# Climatology of marine shallow-cloud-top radiative cooling

Youtong Zheng<sup>1</sup>, Yannian Zhu<sup>2</sup>, Daniel Rosenfeld<sup>3</sup>, and Zhanqing Li<sup>4</sup>

<sup>1</sup>University of Maryland, College Park <sup>2</sup>School of Atmospheric Sciences, Nanjing University <sup>3</sup>Hebrew University of Jerusalem <sup>4</sup>UMD/ESSIC

November 23, 2022

#### Abstract

A one-year's worth of global (except poleward of 65  $^{\circ}$  N/S) marine shallow single-layer cloud-top radiative cooling (CTRC) is derived from a radiative transfer model with inputs from the satellite cloud retrievals and reanalysis sounding. The mean cloud-top radiative flux divergence is 61 Wm<sup>-2</sup>, decomposed into the longwave and shortwave components of 73 and -11 W m<sup>-2</sup>, respectively. The CTRC is largely a reflection of free-atmospheric specific humidity distribution: a dry atmosphere enhances CTRC by reducing downward thermal radiation. Consequently, the cooling minimizes in the "wet" tropics and maximizes in the "dry" eastern subtropics. Poleward of 30  $^{\circ}$  N/S, the CTRC decreases slightly due to the colder clouds that emit less effectively. The CTRC exhibits distinctive seasonal cycles with stronger cooling in the winter and has amplitudes of order 10<sup>-2</sup>0 Wm<sup>-2</sup> in stratocumulus-rich regions. The datasets were used to train a machine-learning model that substantially speeds up the retrieval.

# Climatology of marine shallow-cloud-top radiative cooling

2 Youtong Zheng<sup>1,2</sup>, Yannian Zhu<sup>3</sup>, Daniel Rosenfeld<sup>3,4</sup>, and Zhanqing Li<sup>1</sup>

# 3 Affiliations:

- 4 <sup>1</sup>Earth System Science Interdisciplinary Center, University of Maryland, College Park, Maryland,
- 5 20742, USA.
- 6 <sup>2</sup>GFDL/AOS program, Princeton University, Princeton, New Jersey
- <sup>7</sup> <sup>3</sup>Nanjing University, Nanjing, China
- <sup>4</sup>Herew University of Jerusalem, Jerusalem, Israel

9

1

10

- 11 Main points:
- A one-year's worth of global marine shallow single-layer cloud-top radiative cooling
   (CTRC) is derived from satellite and reanalysis data.
- Spatial and seasonal variations of CTRC are largely reflections of changes in freetropospheric humidity.
- A neural network model for the CTRC was trained, which substantially speeds up the retrieval while maintaining good accuracy.
- 18

19

20

21

22

23

24

25

26

27

28

29

30

## 32 Abstract

A one-year's worth of global (except poleward of 65 ° N/S) marine shallow single-layer cloud-top 33 radiative cooling (CTRC) is derived from a radiative transfer model with inputs from the satellite 34 cloud retrievals and reanalysis sounding. The mean cloud-top radiative flux divergence is 61 Wm<sup>-</sup> 35 <sup>2</sup>, decomposed into the longwave and shortwave components of 73 and -11 W m<sup>-2</sup>, respectively. 36 37 The CTRC is largely a reflection of free-atmospheric specific humidity distribution: a dry atmosphere enhances CTRC by reducing downward thermal radiation. Consequently, the cooling 38 minimizes in the "wet" tropics and maximizes in the "dry" eastern subtropics. Poleward of 30 ° 39 N/S, the CTRC decreases slightly due to the colder clouds that emit less effectively. The CTRC 40 exhibits distinctive seasonal cycles with stronger cooling in the winter and has amplitudes of order 41  $10\sim 20$  Wm<sup>-2</sup> in stratocumulus-rich regions. The datasets were used to train a machine-learning 42

43 model that substantially speeds up the retrieval.

44

# 45 Plain Language Summary

Marine low-lying clouds cool the Earth by reflecting incoming sunlight, thus crucially important 46 for the Earth's climate. Marine low clouds cool by emitting thermal radiation. The cooling is 47 known as cloud-top radiative cooling (CTRC). A change in CTRC can influence the properties of 48 marine clouds via many avenues, ranging from altering the vertical motions of the clouds to 49 50 changing the clouds' ability to reflect sunlight. Despite the importance of CTRC to the climate system, its climatological characteristics, namely how it varies with space and time, remain 51 unknown. This work fills this knowledge gap. We generate the product of the CTRC over the 52 global ocean using a novel satellite methodology developed in our previous work. Analyses of the 53 data show that the spatial and temporal distributions of the CTRC are largely reflections of the 54 atmospheric humidity: the drier the atmosphere, the stronger the cooling. As a result, the CTRC 55 56 maximizes in the wet tropics and minimizes in the dry eastern subtropical ocean such as the west of California. We also use the CTRC data to train a machine-learning algorithm that can 57 substantially speed up the calculation of CTRC. 58

59

#### 68 1. Introduction

Marine shallow clouds (MSC) are crucially important to the Earth's climate because they 69 affect both energy and water cycles. MSC cloudiness is dominated by stratocumulus decks 70 sustained by the convection driven by cloud-top radiative cooling (CTRC). An increase in CTRC 71 destabilizes the stratocumulus-topped boundary layer, driving more intense convective circulation 72 that substantially alter the cloud and radiative properties via many avenues (Lilly, 1968; Deardorff, 73 1976; Nicholls, 1984; Austin et al., 1995; Bretherton and Wyant, 1997; Stevens, 2002; Caldwell 74 et al., 2005; Bretherton et al., 2007; Zheng et al., 2016, 2018; Zhou and Bretherton, 2019). These 75 influences make the CTRC a crucial player in understanding the low cloud feedback, a major 76 source of uncertainty for climate projections (Bony and Dufresne, 2005). For example, as the 77 planet warms, the CTRC will weaken due to the enhanced down-welling thermal radiation in a 78 more opaque atmosphere. The reduced CTRC, via weakening the boundary layer convection, thins 79 the stratocumulus decks, leading to positive low cloud feedback. Representations of CTRC in the 80 global climate models (GCMs) are poor because the cooling typically concentrates near the top 81 several tens of meters of the cloud layer, which the GCMs cannot resolve. An improved 82 representation of CTRC in a modern higher-order turbulence closure scheme in GCMs (Larson et 83 al., 2012) can markedly improve the GCM simulations of low clouds (Guo et al., 2019). 84

85 Despite the fundamental importance of CTRC, its observations have been scarce. Typical approaches are direct observations of radiative fluxes from aircraft (Bretherton et al., 2010b) or 86 tethered balloon (Slingo et al., 1982) and indirect calculations with a radiative transfer model 87 (RTM) with inputs from field campaign measurements (Nicholls and Leighton, 1986; Wood, 2005; 88 Ghate et al., 2014; Zheng et al., 2016). The ensuing CTRC data are inherently highly limited in 89 spatial and temporal coverage. Active satellite sensors have been used to estimate the radiative 90 fluxes in the cloudy atmosphere using a radiative transfer model (L'Ecuyer et al., 2008; Haynes et 91 al., 2013), but the vertical resolution is too coarse (240 m) to resolve the CTRC that takes place 92 chiefly near the upper several tens of meters in MSC. A systematic analysis of the CTRC 93 climatology over the global ocean is still lacking. 94

This study aims to fill the knowledge gap of CTRC climatology. This work builds upon our 95 previous work by Zheng et al. (2019) who proposed a new remote sensing approach for retrieving 96 the CTRC with passive satellite data. This new methodology calculates the CTRC using an RTM 97 with inputs from satellite-derived cloud properties and reanalysis sounding corrected by satellite-98 retrieved cloud-top temperature. Here we used the method to generate a full year of MSC CTRC 99 product from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the National 100 Aeronautics and Space Administration Aqua and Terra satellites. The data were used in two ways: 101 studying the CTRC climatology and training a machine learning model to speed up the retrieval. 102

103 The paper is organized as follows: Section 2 introduces satellite data and the algorithm of 104 CTRC retrieval. Section 3 provides a theoretical background of the environmental dependence of 105 CTRC, paving the ground for the subsequent analyses. Section 4 analyzes the climatology of 106 CTRC in terms of spatial and temporal variabilities. Section 5 shows the machine learning of 107 CTRC and its evaluations, followed by the conclusion in Section 6.

108

## 110 2. Data and Methodology

# 111 **2.1.Data**

Cloud properties are obtained from the MODIS Terra/Aqua Level-1 (MxD06) and Level-2 112 (MxD06 L2) cloud product collection 6.1 (Platnick et al., 2015) over the global ocean in 2014. 113 Each MODIS swath was divided into multiple 110 by 110 km scenes ( $\sim 1^{\circ}$  by  $1^{\circ}$  at the equator). 114 The criteria for scene selection are the same as our previous works (Rosenfeld et al., 2019; Cao et 115 al., 2021). Scenes with single-layer liquid water clouds with cloud geometrical thickness thinner 116 than 800 m were selected. In each scene, the retrieved cloud optical depth, cloud droplet effective 117 radius, and cloud top temperature are averaged over cloudy pixels. Scenes poleward of 65 ° N or 118 S are excluded to avoid the known problems of cloud retrievals for high solar zenith angle 119 (Grosvenor and Wood, 2014). A total of ~ 6 million valid scenes were collected. 120

121 Vertical profiles of temperature and humidity are obtained from the National Centers for 122 Environmental Prediction reanalysis data (Kalnay et al., 1996). The sea surface temperature  $(T_s)$ 123 data are from the National Oceanic and Atmospheric Administration (Reynolds et al., 2007). The 124 reanalysis and  $T_s$  data are interpolated into the geological center and time of each satellite scene.

### 125 **2.2.Retrieval algorithm**

We provide a high-level introduction of this algorithm to elucidate the fundamental concepts 126 (Zheng et al., 2019). The retrieval relies on an RTM (see text S1) with inputs from satellite-127 128 retrieved cloud parameters in combination with the reanalysis sounding. The key merit of this algorithm is the revision of the original reanalysis profiles. It is well known that reanalysis data 129 fail to capture the sharp inversion layer topping MSC. This causes large errors in the simulated 130 radiative fluxes across the cloud top that are particularly sensitive to temperature inversion. We 131 tackled this challenge by revising the reanalysis sounding in a physically coherent way. We use 132 the satellite-retrieved cloud-top temperature to reconstruct the inversion-layer sounding by 133 134 assuming a 100% relative humidity in the cloud layer (see Zheng et al., 2019 for detail).

135 With inputs from the revised sounding and satellite-retrieved cloud parameters, the radiative 136 transfer model outputs the vertical profiles of radiative fluxes. We quantify the CTRC using the 137 divergence of net radiative flux across the cloud top, denoted as  $\Delta F$ . The upper boundary for  $\Delta F$ 138 is 100 m above the cloud top and the lower boundary is the height of the grid in the cloud layer 139 where the radiative cooling shifts to radiative warming as one goes down to the cloud base (there 140 is typically radiative warming layer near the cloud base). The  $\Delta F$  has longwave (LW) and 141 shortwave (SW) components ( $\Delta F_{LW}$  and  $\Delta F_{SW}$ ).

Because Terra/Aqua satellites have fixed overpasses time of approximately 1030 and 1330 h 142 local solar time, the simulated SW fluxes are biased toward the local time of observations when 143 the incoming solar insolation is substantially larger than the daily means. To mitigate such diurnal 144 bias, we follow L'Ecuyer et al. (2008) to correct the instantaneous SW flux by multiplying it by a 145 correcting factor defined as the ratio of the average top-of-atmosphere insolation for the scene's 146 latitude and Julian day to the instantaneous top-of-atmosphere insolation. Figure S1 shows the 147 probability density function (PDF) of the instantaneous  $\Delta F_{SW}$  (red) and corrected daily mean  $\Delta F_{SW}$ 148 (green). The daily mean  $\Delta F_{SW}$  is considerably smaller and more narrowly distributed than the 149 instantaneous  $\Delta F_{SW}$ , consistent with expectation. In the remainder of the manuscript, the  $\Delta F_{SW}$ 150 refers to the daily mean  $\Delta F_{SW}$  unless otherwise noted. 151

Note that the  $\Delta F$  represents cooling averaged over cloudy pixels of a satellite scene and there is no contribution from the cloud-free area. In other words, the cloudiness does not directly influence the  $\Delta F$ . This is important to keep in mind because some studies refer to the CTRC as the average of all pixels, both clear and cloudy (Bretherton et al., 2010a; Vial et al., 2016). Such an all-sky CTRC is not our focus although it will be discussed in Section 4.3.

Aerosols are not included in the calculations because of the lack of aerosol vertical information from passive sensors. We consider it an insignificant issue, motivated by previous research showing the limited radiative role of aerosols compared with the influence of atmospheric thermodynamics (Haynes et al., 2013; Henderson et al., 2013).

#### 161 **3.** Conceptual background: what determines the CTRC?

162 To assist with interpreting the climatology analysis, we briefly discuss what drives the 163 changes in  $\Delta F_{SW}$  and  $\Delta F_{LW}$  using simple illustrative formulas. The  $\Delta F_{LW}$  for a single-layer cloud 164 can be approximated as:

165 
$$\Delta F_{LW} \approx \varepsilon_c \sigma T_c^4 - \varepsilon_a \sigma T_a^4, \quad (1)$$

166 where  $\varepsilon$ ,  $\sigma$ , and T are the emissivity, the Stefan-Boltzmann constant, and emission temperature, 167 respectively. The subscripts "c" and "a" stand for the cloud and the above-cloud atmosphere, 168 respectively. The  $\Delta F_{LW}$  is typically positive, meaning a divergence of radiative flux and thus a 169 cooling. Given the small variability of  $T_c/T_s$  (Figure S2) due to low altitudes of MSC, Eq. (1) can 170 be simplified to:

171 
$$\Delta F_{LW} \approx \sigma T_s^4 \times (\varepsilon_c - \varepsilon_a \frac{T_a^4}{T_s^4}), \quad (2)$$

172 For SW, we use the Schwarzschild equation to derive an illustrative formula for  $\Delta F_{SW}$ :

173 
$$\Delta F_{SW} \approx S \times e^{-\tau_a} \times (1 - e^{-\tau_c}), \quad (3)$$

174 where *S* stands for the incoming SW radiative flux at the top of the atmosphere, which is negative. 175  $\tau$  is a bulk measure of an atmospheric layer's ability to absorb SW energy (i.e. SW optical depth). 176 In a clear atmosphere, its primary contribution is primarily from the water vapor whereas in a 177 cloudy layer both cloud droplets and water vapor contribute (Li and Moreau, 1996). Note that the 178 equation is a simplified formula for an illustrative purpose only.

Equations 2 and 3 show several important CTRC-controlling factors. The first is the optical 179 thickness of the free atmosphere. For LW, an optically thicker free atmosphere enhances the 180 emissivity ( $\varepsilon_a$ ), thereby increasing the downward radiative flux. This decreases the cooling. In the 181 atmosphere, water vapor is the most important absorber so a more humid atmosphere favors 182 weaker cloud-top LW cooling. For SW, a humid free atmosphere absorbs more incoming solar 183 radiation (a smaller  $e^{-c\tau_a}$ ), leaving less energy for the cloud to absorb (Davies et al., 1984). So 184 humid atmosphere weakens cloud absorption of SW radiation. This compensates for the reduced 185 LW cooling. 186

The second CTRC-controlling factor is the cloud liquid water path (LWP). In the LW, the  $\varepsilon_c$ 187 increases with the LWP (Pinnick et al., 1979) so that the LW cooling is larger for thicker clouds 188 (Zheng et al., 2016; Zheng et al., 2019). The degree of dependence is large for thin clouds with 189 LWP < 50 g m<sup>-3</sup> and saturates afterward (Kazil et al., 2017). In the SW, the solar absorption also 190 increases with the LWP (Stephens, 1978). A large LWP typically corresponds to a more humid 191 layer, thereby enhancing the solar absorption due to the high concentration of water vapor. As a 192 result, the  $\Delta F_{SW}$  must increase with LWP. This, again, leads to a cancelation for the net CTRC. 193 The cloud droplet effective radius also alters CTRC but its contribution is much smaller (Zheng et 194 195 al., 2019).

196 Another two factors are the  $\sigma T_s^4$  and *S*. We discuss them together because they are highly 197 correlated in nature. Climatologically speaking, more solar insolation corresponds to warmer sea 198 surfaces to maintain radiative balance. This holds in both spatial (zonal-mean meridional 199 distribution) and temporal (seasonal cycle) senses.

In summary, to the first order, the CTRC variation can be explained from four factors: the free-atmospheric humidity, LWP,  $\sigma T_s^4$  and S. The climatological co-variation of the last two factors can reduce the number of influential factors to three.

# 203 **4. Result**

The CTRC product shows that the  $\Delta F$ ,  $\Delta F_{LW}$ , and  $\Delta F_{SW}$  have means of 61 W m<sup>-2</sup>, 73 W m<sup>-2</sup>, and -11 W m<sup>-2</sup>, respectively (Fig. S1). The  $\Delta F$  PDF is similar to that of  $\Delta F_{LW}$ , but with weaker cooling and less variability due to the compensation by  $\Delta F_{SW}$ . Below we analyze the CTRC climatology in terms of spatial (Sect. 4.1) and temporal (Sect. 4.2) variations.

208 4.1. Annual mean

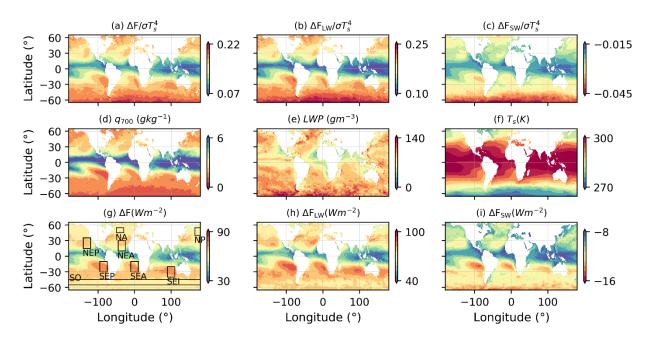
Figure 1 a~c show the annual-mean  $\Delta F$  scaled by the  $\sigma T_s^4$  and its LW and SW components. The scaling temporarily frees us from considering the roles of  $T_s$  and, to a great extent, *S*. The  $\sigma T_s^4$ scaled  $\Delta F$ ,  $\Delta F_{LW}$ , and  $\Delta F_{SW}$  share a similar spatial pattern: a strong latitudinal dependence with the weakest cooling (or heating) in the tropics and the strongest in the extra-tropics, regional peaks in the eastern subtropics adjacent to the major continents, and hemispheric asymmetry with stronger cooling/heating in the Southern Hemisphere.

Such a spatial pattern can be well explained by the free atmospheric humidity. The specific humidity at 700 hPa ( $q_{700}$ ) (Fig. 1d) highly resembles the  $\sigma T_s^4$ -scaled CTRC variables in terms of the spatial pattern. This is consistent with the theoretical argument that drier free atmosphere enhances the cloud-top LW cooling by weakening the down-welling thermal radiation (Fig. 1b) and strengthens the cloud-top SW heating by increasing the exposure of clouds to solar insolation (Fig. 1c). The reduced SW heating compensates for the LW cooling, but because the magnitude of the  $\Delta F_{SW}$  is considerably smaller than the  $\Delta F_{LW}$ , the net effect,  $\Delta F$ , largely follows the  $\Delta F_{LW}$ .

The LWP contributes little. Over most regions, the climatological LWP is large enough ( > 50 gm<sup>-3</sup>) that the sensitivity of  $\Delta F_{LW}$  to the LWP already saturates (Zheng et al., 2016; Kazil et al., 2017). The most illustrative example is the tropical eastern Pacific Ocean where there is a band of high LWP. The local LWP peak is caused by the strong convective activities that also moisten the free atmosphere, leading to large  $q_{700}$ . The two factors oppositely change the  $\Delta F$ . The pattern of

227  $\Delta F/\sigma T_s^4$  and its components still follows the  $q_{700}$  whose influences dominate over the LWP. There 228 are some footprints of LWP on the local variability of  $\Delta F_{SW}/\sigma T_s^4$  such as the scattered blobs and 229 bands of red colors in the southern part of the Southern Oceans, but the overall spatial pattern of

230 the scaled  $\Delta F / \sigma T_s^4$  is a reflection of the free-tropospheric humidity.



231

Figure 1: Global distribution of annually-averaged cloud-top radiative cooling scaled by  $\sigma T_s^4$  (a), its LW (b) and SW components (c), specific humidity at 700 hPa (d), liquid water path (e), sea surface temperature (f), and cloud-top radiative cooling (g) and its LW (h) and SW components (i). In (g), black rectangles mark regions with persistent low clouds and the locations are adopted from Klein and Hartmann (1993), with slight modifications of limiting regions within 55 °N/S to avoid seasonal sampling bias.

Having known the ability of free-tropospheric humidity in explaining the  $\Delta F/\sigma T_s^4$ , we now 238 look at the  $\Delta F$  (bottom panel of Figure 1). The pattern is overall similar to the  $\Delta F/\sigma T_s^4$  in the 239 tropical regions where the variation of  $T_s$  is not large enough to alter the  $\Delta F$  feature. The influence 240 of  $\sigma T_s^4$  is most distinctive in the extratropical regions where the low solar zenith angle and the cold 241 sea surface considerably weaken the SW heating and LW cooling, respectively, despite the bands 242 243 of maximums in the southern flank of the Southern Ocean likely due to the large LWP. As a result, the peaks of  $\Delta F$  no longer concentrate in the extratropical oceans where the  $q_{700}$  is lowest but locate 244 in the eastern subtropical basins where both the dry free atmosphere and the moderate sea surface 245 favor the strong LW cooling. 246

The roles of  $q_{700}$  and  $\sigma T_s^4$  can be more clearly seen from the zonal-mean meridional distributions (Fig. 2). The annual-mean scaled CTRC (Fig. 2b) monotonously increases with the latitude, consistent with the  $q_{700}$  variation (Fig. 2c). Without the scaling of  $\sigma T_s^4$ , the CTRC starts to weaken poleward of ~30 ° N or S (Fig. 2a) due to the cold temperature. This leads to local maximums of  $\Delta F$  in ~ 30 ° N or S where the downward branches of the Hadley circulation generate a very dry atmosphere and thus enhance LW cooling.

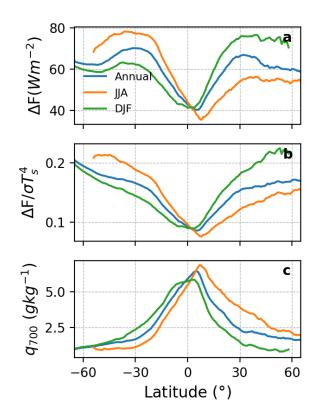


Figure 2: Zonal-mean meridional variations of cloud-top radiative cooling (a), cloud-top radiative cooling scaled by  $\sigma T_s^4$  (b), and specific humidity at 700 hPa (c) for the annual mean (blue) and boreal summer (orange) and winter months (green).

258

259 4.2. Seasonal cycle

The seasonal cycle manifests as the change in atmospheric temperature. The atmospheric 260 temperature influences the  $\Delta F$  both directly (via  $\sigma T_s^4$ ) and indirectly (via  $q_{700}$  under the constraint 261 of Clausius-Clapeyron physics), with the former opposing the latter. The vapor effect dominates, 262 suggested by Figure 2. The  $\Delta F$  is stronger in the winter because of the low specific humidity 263 (favoring the strong cooling) despite the lower temperature (not favoring strong cooling). The 264 determinant control of atmospheric humidity is more clearly seen by the seasonally varying  $\Delta F$ 265 (and the scaled  $\Delta F$ ) being in phase with the  $q_{700}$  (Fig. 2c), both shifting with the seasonal movement 266 of the solar insolation. 267

We further look at specific regions with frequent occurrence of stratocumulus decks: 268 Northeast pacific (NEP), Northeast Atlantic (NEA), North Pacific (NP), North Atlantic (NA), 269 Southeast Pacific (SEP), Southeast Atlantic (SEA), Southeast Indian Ocean (SEI), and Southern 270 Ocean (SO). The locations of these regions are marked by rectangles in Figure 1g. Figure 3 shows 271 the seasonal cycles of  $\Delta F$ , along with the specific humidity profiles in boreal summer (June, July, 272 and August) and winter (December, January, and February), for these regions. All regions show 273 distinctive seasonable cycles with stronger cooling in the winter when the atmosphere is drier. The 274 magnitudes are smallest over the subtropical Pacific oceans (NEP, 10 Wm<sup>-2</sup>, and SEP, 11 Wm<sup>-2</sup>) 275

and largest over northern mid-latitudes (NP, 20 Wm<sup>-2</sup>, and NA, 22 Wm<sup>-2</sup>). There are two reasons 276 for the larger amplitudes in the northern mid-latitudes. First, the atmospheric temperature and thus 277 q experience more distinctive seasonal cycles in the mid-latitudes than the subtropics. Second, the 278 279 response of LW cooling to the humidity of the overlying atmosphere is non-linear. The increase of the CTRC with the atmospheric desiccation is more rapid in a dry atmosphere than in a humid 280 atmosphere (Zheng, 2019). The mid-latitudes are drier than the subtropics. Note that the cloud-top 281 height is another influential factor for the CTRC because for a given humidity profile a higher 282 cloud intrudes into a drier atmospheric layer, increasing the exposure of the cloud to the cold space, 283 which enhances the cooling. In the northern mid-latitudes, cloud tops are higher in the summer 284 due to the stronger convection propelled by warmer sea surface (Fig. 3d and e). This enhances the 285 summertime CTRC, somewhat damping the humidity-driven seasonal cycle. 286

Interestingly, the SO experiences a markedly smaller degree of seasonal cycle (15 Wm<sup>-2</sup>) 287 than its counterparts in the northern hemisphere (NA and NP). The moisture profiles of SO (Fig. 288 3i) show only a slight increase in the moisture in the austral summer. This seems consistent with 289 previous studies documenting a lack of seasonal cycle for SO MSC properties (Huang et al., 2012; 290 Muhlbauer et al., 2014). Note that samples are selected for the single-layer MSC only. In mid-291 latitudes, such a cloud regime typically occurs in the colder section of mid-latitude cyclones, 292 causing a sampling bias toward these regions. This sampling bias may be responsible for the lack 293 of seasonal variation. To confirm this idea, needed is investigating the complex coupling between 294 the low clouds, atmospheric thermodynamics, and synoptic dynamics, which is beyond the scope 295 296 of this study.

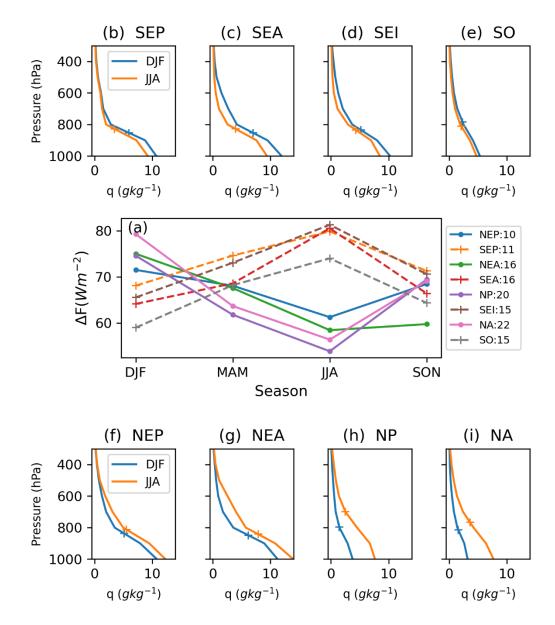




Figure 3: Seasonal cycle of cloud-top radiative cooling for selected regions marked in Fig. 1g
(a). The numbers shown in the legend are the amplitudes of the seasonal cycle. (b)~(i) show the
specific humidity profiles of the boreal summer and winter months for the eight selected regions.
The plus symbols mark the cloud tops.

#### 303 4.3. Discussion: relationship to stratocumulus cloudiness

The scaled  $\Delta F$  spatial distribution closely resembles that of the cloudiness of marine stratocumulus (Fig. 4a in Wood 2012): the cloudiness peaks in the eastern subtropics and midlatitudes, and has minimums in the tropics and western sides of the major ocean basins, and there is a hemispheric asymmetry with greater cloudiness in the southern hemisphere. One might take this resemblance for granted because the convective circulation in the stratocumulus is primarily

driven by the CTRC. Without sufficiently strong CTRC, the stratocumulus decks cannot last long. 309 310 Here we explain the resemblance from another perspective, with a focus on the environmental dependences of the two factors. Stratocumuli typically occur in subsiding atmospheres (Wood, 311 2012). On one hand, the subsidence helps maintain the shallowness of the cloud-topped boundary 312 layer, sustaining the cloud-surface coupling that feeds moisture from the sea surface to the clouds. 313 On the other hand, the subsiding portion of a region typically corresponds to the cold surface (the 314 physics of thermally driven circulation). Cold water favors overcast stratocumuli in two ways. 315 First, the more stable lower troposphere associated with the cold water helps sustain cloudiness 316 via trapping water vapor within the boundary layer (Klein and Hartmann, 1993; Wood and 317 Bretherton, 2006). Second, the weak surface fluxes associated with the cold water prevent the 318 surface-heating-driven convection that breaks the stratocumulus decks (Wyant et al., 1997; 319 Stevens et al., 1998). Both factors (subsidence and coldness) cause strong CTRC. The subsidence 320 dries out the free atmosphere above the cloud top, enhancing CTRC. The cold temperature drops 321 the free atmospheric specific humidity via Clausius-Clapeyron relationship, again strengthening 322 the CTRC. In a nutshell, environments favoring the occurrence of overcast stratocumulus decks 323 also favor strong CTRC. 324

The rough correspondence between CTRC and MSC cloudiness can be used to explain the spatial pattern of all-sky CTRC (Fig. S3), computed as the multiplication of the two. There is a substantial contrast between the eastern subtropics and the tropics. The all-sky CTRC in eastern subtropics and mid-latitudes remain as large as > 50 Wm<sup>-2</sup> due to the large cloud coverage (annual mean of 40 ~ 60%) whereas tropical oceans have all-sky CTRC of only a few W m<sup>-2</sup> largely caused by the small shallow cloud coverage.

331

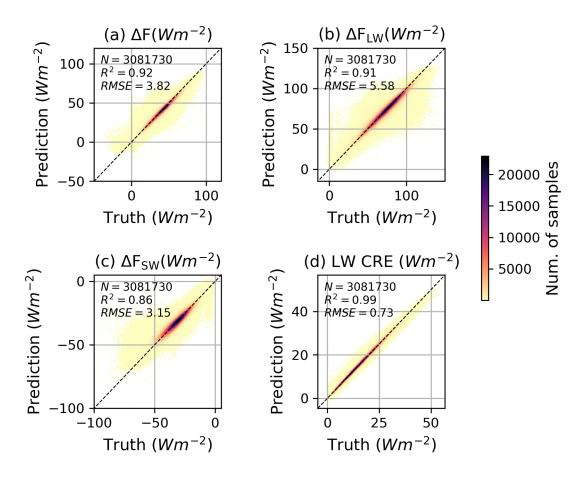
### 332 5. Machine learning the CTRC

The major limitation of this CTRC retrieval algorithm is its reliance on running an RTM that is computationally expensive. To address this issue, we propose to use machine learning. Machine learning has been widely used in radiative transfer modeling (e.g. Krasnopolsky et al., 2010; Ukkonen et al., 2020). Among the machine learning algorithms, the artificial neural network (NN) is of particular interest because of its advantage of low computational cost: once it is trained, it is computationally efficient. This strength makes it suited to our needs.

The NN used in this study is based on the Python library Keras from TensorFlow (see Text S2 for detail). Table S1 lists the input and output variables. We use half of the MODIS data ( $\sim 3$ million) for training and the remaining half for validation. It takes the trained model less than 10 seconds to computes the CTRC for  $\sim 3$  million validation datasets. As a comparison, the original algorithm based on the RTM requires more than a half year on a single regular Central Processing Unit.

Figure 4a~c shows the validations of the NN-predicted CTRC variables. The agreements are overall excellent. There is a certain degree of scattering but the number of scattered samples is small (yellowish area). Most cases concentrate near the one-to-one line. The major source of error stems from the discretization of the RTM, which can induce random fluctuations when extracting

the  $\Delta F$  from the profiles of radiative fluxes. This is particularly so for geometrically shallow clouds 349 whose depth is comparable to the model vertical grid size of 50 m. Such randomness may reduce 350 the NN learning accuracy given the deterministic nature of the NN. This can be demonstrated by 351 the better performance of the NN for the LW cloud radiative effect (Fig. 4d), a parameter that is 352 353 height-independent. The performance is slightly poorer for  $\Delta F_{SW}$  than  $\Delta F_{LW}$ , consistent with a more complex radiation physics in the SW. As expected, the NN-predicted global CTRC climatology 354 well agrees with the "truth" one (Fig. S4) despite a slight overestimation of CTRC in the 355 hemispheric winter when the atmosphere is the driest (Fig. S5). 356



357

Figure 4: Validation of the neural network prediction against the "truth" from MOIDS retrieval
for the instantaneous cloud-top radiative cooling (a), its LW (b) and SW components (c), and the
LW cloud radiative effect (d).

361

#### 362 6. Conclusion

We generate a one-year climatology of cloud-top radiative cooling (CTRC) and its longwave and shortwave components for global (except poleward of 65 ° N/S) marine shallow clouds using a radiative transfer model with inputs of cloud properties from MODIS in combination with reanalysis sounding revised by MODIS-retrieved cloud-top temperature. The CTRC retrieval algorithm was developed in our previous study (Zheng et al., 2019). Analyses of the spatial and
 temporal distributions of the CTRC yield the following findings:

- 369 (1) The global mean cloud-top radiative flux divergence ( $\Delta F$ ) is -61 W m<sup>-2</sup>, decomposed into 370 the LW cooling of -73 W m<sup>-2</sup> and SW heating of 11 W m<sup>-2</sup>. The  $\Delta F$  is largely a reflection 371 of the LW cooling.
- (2) The  $\Delta F$  has a strong latitudinal dependence with a cooling minimum in the tropics. The 372 cooling increases with the latitude until  $\sim 30^{\circ}$  N or S. The increase in cooling is primarily 373 driven by the increasing dryness of the free atmosphere that reduces the down-welling LW 374 flux. The cooling peaks in the subtropical eastern ocean under the downward branches of 375 the Hadley circulation. Poleward of 30 ° N or S, the cooling decreases slightly, primarily 376 due to the colder atmospheric temperature that weakens the cloud's outgoing thermal 377 emission. If we scale the  $\Delta F$  by the  $\sigma T_s^4$  to remove the effect by temperature-driven 378 emission, the zonal-mean scaled cooling increases all the way from the tropics to the extra-379 tropics, a reflection of the decreasing specific humidity of the atmosphere. 380
  - (3) There is a hemispheric asymmetry with stronger cooling in the Southern Hemisphere.
- (4) The CTRC exhibits distinctive seasonal cycles, with amplitudes of the order 10 to 20 W m<sup>-2</sup>. The cooling maximizes during the winter when the atmospheric specific humidity is low, which favors the cooling.
- (5) The CTRC spatial patterns resemble the marine stratocumulus cloudiness. The
   resemblance is a result of the fact that environments favoring the formation of
   stratocumulus decks also favor the strong CTRC.
- Finally, we examine the potential of machine learning in speeding up the CTRC retrieval. Trained by the half-year's worth of CTRC datasets with a sample size of  $\sim 3$  million and validated against the other half, the neural network model exhibits a satisfactory performance with the absolute retrieval error of  $\sim 6\%$ . The neural network model speeds up the radiative-transfer-modelbased retrieval by the order of million times. This will enable generations of much larger CTRC datasets, useful for future more comprehensive research.
- 394

381

# 395 Acknowledgments

This study is supported by the Department of Energy (DOE) Atmospheric System Research program (DE-SC0018996).

# 398 Data Availability Statement

The MODIS data are from ladsweb.modaps.eosdis.nasa.gov. NCEP reanalysis data are collected from <u>rda.ucar.edu/datasets/ds083.2/</u>. NOAA sea surface temperature data are obtained from <u>https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html</u>. The code used to produce the results and the neural network model is available at <u>https://doi.org/10.5281/zenodo.5043713</u>.

403

#### 406 **Reference:**

407 Austin, P. H., Siems, S., & Wang, Y. (1995). Constraints on droplet growth in radiatively cooled 408 stratocumulus clouds. Journal of Geophysical Research: Atmospheres, 100(D7), 14231-14242. 409 Bony, S., & Dufresne, J. L. (2005). Marine boundary layer clouds at the heart of tropical cloud feedback 410 uncertainties in climate models. Geophysical Research Letters, 32(20). 411 Bretherton, C. S., Blossey, P. N., & Uchida, J. (2007). Cloud droplet sedimentation, entrainment 412 efficiency, and subtropical stratocumulus albedo. Geophysical Research Letters, 34(3). 413 Bretherton, C. S., Uchida, J., & Blossey, P. N. (2010a). Slow manifolds and multiple equilibria in 414 stratocumulus - capped boundary layers. Journal of Advances in Modeling Earth Systems, 2(4). 415 Bretherton, C. S., Wood, R., George, R., Leon, D., Allen, G., & Zheng, X. (2010b). Southeast Pacific 416 stratocumulus clouds, precipitation and boundary layer structure sampled along 20 S during 417 VOCALS-REx. Atmospheric Chemistry and Physics, 10(21), 10639-10654. 418 Bretherton, C. S., & Wyant, M. C. (1997). Moisture transport, lower-tropospheric stability, and 419 decoupling of cloud-topped boundary layers. Journal of the Atmospheric Sciences, 54(1), 148-420 167. 421 Caldwell, P., Bretherton, C. S., & Wood, R. (2005). Mixed-layer budget analysis of the diurnal cycle of 422 entrainment in southeast Pacific stratocumulus. Journal of the Atmospheric Sciences, 62(10), 423 3775-3791. 424 Davies, R., Ridgway, W. L., & Kim, K.-E. (1984). Spectral absorption of solar radiation in cloudy 425 atmospheres: A 20 cm-1 model. Journal of Atmospheric Sciences, 41(13), 2126-2137. 426 Deardorff, J. (1976). On the entrainment rate of a stratocumulus - topped mixed layer. Quarterly Journal 427 of the Royal Meteorological Society, 102(433), 563-582. 428 Ghate, V. P., Albrecht, B. A., Miller, M. A., Brewer, A., & Fairall, C. W. (2014). Turbulence and radiation in 429 stratocumulus-topped marine boundary layers: A case study from VOCALS-REx. Journal of 430 Applied Meteorology and Climatology, 53(1), 117-135. 431 Ghate, V. P., Miller, M. A., Albrecht, B. A., & Fairall, C. W. (2015). Thermodynamic and radiative structure 432 of stratocumulus-topped boundary layers. Journal of the Atmospheric Sciences, 72(1), 430-451. 433 Grosvenor, D., & Wood, R. (2014). The effect of solar zenith angle on MODIS cloud optical and 434 microphysical retrievals within marine liquid water clouds. Atmospheric Chemistry and Physics, 435 14(14), 7291-7321. 436 Guo, Z., Wang, M., Larson, V. E., & Zhou, T. (2019). A cloud top radiative cooling model coupled with 437 CLUBB in the Community Atmosphere Model: Description and simulation of low clouds. Journal 438 of Advances in Modeling Earth Systems, 11(4), 979-997. 439 Haynes, J. M., Haar, T. H. V., L'Ecuyer, T., & Henderson, D. (2013). Radiative heating characteristics of 440 Earth's cloudy atmosphere from vertically resolved active sensors. Geophysical Research Letters, 441 40(3), 624-630. 442 Henderson, D. S., L'Ecuyer, T., Stephens, G., Partain, P., & Sekiguchi, M. (2013). A multisensor 443 perspective on the radiative impacts of clouds and aerosols. Journal of Applied Meteorology and 444 *Climatology, 52*(4), 853-871. Huang, Y., Siems, S. T., Manton, M. J., Hande, L. B., & Haynes, J. M. (2012). The structure of low-altitude 445 446 clouds over the Southern Ocean as seen by CloudSat. Journal of Climate, 25(7), 2535-2546. 447 Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., et al. (1996). The NCEP/NCAR 448 40-year reanalysis project. Bulletin of the American Meteorological Society, 77(3), 437-472.

- Kazil, J., Yamaguchi, T., & Feingold, G. (2017). Mesoscale organization, entrainment, and the properties
  of a closed cell stratocumulus cloud. *Journal of Advances in Modeling Earth Systems, 9*(5),
  2214-2229.
- Klein, S. A., & Hartmann, D. L. (1993). The seasonal cycle of low stratiform clouds. *Journal of Climate, 6*(8), 1587-1606.
- Krasnopolsky, V., Fox-Rabinovitz, M., Hou, Y., Lord, S., & Belochitski, A. (2010). Accurate and fast neural
   network emulations of model radiation for the NCEP coupled climate forecast system: climate
   simulations and seasonal predictions. *Monthly Weather Review*, *138*(5), 1822-1842.
- L'Ecuyer, T. S., Wood, N. B., Haladay, T., Stephens, G. L., & Stackhouse Jr, P. W. (2008). Impact of clouds
   on atmospheric heating based on the R04 CloudSat fluxes and heating rates data set. *Journal of Geophysical Research: Atmospheres, 113*(D8).
- Larson, V. E., Schanen, D. P., Wang, M., Ovchinnikov, M., & Ghan, S. (2012). PDF parameterization of
   boundary layer clouds in models with horizontal grid spacings from 2 to 16 km. *Monthly Weather Review, 140*(1), 285-306.
- Li, Z., & Moreau, L. (1996). Alteration of atmospheric solar absorption by clouds: Simulation and
   observation. *Journal of Applied Meteorology and Climatology, 35*(5), 653-670.
- Lilly, D. K. (1968). Models of cloud topped mixed layers under a strong inversion. *Quarterly Journal of the Royal Meteorological Society, 94*(401), 292-309.
- 467 Muhlbauer, A., McCoy, I. L., & Wood, R. (2014). Climatology of stratocumulus cloud morphologies:
  468 microphysical properties and radiative effects. *Atmospheric Chemistry and Physics*, *14*(13), 6695469 6716.
- 470 Nicholls, S. (1984). The dynamics of stratocumulus: Aircraft observations and comparisons with a mixed
  471 layer model. *Quarterly Journal of the Royal Meteorological Society, 110*(466), 783-820.
- 472 Nicholls, S., & Leighton, J. (1986). An observational study of the structure of stratiform cloud sheets: Part
  473 I. Structure. *Quarterly Journal of the Royal Meteorological Society*, *112*(472), 431-460.
- 474 Pinnick, R., Jennings, S., Chýlek, P., & Auvermann, H. (1979). Verification of a linear relation between IR
  475 extinction, absorption and liquid water content of fogs. *Journal of Atmospheric Sciences, 36*(8),
  476 1577-1586.
- Platnick, S., King, M. D., Meyer, K. G., Wind, G., Amarasinghe, N., Marchant, B., et al. (2015). MODIS
  cloud optical properties: User guide for the Collection 6 Level-2 MOD06/MYD06 product and
  associated Level-3 Datasets. *Version*, *1*, 145.
- 480 Reynolds, R. W., Smith, T. M., Liu, C., Chelton, D. B., Casey, K. S., & Schlax, M. G. (2007). Daily high481 resolution-blended analyses for sea surface temperature. *Journal of Climate, 20*(22), 5473-5496.
- Slingo, A., Brown, R., & Wrench, C. (1982). A field study of nocturnal stratocumulus; III. High resolution
  radiative and microphysical observations. *Quarterly Journal of the Royal Meteorological Society*,
  108(455), 145-165.
- 485 Stephens, G. (1978). Radiation profiles in extended water clouds. I: Theory. *Journal of the Atmospheric* 486 *Sciences*, *35*(11), 2111-2122.
- 487 Stevens, B. (2002). Entrainment in stratocumulus topped mixed layers. *Quarterly Journal of the Royal* 488 *Meteorological Society, 128*(586), 2663-2690.
- 489 Stevens, B., Cotton, W. R., Feingold, G., & Moeng, C.-H. (1998). Large-eddy simulations of strongly
   490 precipitating, shallow, stratocumulus-topped boundary layers. *Journal of the Atmospheric* 491 Sciences, 55(24), 3616-3638.
- 492 Ukkonen, P., Pincus, R., Hogan, R. J., Pagh Nielsen, K., & Kaas, E. (2020). Accelerating radiation
  493 computations for dynamical models with targeted machine learning and code optimization.
  494 Journal of Advances in Modeling Earth Systems, 12(12), e2020MS002226.

- Vial, J., Bony, S., Dufresne, J. L., & Roehrig, R. (2016). Coupling between lower tropospheric convective
   mixing and low level clouds: Physical mechanisms and dependence on convection scheme.
   *Journal of Advances in Modeling Earth Systems, 8*(4), 1892-1911.
- Wood, R. (2005). Drizzle in stratiform boundary layer clouds. Part I: Vertical and horizontal structure.
   Journal of the Atmospheric Sciences, 62(9), 3011-3033.
- 500 Wood, R. (2012). Stratocumulus clouds. *Monthly Weather Review*, *140*(8), 2373-2423.
- 501 Wood, R., & Bretherton, C. S. (2006). On the relationship between stratiform low cloud cover and lower-502 tropospheric stability. *Journal of Climate, 19*(24), 6425-6432.
- Wyant, M. C., Bretherton, C. S., Rand, H. A., & Stevens, D. E. (1997). Numerical simulations and a
   conceptual model of the stratocumulus to trade cumulus transition. *Journal of the Atmospheric Sciences*, 54(1), 168-192.
- Zheng, Y. (2019). Theoretical understanding of the linear relationship between convective updrafts and
   cloud-base height for shallow cumulus clouds. Part I: Maritime conditions. *Journal of the Atmospheric Sciences*(2019).
- Zheng, Y., Rosenfeld, D., & Li, Z. (2016). Quantifying cloud base updraft speeds of marine stratocumulus
   from cloud top radiative cooling. *Geophysical Research Letters*, 43(21).
- Zheng, Y., Rosenfeld, D., & Li, Z. (2018). The Relationships Between Cloud Top Radiative Cooling Rates,
   Surface Latent Heat Fluxes, and Cloud Base Heights in Marine Stratocumulus. *Journal of Geophysical Research: Atmospheres, 123*(20), 11,678-611,690.
- Zheng, Y., Rosenfeld, D., Zhu, Y., & Li, Z. (2019). Satellite based estimation of cloud top radiative
   cooling rate for marine stratocumulus. *Geophysical Research Letters, 46*(8), 4485-4494.
- Zhou, X., & Bretherton, C. S. (2019). Simulation of mesoscale cellular convection in marine
   stratocumulus: 2. Nondrizzling conditions. *Journal of Advances in Modeling Earth Systems, 11*(1),
   3-18.
- 519

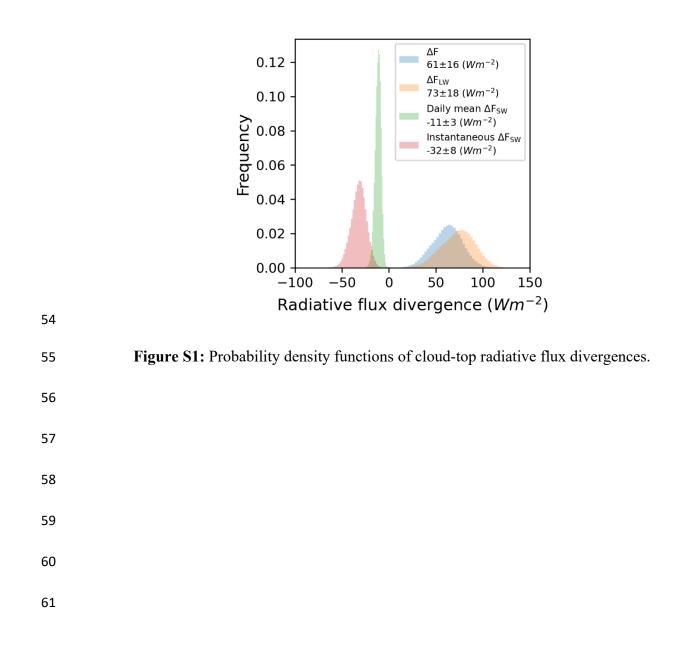
# *<b>@AGU PUBLICATIONS* Geophysical Research Letters Supporting Information for Climatology of marine shallow-cloud-top radiative cooling Youtong Zheng<sup>1,2</sup>, Yannian Zhu<sup>3</sup>, Daniel Rosenfeld<sup>3,4</sup>, and Zhanqing Li<sup>1</sup> **Affiliations:** <sup>1</sup>Earth System Science Interdisciplinary Center, University of Maryland, College Park, Maryland, 20742, USA. <sup>2</sup>GFDL/AOS program, Princeton University, Princeton, New Jersey <sup>3</sup>Nanjing University, Nanjing, China <sup>4</sup>Herew University of Jerusalem, Jerusalem, Israel Contents of this file 1. Text S1~S2 2. Figures S1~S5 3. Table S1

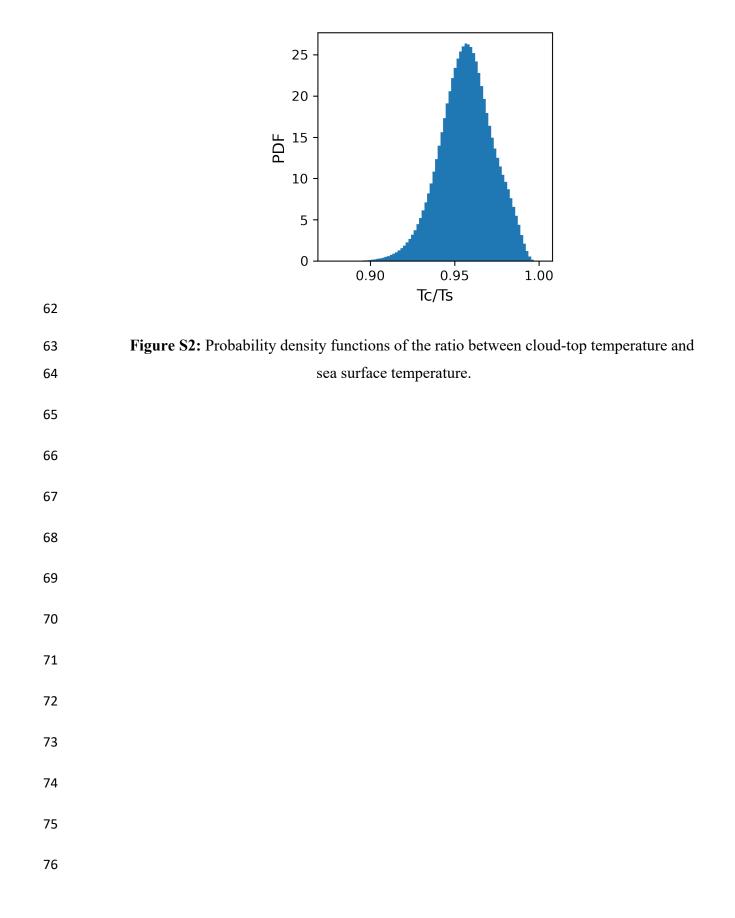
#### **Text S1:** Radiative transfer model

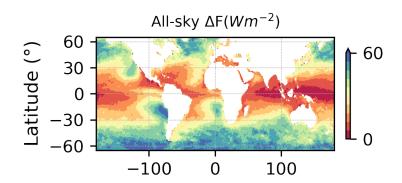
The radiative transfer model we use is the Santa Barbara DISORT Atmospheric Radiative Transfer model (Ricchiazzi et al., 1998). We specify the vertical grids with resolutions of 50 m from the surface to 2.25 km and the grid spacing increases with the altitude until the top of the atmosphere, leading to a total of  $\sim 60$  grids in the vertical. The ozone profile and greenhouse gas concentrations are set to default values. The cloud optical depth is uniformly distributed throughout the cloud layer. The wavelength ranges of longwave and shortwave are set as  $5 \sim 40$  $\mu$ m and 0.1 ~ 5  $\mu$ m, respectively. The wavelength inclement is 0.1  $\mu$ m for shortwave and 0.2  $\mu$ m for longwave.

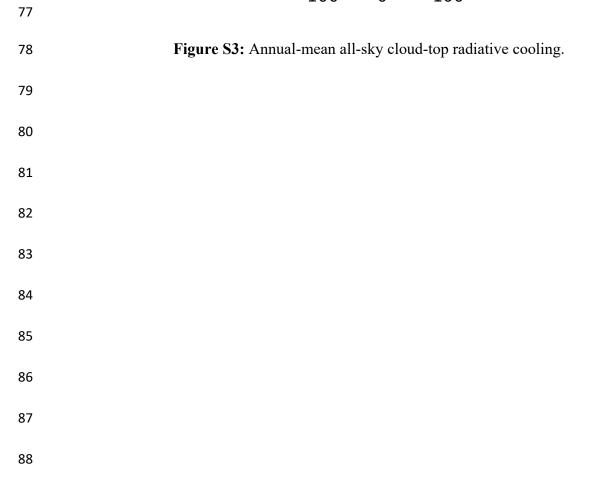
### **Text S2:** Configuration of the neural network model

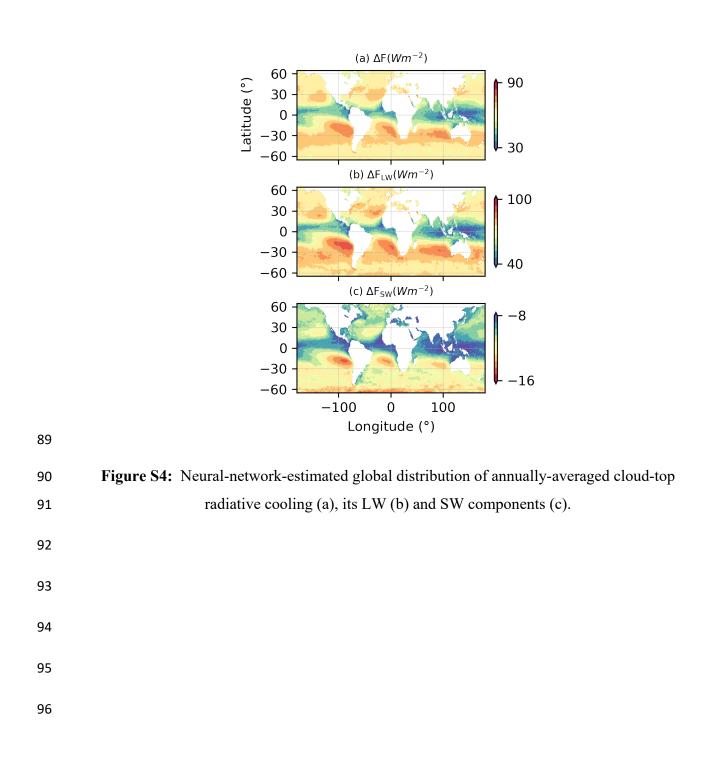
Our NN has a total of four layers. The input and output layers have 25 and 5 nodes respectively, which matches the number of input and output variables. Between them are two fully connected hidden layers with 256 nodes. This adds up to a total of 73733 learnable parameters. We use the Rectified Linear Unit (ReLU) for activation function and the Adam optimizer with a mean squared error loss function. Given the large number of training samples, the specific choices of the hyper-parameters make little difference to the performance. The input data are normalized and shuffled before the training. The total training time was about 7 minutes on a single graphics processing unit. 

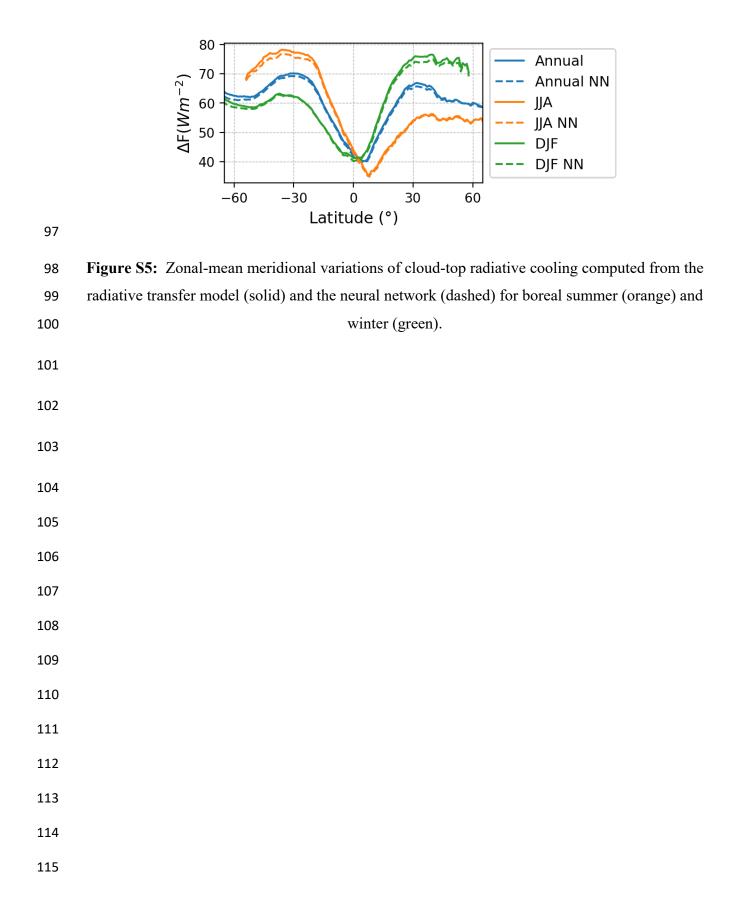












$\begin{array}{c c c c c c c c c c c c c c c c c c c $
$\begin{tabular}{ c c c c } \hline \hline Cloud droplet effective radius $$\mu$m$ Cloud top longwave cooling, $$\Delta F_{LW}$ W m²^2$ \\ \hline Cloud top temperature $K$ Cloud top shortwave heating, $$\Delta F_{SW}$ W m²^2$ \\ \hline Solar zenith angle $degree$ Cloud base longwave heating $W m²^2$ \\ \hline Sea surface temperature $K$ Cloud longwave radiative effect $W m²^2$ \\ \hline Absolute temperature from 1000 $K$ \\ \hline hPa to 100 hPa with 100 hPa \\ interval $Relative humidity from 1000 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to 100 hPa with 100 hPa interval$ $$ 0 to the Neural Network. The CTRC variables used in this study are highlighted in bold. $$$ 0 to 21 \\ \hline 100 hPa with 100 hPa interval$ $$ 0 the Neural Network. The CTRC variables used in this study are highlighted in bold. $$$ 0 to 21 \\ \hline 100 hPa with 100 hPa interval$ $$ 0 the neural Network. The CTRC variables used in this study are highlighted in bold. $$$ 0 to 21 \\ \hline 100 hPa with 100 hPa with 100 hPa with 100 hPa head to 100 hPa head to 100 hPa with 100 hPa head to 100 head to 100$
Cloud top temperature       K       Cloud top shortwave heating, $\Delta F_{SW}$ W m <sup>2</sup> Solar zenith angle       degree       Cloud base longwave heating       W m <sup>2</sup> Sea surface temperature       K       Cloud longwave radiative effect       W m <sup>2</sup> Absolute temperature from 1000       K       hPa to 100 hPa with 100 hPa       m <sup>2</sup> Relative humidity from 1000 hPa       %       interval       me         Table 1: Input and output variables for the Neural Network. The CTRC variables used in       this study are highlighted in bold.         19       100       100       100       100         20       21       22       11       12         21       23       24       25       26         23       24       25       26       27         30       31       32       34       34
Solar zenith angle       degree       Cloud base longwave heating       W m <sup>-2</sup> Sea surface temperature       K       Cloud longwave radiative effect       W m <sup>-2</sup> Absolute temperature from 1000       K       M m <sup>-2</sup> M m <sup>-2</sup> Absolute temperature from 1000 hPa vith 100 hPa interval       M m <sup>-2</sup> M m <sup>-2</sup> Relative humidity from 1000 hPa interval       M m <sup>-2</sup> M m <sup>-2</sup> Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.       M m <sup>-2</sup> 19       20       M m <sup>-2</sup> M m <sup>-2</sup> 21       22       M m <sup>-2</sup> M m <sup>-2</sup> 23       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 24       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 25       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 26       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 27       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 28       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 30       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 31       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup> 32       M m <sup>-2</sup> M m <sup>-2</sup> M m <sup>-2</sup>
Sea surface temperature       K       Cloud longwave radiative effect       W m²²         Absolute temperature from 1000       K       hPa to 100 hPa with 100 hPa interval       hPa to 100 hPa with 100 hPa interval       head to 100 hPa with 100 hPa interval         Relative humidity from 1000 hPa interval       %       head to 100 hPa with 100 hPa interval       head to 100 hPa with 100 hPa interval         Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19         20         21         22         23         24         25         26         27         28         29         30         31
Absolute temperature from 1000       K         hPa to 100 hPa with 100 hPa interval       K         Relative humidity from 1000 hPa to 100 hPa with 100 hPa interval       %         Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19         20         21         22         23         24         25         26         27         30         31
hPa to 100 hPa with 100 hPa interval       hPa to 100 hPa with 100 hPa to 100 hPa with 100 hPa interval       %         17       Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19         20         21         22         23         24         25         26         27         28         29         30         31
Relative humidity from 1000 hPa to 100 hPa with 100 hPa interval       %         17       Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19         20         21         22         23         24         25         26         27         28         29         30         31
to 100 hPa with 100 hPa interval       Image: constraint of the study are highlighted in bold.         17       Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         21       Image: constraint of the study are highlighted in bold.         22       Image: constraint of the study are highlighted in bold.         23       Image: constraint of the study are highlighted in bold.         24       Image: constraint of the study are highlighted in bold.         25       Image: constraint of the study are highlighted in bold.         26       Image: constraint of the study are highlighted in bold.         30       Image: constraint of the study are highlighted in bold.         31       Image: constraint of the study are highlighted in bold.
to 100 hPa with 100 hPa interval       Image: constraint of the study are highlighted in bold.         17       Table 1: Input and output variables for the Neural Network. The CTRC variables used in this study are highlighted in bold.         19       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         20       Image: constraint of the study are highlighted in bold.         21       Image: constraint of the study are highlighted in bold.         22       Image: constraint of the study are highlighted in bold.         23       Image: constraint of the study are highlighted in bold.         24       Image: constraint of the study are highlighted in bold.         25       Image: constraint of the study are highlighted in bold.         26       Image: constraint of the study are highlighted in bold.         31       Image: constraint of the study are highlighted in bold.         32       Image: constraint of the study are highlighted in bold.
18       this study are highlighted in bold.         19       20         20       21         22       23         24       25         26       27         28       29         30       31         32       32
18       this study are highlighted in bold.         19       20         20       21         22       23         24       25         26       27         28       29         30       31         32       32
19 20 21 22 23 24 25 26 27 28 29 30 31 32
20 21 22 23 24 25 26 27 28 29 30 31 32
21         22         23         24         25         26         27         28         29         30         31         32
21         22         23         24         25         26         27         28         29         30         31         32
21         22         23         24         25         26         27         28         29         30         31         32
22 23 24 25 26 27 28 29 30 30 31
23 24 25 26 27 28 29 30 31 32
24 25 26 27 28 29 30 30 31
25 26 27 28 29 30 31 32
26 27 28 29 30 31 32
27 28 29 30 31 32
29 30 31 32
0 1 2
L 2
2
3
7

# **Reference**

Ricchiazzi, P., Yang, S., Gautier, C., & Sowle, D. (1998). SBDART: A research and teaching software tool
 for plane-parallel radiative transfer in the Earth's atmosphere. *Bulletin of the American Meteorological Society, 79*(10), 2101-2114.