Evaluation of CERES and CloudSat Surface Radiative Fluxes over the Southern Ocean

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Abstract

Many studies involving surface radiative fluxes rely on surface fluxes retrieved by the Clouds and the Earth's Radiant Energy System (CERES) project, or derived from spaceborne cloud radar and lidar observations (CloudSat-CALIPSO). In particular, most climate models that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) were found to have too little shortwave radiation being reflected back to space and excessive shortwave radiation reaching the surface over the Southern Ocean – an error with significant consequences for predicting both regional and global climate. There have been few evaluations of CERES or CloudSat retrievals over the Southern Ocean. In this article, CERES and CloudSat retrieved surface shortwave (SW) and longwave (LW) downwelling fluxes are evaluated using surface observations collected over the Southern Ocean during the Macquarie Island Cloud and Radiation Experiment (MICRE). Overall, biases (CERES – surface observations) in the CERES- surface fluxes are found to be slightly larger over Macquarie Island than most other regions, approximately +10 Wm for the SW and -10 Wm for the LW in the annual mean, but with significant seasonal and diurnal variations. If the Macquarie observations are representative of the larger SO, these results imply that CMIP5 model errors in SW surface fluxes are (if anything) somewhat larger than previous evaluation studies suggest. The bias in LW surface flux shows a marked increase at night, which explains most of the total LW bias. The nighttime bias is due to poor representation of cloud base associated with low clouds.

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8	
9	Key Points:
10 11	• CERES and CloudSat-CALIPSO surface shortwave (SW) and longwave (LW) fluxes are compared with surface measurements over the Southern Ocean.
12 13	• Mean CERES surf fluxes are larger in SW (+10 Wm-2) & smaller in LW (-10 Wm-2) than observed with significant seasonal and diurnal variations.
14 15 16	• LW surface fluxes are larger at night (-16 Wm ⁻²), which explains most of the total bias, and is due to incorrect cloud base for low clouds.

17 Abstract –

Many studies involving surface radiative fluxes rely on surface fluxes retrieved by the Clouds 18 19 and the Earth's Radiant Energy System (CERES) project, or derived from spaceborne cloud radar and lidar observations (CloudSat-CALIPSO). In particular, most climate models that 20 21 participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) were found to have 22 too little shortwave radiation being reflected back to space and excessive shortwave radiation 23 reaching the surface over the Southern Ocean – an error with significant consequences for 24 predicting both regional and global climate. There have been few evaluations of CERES or CloudSat retrievals over the Southern Ocean. In this article, CERES and CloudSat retrieved 25 surface shortwave (SW) and longwave (LW) downwelling fluxes are evaluated using surface 26 27 observations collected over the Southern Ocean during the Macquarie Island Cloud and Radiation Experiment (MICRE). Overall, biases (CERES - surface observations) in the CERES-28 surface fluxes are found to be slightly larger over Macquarie Island than most other regions, 29 approximately $+10 \text{ Wm}^{-2}$ for the SW and -10 Wm^{-2} for the LW in the annual mean, but with 30 significant seasonal and diurnal variations. If the Macquarie observations are representative of 31 the larger SO, these results imply that CMIP5 model errors in SW surface fluxes are (if anything) 32 somewhat larger than previous evaluation studies suggest. The bias in LW surface flux shows a 33 34 marked increase at night, which explains most of the total LW bias. The nighttime bias is due to poor representation of cloud base associated with low clouds. 35

36 Plain Language Summary –

37 We compare satellite estimates for the amount of sunlight (solar) and thermal (infrared) energy 38 reaching the surface, with surface observations collected at Macquarie Island. Macquarie Island 39 is located in the Southern Ocean (SO) about halfway between New Zealand and Antarctica. The 40 satellite-based estimates have seen little evaluation over the Southern Ocean. This is a concern 41 because climate models, when compared with the satellite estimates, are not reflecting enough 42 sunlight to space over the SO, which has important implications for simulating the current 43 climate and climate changes. The comparison shows that the satellite estimates are reasonably 44 good, but the differences between the satellite estimates and the surface measurements are 45 somewhat larger at Macquarie than at most other locations, and suggests that (if anything) the 46 satellite data are underestimating the model error associated with having too little reflected sunlight. In the infrared, the satellite errors are due to a systematic overestimation of the altitude 47 48 of cloud base, and in general, the errors in both the solar and infrared have strong seasonal and 49 diurnal variations.

50 **1. Introduction**

51 The Southern Ocean plays a large role in global oceanic heat and carbon uptake, in large 52 measure because this is where much of the world's deep oceanic water returns to the surface, and 53 on long timescales, much of the world's oceanic water passes through the Southern Ocean 54 overturning circulation (Frölicher et al. 2015, Sallée et al. 2013). A number of studies over the 55 past few years have identified a large excess in absorbed shortwave radiation (ASR) at the top of 56 the atmosphere and in downwelling shortwave (SW) surface fluxes over the Southern Ocean in 57 both climate models and reanalyses (e.g. Trenberth and Fasullo 2010, Ma et al. 2015, Kay et al. 58 2016, Zhang et al. 2016). In an analysis of the surface energy budget, Schneider and Reusch 59 (2016) found that most climate models that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5) have excessive shortwave radiation reaching the surface over the 60 Southern Ocean in early summer and midsummer as a result of having an insufficient shortwave 61 (SW) cloud radiative effect (clouds do not reflect enough sunlight back toward space), which 62 causes a warm bias in surface air temperatures during late summer; while in winter, most CMIP5 63 64 models have a negative longwave (LW) bias due to insufficient longwave cloud radiative 65 forcing. On average, the water masses of the Southern Ocean in the CMIP5 models are too warm and light, also likely due in part to excess heat uptake (Sallée et al. 2013). These model 66 67 radiative errors and associated excess heat uptake are of profound importance to global climate, 68 including influencing the position of the Southern Hemisphere midlatitude jet and the Inter-69 Tropical Convergence Zone (ITCZ), as well as cross-hemispheric energy transports (Ceppi et al. 2012, 2013, Hwang and Frierson 2013, Kay et al 2016). 70

71

72 All of the above evaluations of model radiative fields rely on satellite top-of-atmosphere (TOA) 73 or surface fluxes derived by the Clouds and the Earth's Radiant Energy System (CERES) 74 project, specifically, the Energy Balanced and Filled TOA product (EBAF-TOA) (Loeb et al. 2018) and the EBAF-Surface flux product (Kato et al 2018). While CERES EBAF-Surface and 75 76 related products have been evaluated against surface observations over some land regions and 77 using data from (primarily tropical) buoys (e.g., Rutan et al. 2015, Kato et al 2018, Zhang et al. 78 2016), there has been little evaluation over the Southern Ocean. An exception is Rutan et al. 79 (2018) who compared CERES retrievals with observed SW and LW downward surface fluxes 80 measured from several Australian research vessels, including the Australian Aurora Australia

81 ice-breaker. We summarize and discuss uncertainties estimated from these and other evaluation
82 studies in detail later in this manuscript.

83

84 In response to the need for additional measurements of surface radiative fluxes, as well as precipitation, cloud and aerosol properties over the Southern Ocean, the U.S. Department of 85 86 Energy Atmospheric Radiation Measurement (ARM) program, the Australian Antarctic Division (AAD) and the Australian Bureau of Meteorology (BoM) collaborated in deploying a variety of 87 88 ground-instrumentation to Macquarie Island between March 2016 and March 2018. Macquarie Island is located at 54.5° S, 158.9° E and has a small research station operated by AAD that is 89 90 staffed year-round, in part by the BoM. The station supports a variety of research activities and 91 includes a long history of surface weather and radiosonde observations (Hande et al. 2012, Wang 92 et al. 2015).

93

94 The primary objective of the March 2016 to March 2018 deployment, hereafter the Macquarie 95 Island Cloud and Radiation Experiment (MICRE), was to collect observations of surface 96 radiation, precipitation, cloud and aerosol properties in order to evaluate satellite datasets and to 97 improve knowledge of diurnal and seasonal variations in these properties, especially as pertains 98 to the vertical structure of boundary layer clouds, precipitation, and the pervasive supercool 99 liquid clouds which occupy this region.

100

101 In this article, CERES synoptic (SYN) 1 degree hourly SW and LW downwelling surface fluxes and monthly CERES EBAF-Surface fluxes are evaluated using surface observations collected 102 103 during MICRE. The hourly CERES-SYN fluxes are derived using both Moderate Resolution Imaging Spectroradiometer (MODIS) and geostationary satellite imagery (Doelling et al 2013), 104 105 and are subsequently used in the generation of the CERES EBAF-Surface fluxes, which includes 106 corrections and adjustment to the SYN data to ensure consistency with CERES EBAF-TOA 107 fluxes. This evaluation also briefly examines SW and LW surface fluxes derived operationally 108 from spaceborne cloud radar (CloudSat) and lidar (Cloud–Aerosol Lidar and Infrared Pathfinder 109 Satellite Observations, CALIPSO) observations by the CloudSat project (Henderson et al. 2013). 110 Section 2 summarizes the surface and satellite datasets used.

111

Results are given in section 3 and summarized in the context of previous surface-based 112 evaluations in section 4, with conclusions and additional discussion given in section 5. Overall, 113 114 biases (CERES - surface observations) in the CERES-SYN and EBAF downwelling surface fluxes are found to be slightly larger over the Macquarie Island than most other regions, 115 approximately $+10 \text{ Wm}^{-2}$ for SW and -10 Wm^{-2} for the LW in the annual mean, but with 116 significant seasonal and diurnal variations. Of particular note is that bias in LW surface flux 117 shows a marked increase in bias (to about -16 Wm⁻²) at night, which explains most of the total 118 119 LW bias. The nighttime bias is found to be due to poor representation of cloud base associated 120 with low clouds.

121

122 **2. Description of Data**

123

124 2.1 Surface dataset

125 In this manuscript we use observations of surface broadband SW and LW fluxes collected by the

126 ARM broadband radiometers (ARM SKYRAD datastream mcqskyrad60sS1.b1, DOI:

127 10.5439/1025281), and in the later analysis, cloud base from the ARM ceilometer (ARM

datastream mcqceilS1.b1, DOI: 10.5439/1181954) collected during MICRE. The shortwave

129 radiometer calibration is traceable to the World Radiometric Reference and follows the

130 Broadband Outdoor Radiometer CALibration (BORCAL) methods developed at the U.S.

131 National Renewable Energy Laboratory, while calibration of the longwave radiometers is

traceable to the interim World Infrared Standard Group standard (Andreas et al. 2018). The

133 measurement uncertainty is expected to be about +/- 4% for the total downwelling shortwave

134 flux and +/- 2% for the total downwelling longwave flux. The uncertainty in the field maybe

slightly larger than the expected values, and we will return to this topic in the later discussion.

137 While data collection for most MICRE instrumentation began near the end of March or

beginning of April 2016, there was unfortunately, a wire/grounding problem with the

139 pyrgeometer (LW flux) measurements that was not corrected until August 15, 2016. Thus, the

analysis presented is section 3 include SW flux measurements from April 3, 2016 to March 13,

141 2018 (a little over 23 months) and LW flux measurements from August 15, 2016 to March 13,

142 2018 (just under 19 months).

143 2.2 Satellite Datasets

- 144 In this study downwelling shortwave (SW) and longwave (LW) radiative fluxes from (1) the 145 hourly CERES SYN 1 degree Edition 4A product (Doelling et al., 2013; Rutan et al., 2015), (2) 146 the monthly CERES Energy Balanced and Filled (EBAF) Surface Product Edition 4 (Kato et al. 147 2018), and (3) the CloudSat Fluxes and Heating Rate with Lidar (FLXHR-LIDAR) version R05 148 (Henderson et al. 2013) are examined. The analysis includes comparison of hourly SYN data 149 from the grid cell that contains Macquarie Island, and uses larger regional scale (mean fluxes) 150 taken over a 10° x 10° area for the purpose of evaluating the EBAF and FLXHR-LIDAR 151 products. We briefly summarize each dataset, below.
- 152

153 2.2.1 CERES SYN Product

154 Among other parameters, the CERES SYN 1 degree product provides hourly surface LW and 155 SW fluxes computed based on cloud and aerosol properties derived from several satellites 156 (MODIS Terra, MODIS Aqua, and Geostationary imagers), meteorological profiles from the 157 NASA Global Modeling and Assimilation Office (GMAO), and surface properties from several 158 sources (Rutan et al. 2015, Kato et al. 2019). Here we use the Edition 4.0 product (Doelling 159 2017, DOI: 10.5067/TERRA+AQUA/CERES/SYN1DEG-1HOUR L3.004A). At MODIS Terra 160 and MODIS Aqua overpass times, cloud properties (more details below) are derived from 161 MODIS data, while at other times of the day cloud properties are based on geostationary satellite 162 observations (calibrated against MODIS) using similar retrieval algorithms (Doelling et al. 163 2013). Cloud properties from MODIS and geostationary imager data are collected (averaged) on the SYN 1 degree grid using four groups defined by the cloud top pressure. The four cloud-top-164 165 height categories are surface-to-700 hPa, 700-500 hPa, 500-300 hPa, and less-than-300 hPa. We 166 note that the cloud *bases* are independent of the cloud *tops*, meaning that the cloud *base* in each 167 category can be *below* the *top* or even the *base* of other cloud-top-height categories. For 168 example, the cloud base of the 700-to-500 hPA category may be at a pressure-altitude that is 169 larger than 700 hPA. The four cloud categories are randomly overlapped, as described in Kato et 170 al. (2019, see Appendix A), creating 16 possible cloud vertical configurations. We provide some 171 additional details and clarifications to the description given by Kato et al. 2019 in Appendix A of 172 this document. Radiative fluxes are computed using a gamma-weighted two-stream model 173 applied to (as many as) 4 of the 16 vertical configurations (as explained in Appendix A).

174

175 In general, the method of determining cloud geometric and optical properties in a given MODIS 176 or geostationary pixel depends on the wavelength bands of the available observations, as 177 described in Minnis et al. (2011). When the solar zenith angle is less than 82° (defined as 178 "davtime"), several shortwave and infrared channels are used to retrieve cloud top effective 179 temperature, phase, optical depth, and particle size using an iterative method. Beyond 82° 180 (defined as "nighttime"), only infrared wavelengths are used. The nighttime algorithm includes 181 an iterative process for clouds determined to be optically thin (based on thermal channel 182 brightness temperature differences) that accounts for the cloud emissivity being less than 1 (i.e. 183 not opaque in the infrared) and retrieves the cloud microphysics (optical depth and effective 184 radius), while optically thick clouds are taken to be opaque and cloud microphysics are set to fixed values at night (depending on the inferred phase and cloud top temperature). Cloud base 185 186 height is particularly important in determining downwelling LW surface flux. Because only 187 passive remotely sensed data are used to construct the cloud profiles, the location of cloud base 188 is not directly measured and not well constrained. The location of cloud base is determined from 189 the retrieved cloud-top temperature and cloud thickness, where the cloud thickness is estimated 190 in one of two ways. For liquid clouds, a relationship between optical depth and thickness 191 derived from satellite and field data are applied (Minnis et al. 2011), while for ice clouds, a new 192 latitude-dependent parameterization is used in SYN edition 4A. The new parameterization was 193 developed using cloud property profiles constructed from the active remote sensors CloudSat and 194 CALIPSO.

195

196 2.2.2 CERES Energy Balanced and Filled (EBAF) Surface Product

197 As described by Kato et al. (2018), the CERES project derives both top of atmosphere and 198 surface radiative fluxes at several temporal and spatial scales, with the top-of-atmosphere (TOA) 199 and surface irradiances determined separately. The TOA fluxes are derived directly from 200 radiances measured by CERES instruments, and includes the Energy Balanced and Filled 201 (EBAF) TOA product, which applies an algorithm that adjusts SW and LW TOA fluxes (within 202 their uncertainties) in order to remove inconsistency between average global net TOA flux and 203 heat storage in the earth-atmosphere system (Loeb et al. 2018). Surface fluxes, on the other 204 hand, are computed using radiative transfer calculations following the discussion for the SYN

205 product. The SYN TOA fluxes do not necessarily match those from the CERES EBAF-TOA 206 product. In the CERES EBAF-Surface product, the atmospheric properties used to calculate the 207 SYN fluxes are *bias corrected* and *adjusted* so that they produce TOA fluxes that match closely 208 the EBAF-TOA fluxes. Here we use the CERES EBAF-Surface product Edition 4.0 (Loeb et 209 2017, DOI: 10.5067/TERRA+AOUA/CERES/EBAF-SURFACE L3B004.0). The bias 210 *correction* and *adjustment* procedures are complex, and a lengthy description is given by Kato et 211 al. (2018). Very briefly, AIRS, CloudSat, and CALIPSO are used to estimate bias errors in some 212 SYN inputs at the monthly scale. Specifically upper-tropospheric (200-500 hPa) temperature 213 and specific humidity, low-level cloud fraction as viewed from space (over ocean), and total 214 cloud fraction and cloud-base as viewed from the surface are bias corrected on spatial scales of 1 degree (but with some smoothing that includes the use of zonal averages in some cases). 215 216 Following the bias correction (which nominally is correcting for errors in the SYN inputs), the 217 monthly mean computed SYN-bias-corrected fluxes and EBAF-TOA fluxes are compared and differences are then minimized utilizing a Lagrange multiplier, which further adjusts 218 219 temperature, water vapor, cloud, aerosol, and surface properties (within their uncertainties) in 220 order to bring the computed TOA fluxes into close agreement with EBAF-TOA fluxes. 221

222 2.2.3 CloudSat Fluxes and Heating Rate with Lidar (FLXHR-LIDAR)

223 The CloudSat 2B-FLXHR-LIDAR product (Henderson et al. 2013) provides vertical profiles of 224 SW and LW radiative fluxes and heating rates. The fluxes and heating rates are calculated using a two-stream plane-parallel doubling-adding radiative transfer model (L'Ecuver et al. 2008. 225 226 Henderson et al. 2013), based on vertical profiles constructed from radar and lidar backscatter 227 from the CloudSat Cloud Profiling Radar (CPR) and the Cloud–Aerosol Lidar with Orthogonal 228 Polarization (CALIOP) aboard CALIPSO, respectively, along with auxiliary cloud information 229 from MODIS, and environmental information from ECMWF. The radar and lidar data enable an 230 explicit representation of vertical cloud properties, and in particular the representation of multi-231 layered cloud structures has been shown to improve the impact of cloud impacts on TOA and 232 surface radiation (L'Ecuyer et al, 2019, Hang et al, 2019). This article uses the most recently 233 released Revision 05 (R05) 2B-FLXHR-LIDAR data, available from the CloudSat data 234 processing center (http://www.cloudsat.cira.colostate.edu/data-products/level-2b/2b-flxhr-lidar). 235 The R05 data includes several improvements in land surface characteristics (i.e., surface

236 emissivity and albedo) compared with R04 and is based on cloud properties from R05 CloudSat 237 and V4 CALIPSO datasets. Major changes related to the R05 retrieval are described in Matus 238 and L'Ecuyer (2017). Of particular note is that cloud properties for cirrus are now based on the 239 CloudSat 2C-ICE product (Deng et al. 2013) and mixed phase clouds are more explicitly 240 represented (Van Tricht et al. 2016), which has improved surface flux comparisons against 241 ground sites in Greenland (McIlhattan et al. 2017). More generally, Matus and L'Ecuyer (2017) 242 demonstrate that the improvements in R05 yield better agreement with respect to TOA global 243 and regional fluxes when compared to the CERES CloudSat, CERES, and MODIS (CCCM) 244 product (Kato et al. 2010).

245

3. Results

247 3.1 Comparison of coincident SYN hourly data with surface observations during MICRE Figure 1 compares hourly CERES SYN SW and LW downwelling surface fluxes with hourly 248 249 averages of measured values at Macquarie Island during MICRE. Specifically, Figure 1 shows 250 the frequency of occurrence for a given pair of satellite-derived and surface-measured values. 251 Here the frequency of occurrence values have been scaled logarithmically because the frequency 252 is very large in some sections of the plots and low in others. Nominally, both observations 253 would be equal and fall along the one-to-one line (shown in black), but with some scatter 254 (departure from the line) due to the different spatial-scale in each dataset (the surface radiometers 255 observe a much smaller area). We note nighttime values (defined here as times when the SW flux is less than 10 W/m^2) are not used in the SW comparison in Figure 1. The SYN SW values 256 have a bias of 21.5 Wm⁻² relative to the ground measurements during daylight. The bias would 257 258 be roughly half this value if both day and night time samples were included, as is often done 259 when reporting monthly or annual means. There are more than 8000 samples in this comparison 260 and even considering serial correlation, the bias is significant at the 95% level of confidence. 261 Nonetheless the points in the SW histogram appear to fall reasonably symmetrically about the 262 one-to-one line.

263

The comparison of ground-measured and SYN LW fluxes in Figure 1 shows a bias of about -8.3 Wm⁻². We note that the SW and LW biases are in the opposite direction such that the bias in the total (SW + LW) radiative flux is small, with a magnitude of less than 2 Wm⁻² in the daily (day + night) average. We will discuss SW and net radiative flux in more detail later in the manuscript,and focus for the time being on the downwelling LW flux.

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Figure 1. Comparisons between downwelling radiative fluxes from CERES SYN 1degree-hourly and
 ground-based measurements: a) Shortwave, b) Longwave. Nighttime values are not included in the SW
 comparisons.

274

275 Much of the LW bias is due to a cluster of points where SYN has LW fluxes near 300 Wm⁻² and

the ground observations have values near 340 Wm⁻², which stands out from the otherwise fairly

277 linear distribution. Separating the LW data into daytime and nighttime populations (Figure 2)

278 reveals that the offset cluster consists of fluxes occurring at night. While the magnitude of the

279 SYN1deg daytime LW bias is only -1.4 Wm⁻², it increases to -16 Wm⁻² at night.





Figure 2. Comparisons between downwelling longwave fluxes from CERES SYN1deg-hourly and
ground-based measurements. a) Daytime data. b) Nighttime data.

284 The vertical profiles of temperature, water vapor, and cloud base height are the primary 285 determinants of downwelling LW flux at the Earth's surface. Given the relatively weak diurnal 286 variations in temperature and water vapor in this region, and the algorithmic differences in the 287 treatment of clouds between davtime and nighttime conditions in the satellite retrievals, one 288 expects that the differences between the panels in Figure 2 are likely due to errors in cloud base. 289 The SYN product provides cloud base pressure for each of the four cloud top height categories 290 discussed in section 2.2, which we have converted to altitude above ground level using monthly 291 mean profiles from radiosonde observations and accounted for cloud overlap (Appendix A). In 292 Figure 3, we compare the distribution of the SYN lowest cloud base height to the distribution of 293 the lowest cloud base determined by a Vaisala laser ceilometer (lidar) deployed during MICRE. 294 The bars on the far right show the fraction of clear-sky (no clouds in the column). The ceilometer suggests somewhat more clear sky than the satellite. While this is not surprising 295 296 given the ceilometer observes a smaller area than the satellite imager pixels used in SYN, it is also likely due in part to the inability of the ceilometer to detect clouds above 5 km and some 297 298 optically thin ice clouds. Regardless of these issues, it is clear the CERES SYN data 299 substantially under represents the occurrence of clouds with bases below 900 hPa at the 300 Macquarie Island site.

301



302

Figure 3. Cloud base distributions from CERES (blue) and ceilometer (orange). The bars on the far right
show the fraction of clear-sky.

306 Figure 4 further divides the cloud base height distributions into cases where (top) the LW

307 difference (SYN – ARM surface radiometer) is large and negative (less than -30 Wm⁻²), (middle)

308 the LW difference is small (within 10 Wm⁻²), and (bottom) the LW difference is large and

309 positive (greater than 30 Wm⁻²). The top panel further demonstrates that large underestimates in

310 the SYN LW flux occur when the ceilometer data is dominated by low clouds. This "large error"

311 condition occurs about 13% of the time. There is very little clear during these 1-hour periods (in

312 either dataset), which shows that this occurs when extensive low cloud cover is present.

313 Examination of W-band radar shows that much of the time, the clouds in this category are

314 multilayered, but also includes periods that are apparently dominated by only low-altitude

315 stratocumulus (though it is possible the radar is failing to detect some high altitude cloud).

316

Not surprisingly, the middle panel shows that when the LW flux bias is small (less than 10 Wm⁻), the cloud base distributions are much more similar. Even considering the roughly 10% difference in the amount of clear sky (which again may be due to higher altitude clouds missed by the ceilometer), it is clear that the presence of clouds with bases below 900 hPA remains too small, and the occurrence of cloud-base above about 950 hPA is too large. In short, the same cloud base issue still occurs but is less severe.

323

In the bottom panel, biases greater than $+30 \text{ Wm}^{-2}$ are relatively uncommon, occurring 3% of the 324 325 time, and are dominated by cases where the laser ceilometer does not detect any cloud over the 326 one hour periods being analyzed. It is likely that most of the LW difference here is due to 327 regional variability. Simply put, there are fewer clouds over the island (during the 1 hour over 328 which ceilometer data is aggregated) as compared with the 1 degree region surrounding the site. 329 Setting aside the difference in the amount of cloud, the distribution of cloud-base during these 330 apparently-broken-low-cloud periods appears to be well captured by SYN. It is perhaps also 331 noteworthy that the broken clouds (in this category) have an overall higher cloud base than the 332 clouds in the other two categories.

333 334





346

As mentioned in the description of the SYN product, there are four different retrieval paths usedin SYN. These are distinguished by whether MODIS or geostationary imager data are used, and

Figure 4. Same as figure 3 except limited to cases where (top) $\Delta LW = (SYN - ARM$ Ground) < -30 Wm⁻², (middle) -10 Wm⁻² < $\Delta LW < 10$ Wm⁻², (bottom) $\Delta LW > 30$ Wm⁻².

350 by whether daytime (solar zenith angle less than 82°) or nighttime algorithms are used. In Figure 351 5, we further examine the satellite and lidar cloud base distributions according to the four 352 retrieval paths. Here, MODIS-based retrievals are given in the upper two panels and Geostationary-based retrievals (Himawari for the region and time-period being studied) in the 353 lower two panels, while the two panels on the left are daytime retrievals (retrievals using visible 354 355 and infrared channels) and on the right are nighttime retrievals (infrared channels only). Regardless of retrieval path, SYN under represents the presence of cloud bases below 900 hPA. 356 357 However, the SYN and lidar cloud base height distributions do agree better during the daytime 358 (left panels) than at night (right panels), regardless of whether MODIS or Geostationary data are 359 being used. The overall similarity of the MODIS and Geostationary-based satellite retrievals 360 indicates the flux differences are not being driven by problems with the calibration of the 361 Geostationary data (at least for Himawari-8 in this region).





Figure 5. Same as Figure 3, except: (top left) MODIS daytime, (top right) MODIS nighttime, (bottom
left) Geostationary (Himawari) daytime and (bottom right) Geostationary nighttime.

366 *3.2 The Diurnal Cycle and the CloudSat FLXHR-LIDAR*

367 Figure 6 plots the diurnal cycle of mean surface fluxes for all of the coincident SYN and 368 observed surface fluxes during MICRE. Here the orange and light blue shading indicates the 369 two-sigma sampling uncertainty (95% confidence) interval (given by twice the standard 370 deviation divided by the square root of the number of samples) for the ceilometer and SYN data, 371 respectively. Values from the CloudSat FLXHR-LIDAR product (R05) are shown as black dots. 372 CloudSat and Calipso are sun-synchronous polar orbiting satellites which pass near Macquarie 373 island at about 2 pm and 12:30 am local time. The CloudSat data shown here is the mean taken 374 over the period August 15, 2006 until December 30, 2009, during which time CloudSat was 375 operating nominally during both daytime and nighttime overpasses. While CloudSat did collect 376 data between March 2016 and December 2017, data for this period (coincident with MICRE) has 377 not yet been processed. In addition, owing to problems with the CloudSat satellite battery, 378 CloudSat has only been able to collect data during the afternoon (2 pm), daylight overpass (at 379 Macquarie Island) since April of 2011. Thus some level of statistical comparison becomes 380 necessary. Comparing CloudSat and SYN data in this way requires there be little variation in the 381 mean fluxes between the two time periods examined. In this regard we note the standard 382 deviation of annual mean SW and LW flux in the CERES SYN product between 2001 and 2017 is only 1.7 and 2.1 Wm⁻², respectively. 383

384

385 The left panel in Figure 6, shows that the diurnal cycle of the SYN downwelling SW fluxes 386 compares well with the observed SW fluxes. The largest difference occurs at about 11 am, where the difference is about 38 Wm⁻². The two-sigma (95% confidence) intervals barely overlap at 11 387 388 am, suggesting the difference between SYN and the surface SW fluxes are not likely due to 389 sampling limitations. However, a calibration error of 4% in the surface observations would 390 create greater overlap between the uncertainty shading, such that the possibility of a combination 391 of calibration error and sampling differences cannot be rejected. Nonetheless, the fact that the 392 difference has a diurnal cycle (in which differences are larger at 11 am than 1 pm, for instance) 393 suggests that a large calibration error is not likely. We will discuss this result and SW fluxes in 394 more detail later in section 5. At the time of the CloudSat afternoon overpass, the SYN, 395 CloudSat, and measured values all agree within the sampling uncertainty. The sampling 396 uncertainty in the CloudSat result is comparable, but slighter larger, than the size of the dot used

to denote the CloudSat fluxes. In the LW (right panel), the SYN LW downwelling fluxes

- 398 compare well with the surface measurements between about 9 am and 3 pm, but poorly overnight
- 399 consistent with the results shown in Figure 2 and associated discussion. The CloudSat
- 400 downwelling fluxes, on the other hand, compare well with the surface measurements during both
- 401 afternoon and night overpasses.





Figure 6. Diurnal cycle of the mean SYN retrieved and measured surface fluxes during MICRE. Left
panel shows downwelling SW flux and right panel shows downwelling LW flux. Shading indicates
sampling uncertainty in the mean. Black dots denote mean fluxes from the CloudSat FLXHR-LIDAR
product (R05) based on data from 2006 through 2009 (note a different time period, see text). Sampling
uncertainty of CloudSat data is comparable to the size of the dot.

408

409 Figure 7 shows that the same pattern found in figure 6 for all coincident data, is found in each individual season. Seasonal and annual means and biases are given in Table 2. As there is less 410 411 night during the Spring and Summer, it is not surprising to find the SYN LW biases (averaged 412 over the day in Table 2), are less in Spring and Summer than during the Fall and Winter. 413 Likewise, disagreement between SW SYN and surface fluxes are largest in Spring and Summer. 414 Differences between CloudSat fluxes and surface values are within or near the sampling 415 uncertainty (depicted by bars shown on Figure 7). In Summer, the CloudSat mean SW fluxes is 416 high relative to the observations, but the bias remains within or close to the sampling uncertainty 417 and we note there is additional uncertainty related to the differing time periods (these are not 418 coincident data) which is not represented by the uncertainty bars in Figure 7. The sampling 419 uncertainty for the CloudSat fluxes is much larger than that for CERES because CloudSat 420 observes the region far less frequently than CERES.





- 425 Figure 7. Same as Figure 6, except showing result for Southern Hemisphere Winter (JJA), Spring (SON),
- 426 Summer (DJF), and Fall (MAM). CloudSat data are from different time period (see text). Bars on
- 427 *CloudSat dots show sampling uncertainty (and do not include uncertainty due to interannual variability).*
- 428

W/m^2	Surface	CERES SYN (1°)	CERES SYN (10°)	CERES EBAF (10°)	CloudSat (1°) day *	CloudSat (1°) night *
,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	obs.	Coincident	2001-2017	2001-2017	2006-2009	2006-2009
Winter (JJA)						
SW mean	24.5	27.0	27.1 [1.5]	27.4 [1.3]	72.2*	-
SW bias	-	2.6	2.6	2.9	-8.2*	
LW mean	302.3	291.1	294.4 [2.8]	291.5 [3.0]	<i>311.2</i> *	<i>309.5</i> *
LW bias	-	-11.2	-7.9	-10.8	5.8*	6.9*
Spring (SON)						
SW mean	122.8	138.4	138.8 [4.3]	141.7 [4.0]	311.8*	-
SW bias	-	15.6	16.0	18.9	-1.6*	
LW mean	309.7	302.5	302.3 [2.1]	297.7 [2.1]	304.6^{*}	309.0*
LW bias	-	-7.1	-7.4	-12.0	-3.9 [*]	-2.7*
Summer (DJF)						
SW mean	177.0	195.3	192.6 [4.8]	197.0 [4.3]	510.4*	-
SW bias	-	18.4	15.6	20.0	70.5*	
LW mean	318.8	312.5	315.5 [2.5]	310.2 [2.5]	<i>312.2</i> *	<i>319</i> .7 [*]
LW bias	-	-6.3	-3.3	-8.6	-6.8*	-0.1*
Fall (MAM)						
SW mean	55.5	61.1	60.3 [2.6]	62.8 [2.6]	153.9 [*]	-
SW bias	-	5.6	4.8	7.3	4.3*	
LW mean	318.9	308.2	307.6 [3.3]	303.8 [3.5]	317.6	<i>319</i> .7 [*]
LW bias	-	-10.7	-11.3	-15.1	-4.3*	1.4^{*}
Annual						
SW mean	94.9	105.5	104.7 [1.7]	107.2 [1.1]	<i>262.1</i> *	-
SW bias	-	10.5	9.8	12.3	<i>16.3</i> *	
LW mean	312.4	303.6	304.9 [2.1]	300.8 [2.1]	311.4*	314.5*
LW bias	-	-8.8	-7.5	-11.6	-2.3*	1.43*

429 Table 2 – Seasonal and annual means in downwelling SW and LW fluxes. All values have units of Wm^{-2} .

430 Biases given with respect to mean surface fluxes (e.g. SYN – Surface Obs). Surface and CERES values

431 *are 24-hour averages.* **CloudSat values are NOT 24-hour averages, but the average value at the time of*

432 the CloudSat overpass (and biases are the difference with surface obs during the same hour). When

433 present, parentheses "[]" show year-to-year standard deviation. Data for CERES SYN is given for

434 coincident points in the 1 degree grid cell that contains Macquarie Island ground site, and for 10 x 10

435 *degree (lat/lon) region centered on the island.*

437 3.3 Monthly SYN and EBAF-Surface Fluxes

438 CERES EBAF-Surface fluxes are only available on monthly (and longer) time scales. Thus 439 rather than compare EBAF to coincident surface data (which would include only 18 to 24 points), we instead compare the CERES SYN and CERES EBAF for the 17 years of Edition 4 440 data available at the present time. EBAF Monthly values are close to SYN values in the 10 x 10 441 442 degree region surrounding Macquarie Island. Figure 8 shows the distribution of EBAF – SYN (Edition 4) downwelling surface fluxes for the period 2001 to 2017. As discussed in section 3.3, 443 444 CERES EBAF-Surface fluxes contain both *bias corrections* and *adjustments*, which nominally 445 include bias corrections for cloud base (see section 2.3). However, the net effect of the 446 corrections appears to be in the wrong direction. EBAF SW fluxes are typically somewhat larger than SYN fluxes by a small amount (2.5 Wm^{-2} on average), when the surface measurements 447 suggest the SYN fluxes are already too large. And similarly, EBAF LW fluxes are typically 448 smaller then SYN fluxes (by 4.1 Wm⁻² on average), when the surface measurements suggest the 449 SYN fluxes are already too small. In short, CERES EBAF fluxes appear to have (if anything) 450 451 slightly larger biases in the region surrounding Macquarie Island.





Figure 8. Distribution of monthly SW (left) and LW (right) downwelling surface flux differences between
Edition 4 CERES EBAF and CERES SYN 1° data (EBAF –SYN) for all grid points within 10° of

455 Macquarie Island between 2001 and 2017.

456

457 **4. Results from Previous CERES Evaluation Studies**

- 458 Several studies have evaluated CERES SYN and EBAF surface fluxes against surface
- 459 observations. Rutan et al. (2015) evaluated the SYN Edition 3 and EBAF Edition 2.7 surface
- 460 fluxes, comparing both to other satellite based estimates and measurements recorded at 37

globally distributed land-based sites and 48 buoys (over subtropical and tropical oceans) between 461 462 2000 to 2007. There were no buoy sites at mid or high latitudes in this data set. Relative to the surface measurements, SYN monthly mean downwelling SW fluxes were biased +1.8 Wm⁻² over 463 the land sites and $+4.9 \text{ Wm}^{-2}$ over the ocean sites with a standard deviation (in the monthly 464 means) of about 12 Wm^{-2} , while EBAF Edition 2.7 surface fluxes were found to have a bias of 465 only -0.5 Wm^{-2} over land and +5.0 over ocean with again a standard deviation of about 12 Wm^{-2} 466 in the monthly means. For LW fluxes, Rutan et al. (2015) found biases for SYN of -4.2 Wm⁻² 467 over land and -3.6 Wm⁻² over the ocean, with a standard deviation (in the monthly means) of 468 about 10 Wm⁻², while for EBAF (Edition 2.7) the bias was just 1.2 Wm⁻² over land and -3.5 Wm⁻ 469 2 over ocean, with a standard deviation in the monthly means of about 10 Wm⁻². 470

471

Kato et al. (2018) present a similar assessment for the EBAF Ed. 4.0 surface fluxes, using many
of the same sites as Rutan et al. (2015) but using data from March 2000 through February 2016.
The EBAF monthly mean SW downwelling fluxes were found to have biases of -0.8 Wm⁻² and
4.8 Wm⁻² over land and ocean, respectively (quite similar to values found by Rutan et al. 2015
using the previous edition of the EBAF data), while LW downwelling were improved with
overall (taken across all station) mean biases of only -0.04 Wm⁻² over land and 1.0 Wm⁻² over
standard deviations in the monthly means remained about 10 Wm⁻².

479

Studies by Ma et al. (2015) and Zhang et al. (2016) also compared CERES EBAF downwelling SW fluxes with data from a wider range of sites/networks including (i) the Global Energy Balance Archive (GEBA) with sites located primarily in Europe and Japan but also some sites in Austrailia, Asia, South America, and Africa, (ii) the Greenland Climate Network (GC-NET) and (iii) Climate Data Center of Chinese Meteorological Administration (CDC/CMA). Most of these additional sites had mean biases less than 5 Wm⁻², with the large set of GEBA sites having an average bias of less than 2.5 Wm⁻² in both summer and winter seasons.

487

488 In all of the above studies, some individual stations were found to have larger biases, and in

489 some locations biases exceeded 20 Wm⁻². In most cases, these large differences were associated

490 with suspect measurements (e.g., measurements which may suffer from dust contamination) or

491 occur in mountainous or snow and ice covered regions, where larger differences might be due to

492 spatial heterogeneity (of clouds and surface conditions) and challenges presented by snow and 493 ice covered surfaces to the retrieval of both cloud and surface albedos (Hinkelman et al. 2015, 494 Riihelä et al. 2017, Kato et al. 2018). Macquarie Island is far removed from Antarctic Sea Ice, 495 and while it does snow on the island, it is largely free of snow (especially during Spring and 496 Summer when SW flux errors are largest) and covers only a very small fraction of the area. As 497 such, snow and ice is not a concern in this study. The possibility that the biases we find at 498 Macquarie Island could be caused by spatial heterogeneity is more difficult to assess and we will 499 return to this topic in the next section.

500

501 The poster presentation by Rutan et al. (2018) provides the only other direct evaluation of 502 CERES surface fluxes over the Southern Ocean of which we are aware. This study utilized 503 radiometric data collected from New Zealand and Australian research vessels over the period 504 2008-2016. This included data collected from the Australian Aurora Australis ice breaker during its resupply mission to Macquarie Island and Australian Antarctic stations, as well as data 505 506 collected from the New Zealand Research Vessel (R/V) Tangaroa, which also include a few 507 voyages which passed south 50° S. In total, the number of hourly samples gathered over the 8-508 year ship record is roughly equivalent to what was collected during MICRE over two years. In the latitude range between 50° to 60° S, Rutan et al. 2018 show differences between the SYN 509 and surface LW fluxes between about 5-10 Wm⁻² from both the Aurora Australis and R/V 510 511 Tangaroa, consistent with what we find from Macquarie Island. Rutan et al. 2018 also generally 512 find noteworthy day to night differences in the LW bias. For the Aurora Australis (which spent most of its time south 50° S) the day to night difference was about -8 Wm⁻² in Summer and Fall. 513 but near zero in Spring during which both day and night have a bias near -10 Wm^{-2} . On a minor 514 515 note, the original poster presented by Rutan et al. 2018 contained an error in the seasonal-and-516 diurnal bias bar charts, and we thank Dr. Rutan for kindly providing us with corrected figures. 517 The R/V Tangaroa data suggest similarly large day-to-night differences in Spring, Fall and 518 Winter, but the seasonal-to-diurnal bias analysis was not subdivided by latitude, and a large 519 fraction of the data being gathered from the R/V Tangaroa was gathered North of 45° S (and not 520 over the Southern Ocean). In summary, the LW results of Rutan et al. (2018) are reasonably 521 consistent with the present analysis.

522

In the SW, however, Rutan et al. (2018) found no significant bias in the annual mean between 523 524 50° to 60° S from the Aurora Australis (though there appears to be a bias south of 60° S in these 525 data), but do show a SW bias from the R/V Tangaroa in this latitude range, which is consistent 526 with the data collected at Macquarie. Taken over all SO latitudes, data collected from Aurora Australis suggest a seasonal SW bias of about: +5 Wm⁻² in the Spring, -2 Wm⁻² in the Summer, 527 and $+8 \text{ Wm}^{-2}$ in the Fall with sampling uncertainty in each season of about 5 Wm⁻². During its 528 529 vovages, the R/V Tangaroa passed by Macquarie Island whereas much of the Aurora Australis 530 data was collected further to the east. Thus one possibility for the differences between the two 531 ship datasets is that there is a longitudinal variation. However, we note that the ship cruises do 532 not randomly sample Southern Ocean meteorological conditions. For good and obvious reasons, 533 the resupply transits try to avoid Southern Ocean cyclones. We speculate that sampling 534 uncertainty and conditional meteorological sampling more likely explain the differences. A 535 regime-based analysis of the MICRE and ship datasets might prove worthwhile but such is beyond the scope of this first analysis, and as discussed in the next section it is possible the 536 537 MICRE data could also be biased by island effects (local surface heterogeneity).

538

539 **5. Discussion and Conclusions**

540 We find the annual mean bias in the CERES SYN and EBAF SW downwelling flux during MICRE to be about $+10 \text{ Wm}^{-2}$ with a larger bias occurring in the Spring and Summer (15 to 20) 541 Wm^{-2}), see Table 2. This is larger than the mean bias of about +5 Wm^{-2} found from using 542 543 measurements from ocean buoys (primarily located in the subtropics and tropics) by Rutan et al. 544 (2015) and Kato et al. (2108). This bias is also larger than the 95% sampling uncertainty of about 2 to 3 Wm^{-2} and the expected calibration uncertainty +/- 4% or a little over 4 Wm^{-2} in the 545 546 annual mean for the surface measurements. Nonetheless, while neither sampling uncertainty nor 547 calibration alone can account for the bias, in combination these two factors could account for 548 much of the apparent bias. Another possibility is that the SW bias we find might be due to an 549 "island effect", where clouds reflect more sunlight back toward space at the measurement site 550 (because there is more cloud cover or clouds are more reflective over the island site) than over 551 the surrounding ocean. If so, the results presented here suggest that this occurs preferentially in 552 Spring and Summer and preferentially between roughly 9 am and noon. An analysis of cloud 553 properties form MICRE (which will include analysis of ground-based cloud radar and

depolarization lidar data, as well as satellite retrievals) is ongoing, and may provide some insight
into the existence and cause of the SW bias.

556

557 As regards climate models, in many CMIP3 and CMIP5 models the downwelling SW surface 558 flux is too large as compared against CERES-EBAF, with multimodel averages have differences that range between 10 and 25 Wm⁻² over much of the Southern Ocean (Trenberth and Fasullo 559 560 2010, Ma et al. 2015, Kay et al. 2016, Zhang et al. 2016). If the Macquarie observations are 561 correct and representative of the larger SO, the CERES SW fluxes are too small by roughly 10 Wm⁻² in the SW and the model errors are larger than these previous studies have found. This 562 563 suggests that additional measurements and analysis should be undertaken at Macquarie Island and other locations, to more firmly establish the SW bias we have found at Macquarie Island. 564 565 and to determine the extent to which the Macquarie data are representative of other parts of the 566 Southern Ocean, and nominally, to identify the underlying cause of the CERES bias.

567

We find the annual mean bias in the CERES SYN LW downwelling flux during MICRE is also 568 of similar magnitude but opposite in sign, about -10 Wm⁻² (see Table #2), with slightly larger 569 570 values in the Fall and Winter than in the Spring and Summer. Unlike the situation in the SW, it 571 is clear that the LW bias is not due to calibration or sampling. Rather an examination of the diurnal cycle shows the LW bias occurs almost entirely at night, which in turn is clearly related 572 573 to the cloud-base being too high (and too cold) in the CERES SYN flux retrievals at night. In 574 most respects, this result is not surprising. Comparison of LW fluxes from the previous version 575 of CERES-MODIS retrievals (used in SYN) with retrievals based on a combination of CloudSat 576 (radar), Calipso (lidar) and MODIS by Kato et al. (2011, see their figure 3) show a seasonally 577 varying zonal bias in LW surface fluxes over the Southern Hemisphere, with values that range between about -3 to -7 Wm^{-2} at the latitude occupied by Macquarie Island. Kato et al. (2011) 578 579 likewise identified the LW surface bias as being due primarily to problems with cloud base. As 580 regards the current version of SYN (Edition 4), Kato et al. (2019, see their figure 1) suggest the 581 near surface cloud occurrence profile (the volume of atmosphere containing cloud) remains too 582 low near the surface in Edition 4 as compared with active sensors (radar and lidar profiles) from 583 CloudSat and Calipso, and show there is a stark reduction in near surface cloud at night (Kato et 584 al. 2019, their figure 2). Given the algorithmic nature of the error, which originates from errors

585 in the cloud-base retrieval, it is likely that this LW bias affects much of the Southern Ocean,

though the magnitude will likely vary with the amount of low cloud. Again additional

587 measurements should be undertaken to establish the Macquarie results are correct and to

examine the degree to which variations in sea surface temperature, cloud type and other factorsmatter.

590

591 We note that while the distribution of cloud bases in the SYN product is better during the 592 daytime (when satellite visible channels are used in the cloud property retrievals), we find cloud 593 bases below 900 hPA are still underrepresented (just not as severely as at night). Indeed Figure 2 594 (left panel) shows that during the day SYN LW fluxes tend to be too small (below the 1-to-1 line) when the observed fluxes are above 300 Wm⁻² (because low based clouds are present) and 595 too large (above the 1-to-1 line) when the observed fluxes are below about 300 Wm⁻². This 596 suggests that the low daytime LW bias of less then 2 Wm⁻² at Macquaire reported here is likely 597 598 due in some part to a fortuitous cancellation of errors with other factors, and analysis of surface 599 temperatures and boundary layer thermodynamic profiles (based on radiosonde data) should 600 perhaps be undertaken to explore this issue, further.

601

The results presented in section 3, also demonstrate that the CERES-EBAF SW and LW fluxes track the CERES-SYN values closely in (at least) the 10 degree region surrounding Macquarie Island. While the *bias corrections* and *adjustments* applied to monthly EBAF data appear to have reduced biases in other regions (Kato et al. 2018), such does not seem to be the case at this location.

607

608 Overall, the LW flux comparison undertaken here reinforces the need for further improvements 609 in CERES SYN (including CERES-MODIS retrievals) and EBAF treatments of low clouds and 610 low cloud base at night, in particular. As mentioned briefly in section 3, our initial impression is 611 that much of the LW error occurs when multilayer clouds are present, and an ongoing analysis of 612 cloud properties from MICRE should provide additional details in this regard. Regardless, the 613 relative success of LW fluxes during the day suggests that the nighttime problem is inherently 614 rooted in the loss of information contained in the visible-radiances used in the daytime retrievals, 615 and it may well be that what is needed is a greater reliance on climatological constraints or other

616 aprori knowledge during the night. For example, for regions with small diurnal cycles in

- 617 boundary layer thermodynamics, precipitation and clouds such as the Southern Ocean (Hande et
- al. 2012, Wang et al 2012), a simple approach might be to consider using statistical retrievals
- 619 (tuned regressions) rather than the current "physical retrievals" to ensure the cloud geometric and
- 620 microphysical properties at night match those during the day (for a given set of infrared channel
- 621 measurements and perhaps meteorological variables).
- 622

623 While the most obvious (and arguably best) route to improving LW flux would be to focus on 624 improving CERES SYN and CERES-MODIS retrievals that flow into CERES EBAF, an

625 alternative might be to applied EBAF cloud base *bias corrections* separately to data collected

626 during nighttime. That is, EBAF *corrections* could still be based on monthly data, but monthly-

627 daytime and monthly-nighttime averages could be calculated and corrected separately, before

628 being combined to calculate the 24-hour averaged monthly mean.

629

630 The CERES SYN and EBAF surface SW and LW biases nearly cancel (sum to near zero) in the 631 annual mean. As far as we can conceive this is a coincidence, and we stress that it is true only in 632 the annual mean. There is a significant imbalance on seasonal scales in the net radiation, with 633 too much net radiative heating of the surface occurring in the Spring and Summer (because the 634 magnitude of the positive SW bias is larger during these seasons and greater than the magnitude 635 of the negative LW bias); and there is net radiative cooling of the surface in the Fall and Winter 636 (because the magnitude of the negative LW bias is larger in these seasons and greater than the 637 magnitude of the positive SW bias); and likewise in the diurnal cycle where there is too much 638 SW heating during the day (which is strongest in the summer) and too little LW heating at night. 639 Accordingly, evaluations of model output on seasonal or diurnal time scales with CERES SYN 640 and EBAF datasets should consider these differences in seasonal and diurnal biases.

641

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- 645 Center Atmospheric Science Data Center (https://eosweb.larc.nasa.gov/project/ceres) with DOI
- 646 for the specific Edition 4 product used given in Section 2. Likewise, CloudSat FLXHR-LIDAR

- 647 data are available via the CloudSat Data Processing center
- 648 (http://www.cloudsat.cira.colostate.edu/data-products/level-2b/2b-flxhr-lidar). MICRE
- observations made by the U.S DOE ARM program instrumentation (including surface radiation
- and ceilometer data sets) are available through the DOE ARM program data archive
- 651 (https://adc.arm.gov/) (DOIs are given in section 2.1) and can also be obtained by request to
- 652 Roger Marchand at the University of Washington (rojmarch@u.washington.edu).

653 Appendix A: Cloud Overlap Treatment in CERES SYN/EBAF-Surface Edition 4

- The cloud overlap scheme described below is applied in CERES Edition 4, and was not used in
- earlier editions. As described in Kato et al. (2019) there are four cloud type categories, which
- are defined by the cloud-top pressure: low = surface-to-700 hPa, mid-low= 700-500 hPa, mid-
- high = 500-300 hPa, and high = less-than-300 hPa. These 4 cloud type categories are overlapped
- 658 (in Edition 4) to give 15 different combinations of cloud overlap plus one clear scene. Table A1
- 659 shows the cloud overlap combinations. The cloud fraction associated with each of the 15
- 660 combinations is obtained assuming random overlap of the 4 cloud-types and simply given by the
- 661 product of the "true" cloud fraction (or clear fraction) associated with each layer, such that
- 662 c1 = C1*C2*C3*C4
- 663 $c2 = C1*C2*C3*(1-C4) \dots$
- 664 $c_{15} = (1-C_1)^*(1-C_2)^*(1-C_3)^*C_4$

We stress that C1 to C4 are nominally the "true" cloud fraction for each pressure category NOT the cloud fraction observed from space (S1 to S4). In CERES processing C1 to C4 are derived from S1 to S4 assuming random overlap, see equations B1 to B4 in Kato et al. 2019.

669	Table A1 – Cloud Overlap Categories.	
-----	--------------------------------------	--

	c1	c2	c 3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15
C1	X	X	x	X	X	X	X	X							
high															
C2	x	x	x	X					X	х	х	х			
mid-high															

	С3	x	x			x	x			x	x			x	x	
	mid-low															
	C4	x		x		x		x		x		x		x		x
	low															
0'				J			1		I	1		1				-1
1	As describe	ed in	Kato	et al	(201	9) at	mos	t four	of th	nese 1	15 ove	rlap ca	tegori	es are	used i	n the f
2	calculation	s, but	t the 1	rules	for se	electi	ing th	ne 4 p	orofil	es we	ere not	clearl	y desc	ribed.	It is	not sin
3	the largest	four	value	s tak	en ov	er th	e col	lectio	on c1	to c1	5, but	rather	up to	four v	alues	are cho
4	within the	follov	wing	subse	ets:											
5																
6	Hig	gh_clo	oud_p	profil	e = tl	ne ve	rtical	l prof	file as	ssocia	ated w	ith hig	h clou	ds is re	eprese	ented by
7	the	categ	gory v	with t	he la	rgest	valu	e bet	ween	c1 to	o c8.	If all a	re zero	o then	no pro	ofile w
8	hig	h-clo	ud is	used												
9																
0	Mic	l-hig	h_pro	ofile =	= the	profi	le wi	ith a 1	mid-l	nigh t	op is r	eprese	ented b	y the o	catego	ory with
1	the	large	st va	lue b	etwee	en c9	to c]	12 (if	not a	all ze	ro).					
2																
3	Mic	d_low	v_pro	file =	= the	mid-	low p	orofil	e foll	ows	that w	ith the	larges	t value	e betw	veen c1
4	and	c14	(if nc	ot bot	h zer	o).										
5																
6	Lov	v_clo	oud_p	orofil	e = c	15, if	not	zero.								
7																
8	In short, th	ere a	re up	to 4	cloud	l prof	files	used	in the	e RT	calcula	ations,	but w	ith one	e profi	ile
9	associated	with	each	of th	e orig	ginal	high	, mid	-high	, mic	l-low a	nd lov	v categ	gories.	The	cloud
0	fraction assigned to each of these 4 categories remains that of the original category (S1 to S4).															
1	The overlap values c1 to c15 are only used to select a single profile for each of the four															
2	categories.	Not	te the	clou	d-bas	se ass	socia	ted w	vith e	ach p	rofile	is take	n from	the lo	owest	layer.
3																
4	Last, but no	ot lea	st, if	the r	etriev	ed o	ptica	l dep	th ass	sociat	ted wit	h any	of the	origin	al fou	r
5	categories	(high	, mid	-higł	ı, mic	l-low	, low	/) is l	ess tł	nan si	ix, the	overla	p is ig	nored.	Mea	ning tł
6	vertical pro	ofile o	of the	clou	d is a	issun	ned to	o hav	e a c	loud	base e	ual to	that o	f the c	origina	al grou

697

- 698 So, for example, suppose we have a scenario in which S1 = 0, S2 = 0, S3=0.4 and S4=0.4
- 699 (meaning no high or mid-high clouds only mid-low and low clouds are present), with a cloud
- base for layer 3 (CB3) of 850 hPa and for layer 4 (CB4) of 780 hPA, and a cloud optical depth
- for layer 3 (OD3) of 10 and layer 4 (OD3) of 3. Yes, it is possible for CB3 to be lower (closer
- to the surface) than CB4 (each are retrieved independently).
- 703

In this scenario, (following Kato 2019 equations B1 to B4) one obtains C1 = C2 = 0 and C3 = 0.4 and C4 = S4/(1-S3) = ~ 0.67. Consequently, c1 to c8 = 0, and c9 to c12 = 0 and ONLY two

- cloud profiles of the possible four will be used in the radiative transfer (RT) calculations.
- 707

708	c13 = (1-C1)*(1-C2)*C3*C4	= 0.267

c15 = (1-C1)*(1-C2)*(1-C3)*C4

- 709 $c_{14} = (1-C_1)^*(1-C_2)^*C_3^*(1-C_4) = 0.133$
- 710 711

Since c13 is larger than c14 and OD3 is larger than 6, profile c13 will be used for the mid-low

category in the RT calculations with a total area covered by the c13 profile set to 0.4 (S3), with a

= 0.4

cloud base set to CB4 or 780 hPA, and a optical depth of 10 (OD3). If OD3 had been 5, then the

overlap would be ignored (equivalent in this case selecting profile c14), with a resulting cloud

- fraction of 0.4 (S3), cloud base at 850 hPA (CB3) and the same optical depth 10 (OD3). The
- second profile used in the RT calculation would be a single-layer low cloud with a cloud fraction

of 0.4 (S4), with a base at 780 hPA (CB4) and an optical depth of 3 (OD4).

719

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721

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