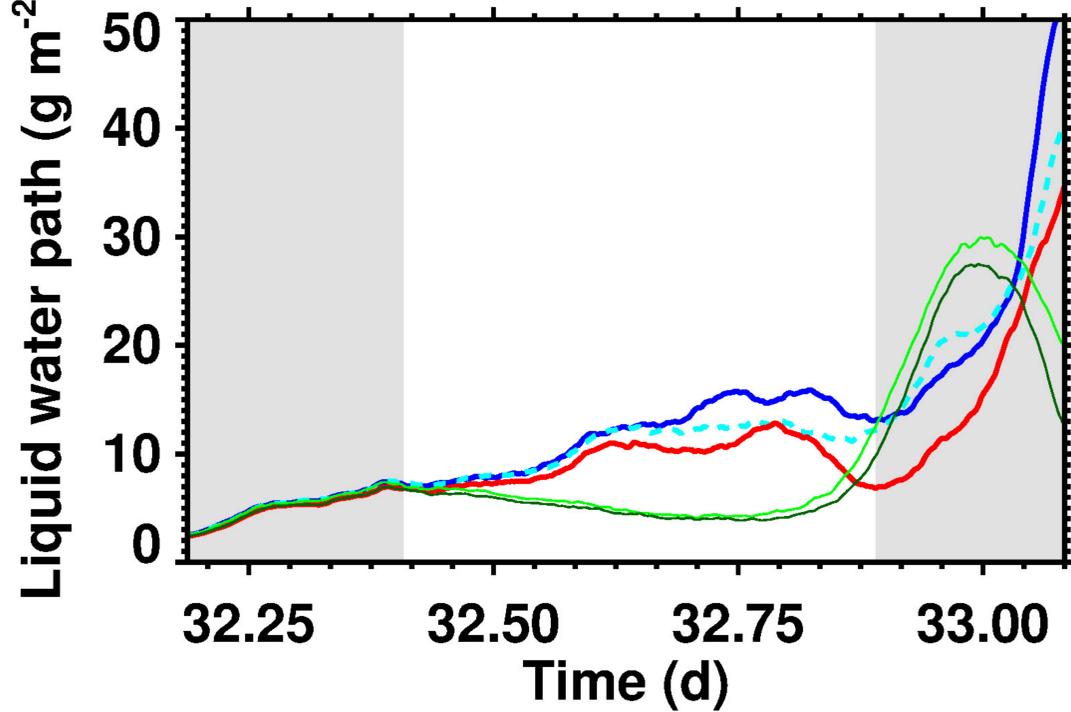
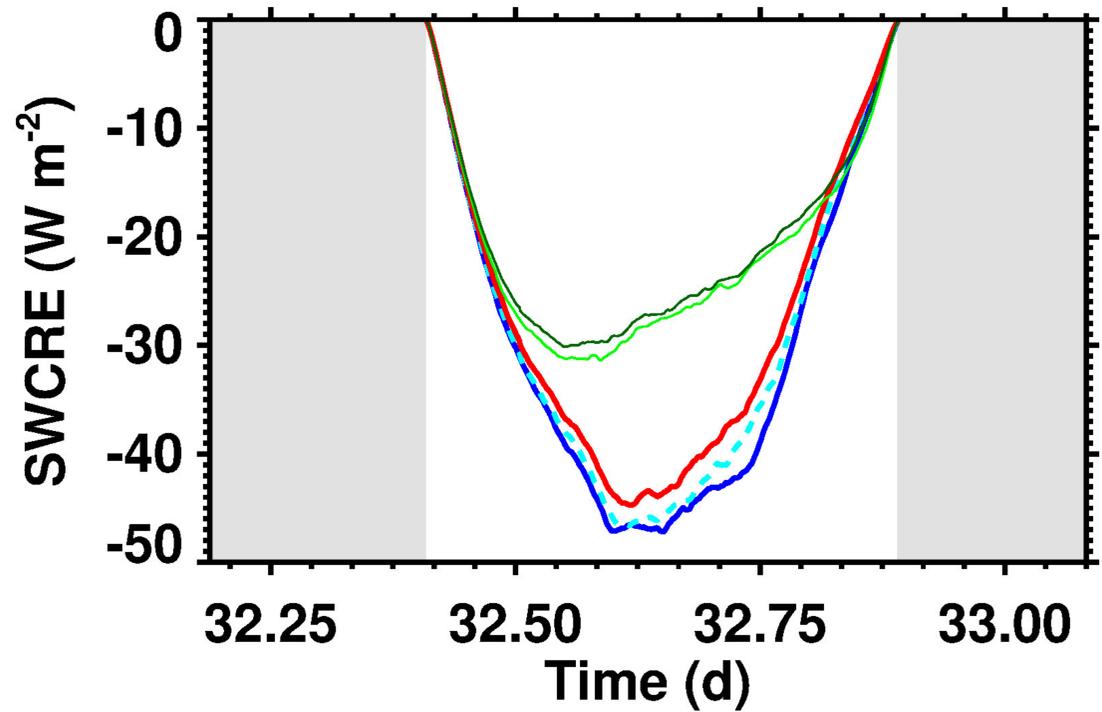
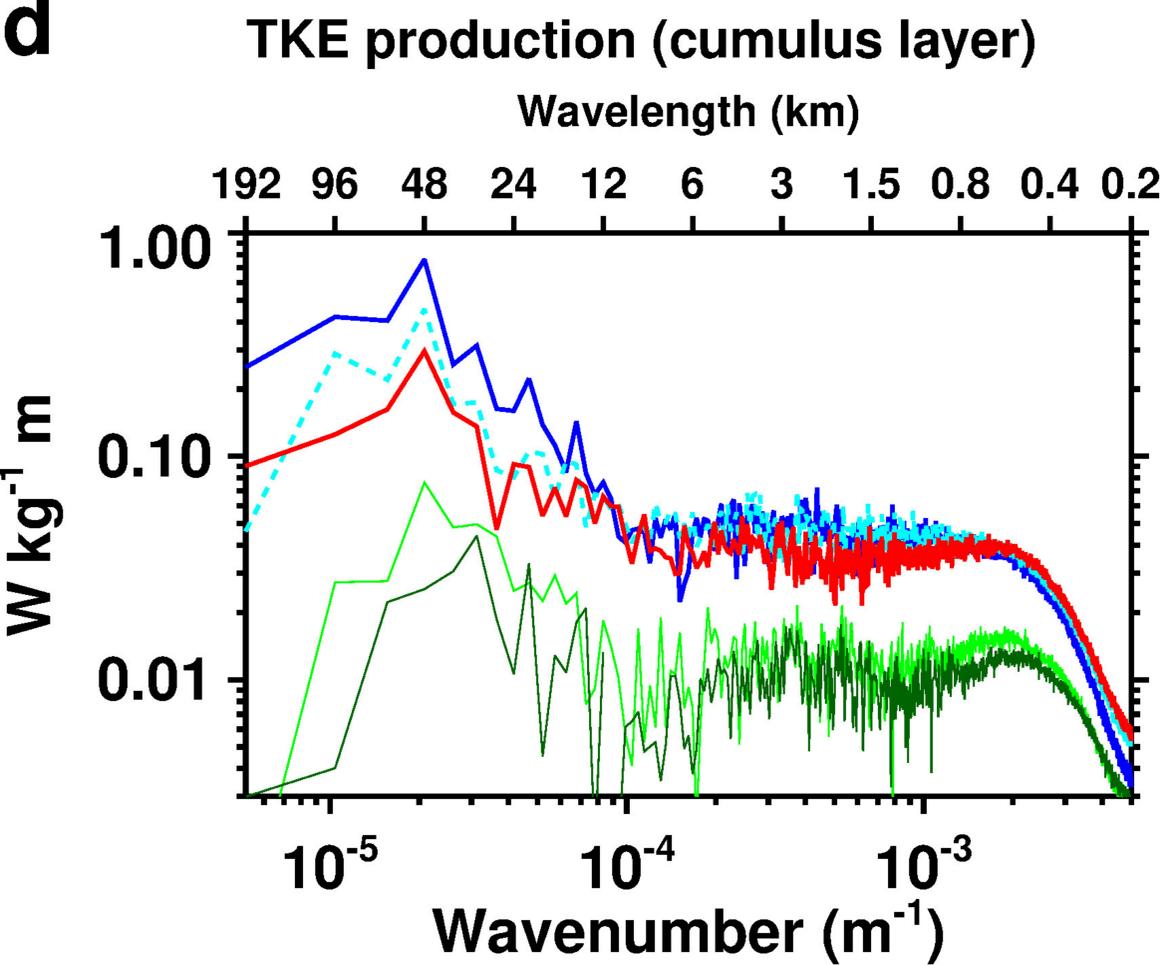
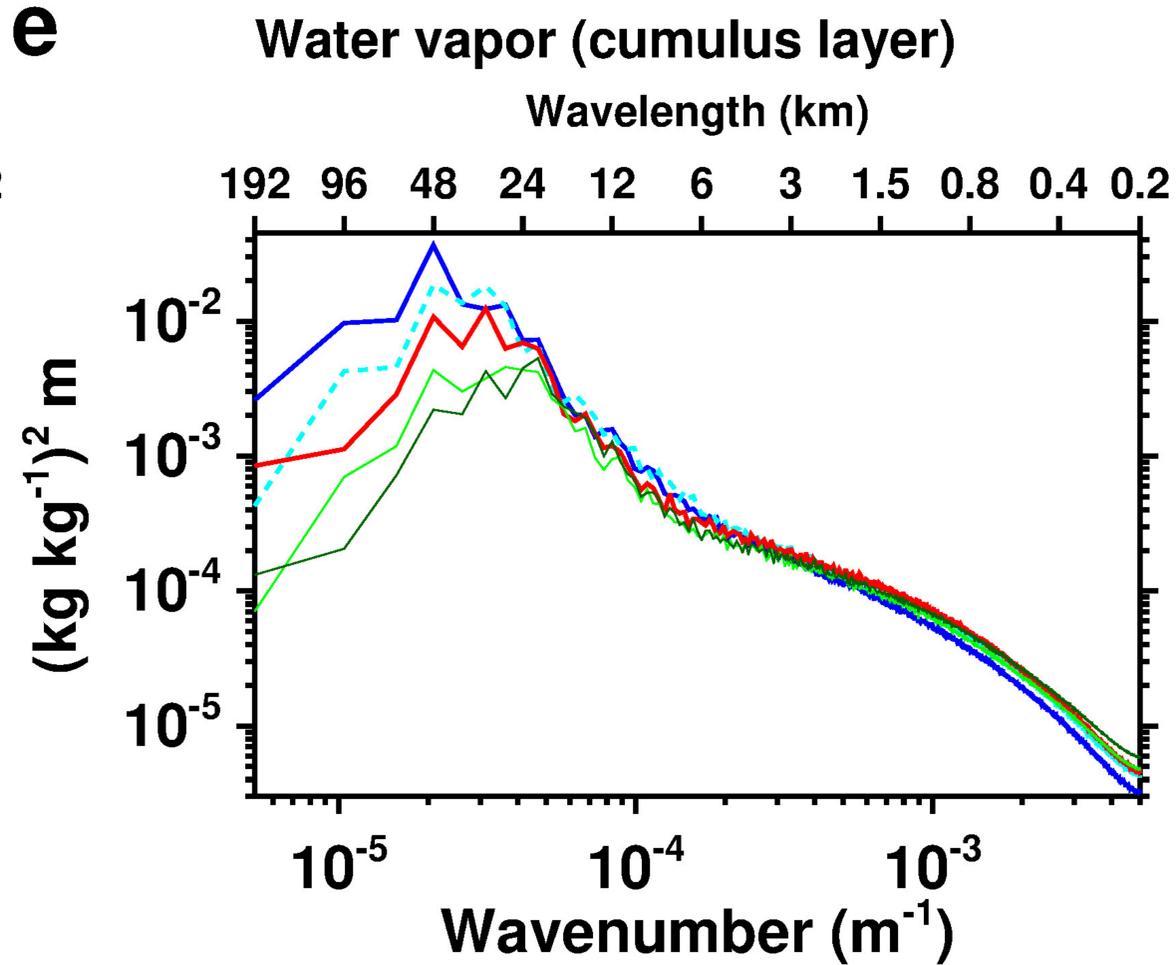
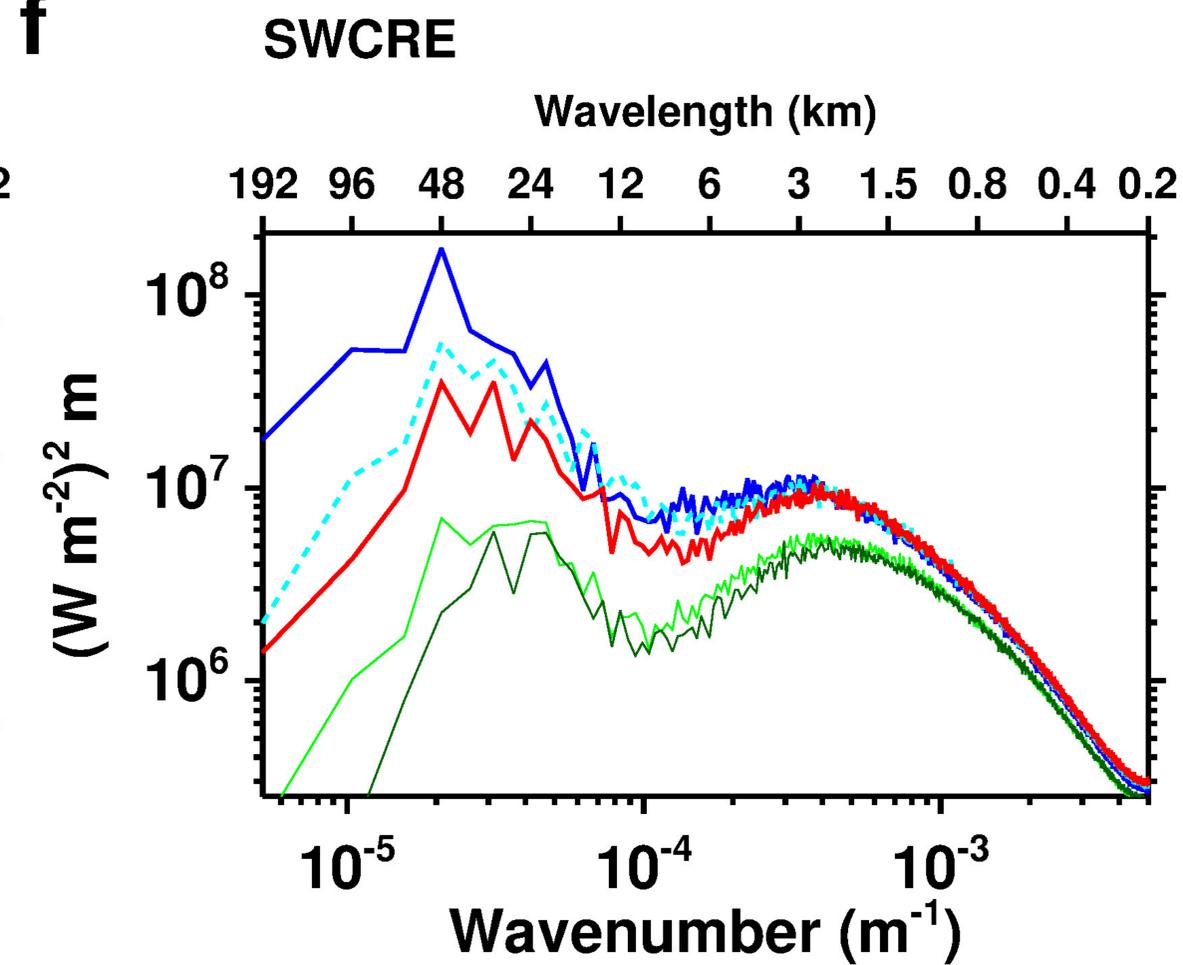
a**b****c****d****e****f**

Figure 3.

