

1 **Sub-Diurnal to Interannual Frequency Analysis of Observed and Modeled Reflected**
2 **Shortwave Radiation from Earth**

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10

11 **Abstract:**

12 Observational estimates of global top-of-atmosphere radiation on monthly, seasonal,
13 annual, and longer time-scales require estimates of the diurnal variability in insolation and
14 the asymmetry of surface and atmospheric reflection. We compare EPIC and NISTAR
15 observations from the DSCOVR satellite with CERES hourly synoptic fluxes, which are filled
16 through geostationary observations, and find that a Fourier analysis of these data
17 substantially agree, showing strong relative power at sub-diurnal, diurnal, seasonal, and
18 annual time-scales, and power growing from diurnal to seasonal time-scales. Frequency
19 analysis of fluxes from several models shows that they distribute too much power over
20 periods greater than 1 day but less than one year, indicating that a closer look is needed
21 into how models achieve longer-term stability in reflected shortwave radiation. Model
22 developers can consider using these datasets for time-varying energetic constraints, since
23 tuning parameter choices will impact modeled planetary shortwave radiation across
24 timescales ranging from sub-diurnal to decadal.

25

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27 **Key Points:**

- 28 • We present the first intercomparison of observational estimates of the Earth's
29 albedo at sub-diurnal through inter-annual time-scales.
- 30 • These observational estimates, from CERES, EPIC, and NISTAR, are in consensus,
31 and can therefore be used to confront models.
- 32 • Model estimates of planetary albedo show that models mostly disagree with
33 observations at time-scales of longer than one day.

34

35 **Plain-Language Summary:**

36 The balance between incoming solar and outgoing thermal energy exerts a strong influence
37 on the Earth's climate. The part of the incoming solar energy that is reflected back to space
38 is called albedo. Even a slight change in albedo would dwarf the impacts of greenhouse
39 gases, but direct observations indicate that on time-scales longer than a few years, it is
40 remarkably stable and has been for decades. However, this albedo does fluctuate greatly at
41 shorter time-scales, meaning that the underlying causes that ultimately shape albedo
42 interact in a variety of ways to achieve this stability. Using novel data, we present three
43 different observational estimates of how this reflected energy varies at these shorter time-
44 scales, and they all substantially concur. However, a wide variety of climate models do not
45 capture the observed variability, suggesting that further model developments is needed to
46 better represent the underlying contributions to the Earth's albedo and the causes for its
47 stability to date.

48

49 **Keywords:**

50 Albedo, shortwave radiative energy budget, diurnal cycle, DSCOVR

51

52 **Index Terms:**

53 1616, 1622, 1626, 1640, 1694

54 **Introduction:**

55 Modeling centers have recognized that the achievement of a long-term top-of-atmosphere
56 (TOA) energy imbalance of less than 1 W/m^2 is a prerequisite that their models must
57 achieve to produce credible historical simulations and future projections of the Earth's
58 climate system [Willis et al, 2004; Hansen et al, 2005]. As part of the development process,
59 model component interactions and model free parameters are tuned so that the version of
60 each model that reports to publicly-available repositories yields results that lie within that
61 range [Mauritsen et al, 2012; Golaz et al, 2013; Hourdin et al, 2017; Schmidt et al, 2017].
62 While there are other observational constraints on model tuning many of which vary from
63 model to model, the TOA radiative tuning approach is, as far the publications to date on
64 tuning indicate, generally consistent across models.

65
66 TOA radiative fluxes, specifically reflected shortwave and outgoing longwave radiation, are
67 derived from NASA's Clouds and Earth's Radiant Energy System (CERES) mission [Wielicki
68 et al, 1996; Loeb et al, 2009] and form the observational basis for model tuning. That
69 mission directly measures broadband radiances at a fixed set of local solar hours, and from
70 these derives best-estimates of the spatially-resolved broadband, diurnally-averaged
71 shortwave and longwave fluxes at the TOA [Loeb et al, 2018]. However, there are
72 numerous steps involved in the process chain to develop these fluxes. With respect to
73 reflected shortwave radiation, and the associated unitless quantity of planetary albedo,
74 some of these steps, most notably the development of diurnal averages from sun-
75 synchronous observations, have received relatively little scrutiny.

76
77 At the same time, the importance of diurnal variability in shortwave reflection for models
78 has long been recognized (e.g., [Bergman and Salby, 1997]). More recently, it was suggested
79 that the diurnal cycle of clouds could be important to understand constraints on cloud
80 adjustments and identify where models redistribute clouds in a warmer climate [Webb et
81 al, 2015]. Over land, cloud diurnal cycles, especially, are not well-captured by models [Yin
82 and Porporato, 2017]. Model errors in the diurnal cycle of cloud fraction (DCC) have been
83 suggested to be the result of tuning the models without properly capturing the processes
84 controlling the DCC over land [ibid]. Recent work has shown that Earth System Model

85 tuning for centennial-length simulations can be developed from ensembles of 3-day model
86 runs that better explore structural vs. parametric error [Qian *et al*, 2018], suggesting that
87 model constraints at high frequencies are warranted.

88
89 In spite of the recognized importance of diurnal variability in reflected shortwave radiation
90 (RSR), the lack of scrutiny of this quantity is due primarily to a lack of observational
91 datasets that directly measure RSR across the diurnal cycle. To date, the approach has
92 been to fill in the gaps in the diurnal cycle in direct broadband radiance observations from
93 CERES data with geostationary observations, where the latter dataset provides high-
94 frequency observations over a limited set of wavelengths [Doelling *et al*, 2013]. This
95 diurnal filling has been tested with data from the Geostationary Earth Radiation Budget
96 (GERB) mission [Clerbaux *et al*, 2009], but only over the Meteosat domain (60°S–60°N,
97 60°W–60°E). Global testing of the filling algorithms is warranted.

98
99 Instruments from the Deep Space Climate Observatory (DSCOVR) spacecraft provide more,
100 and potentially complete, information about the diurnal cycle of shortwave radiation,
101 because the spacecraft resides at the L-1 Lagrange Point between the Earth and the Sun
102 and continuously observes almost all of the illuminated portion of the Earth from that
103 vantage point [Burt and Smith, 2012; Marshak *et al*, 2018]. By virtue of DSCOVR’s viewing
104 geometry, there may be additional information about the diurnal cycle in radiative fluxes
105 from DSCOVR beyond what has been observed previously. The DSCOVR spacecraft has two
106 primary instruments onboard that are of direct relevance to shortwave radiation
107 observations: the Earth Polychromatic Imaging Camera (EPIC) and the National Institute of
108 Standards and Technology Advanced Radiometer (NISTAR). Recent work has shown how
109 data from these instruments can be used to produce globally averaged broadband
110 shortwave fluxes [Su *et al*, 2018; Su *et al*, 2020]. These data can be used to directly test the
111 diurnal filling algorithms, establish the temporal structure of variability by which the Earth
112 achieves albedo stability, and evaluate whether models capture this structure.

113
114 Here, we first compare fluxes derived from the CERES diurnal filling algorithm with fluxes
115 derived from EPIC and NISTAR, and then evaluate the skill that models exhibit in

116 reproducing the observed modes of variability. From these results, we conclude by
117 discussing how high-frequency observations may be useful for model development.

118

119 **Materials and Methods:**

120 Here, we use three distinct observational datasets. First, we use the CERES Synoptic hourly
121 shortwave radiative flux product, Edition 4.1 [Rutan *et al*, 2015]. Second, we use the hourly
122 flux product produced from EPIC narrow-band radiances [Su *et al*, 2018], and third, we use
123 the hourly fluxes produced from NISTAR Band-B radiances [Su *et al*, 2020]. These datasets
124 were collected covering 2017 and 2018, and all datasets use the same angular distribution
125 modeling (ADM) framework built from CERES [Loeb *et al*, 2003; Su *et al*, 2015]. We
126 recognize the potential challenges of using CERES ADMs on data acquired with a
127 substantially different viewing geometry, and will discuss implications thereof at the
128 conclusion of this paper.

129

130 For comparing observations to models, data from the CMIP5 [Taylor *et al*, 2012] archive is
131 used. Model radiative fluxes are taken from the Atmospheric Model Intercomparison
132 Project (AMIP) which provides 3-hourly flux values for 1 year and includes the following
133 models: CNRM-CM5 [Voldoire *et al*, 2013], MRI-CGCM3 [Yukimoto *et al*, 2012], and
134 HadGEM2-ES [Jones *et al*, 2011], and 21 years for the CanESM2 model. The 3-hourly fluxes
135 are convolved with a mask with the time-varying portion of the Earth that is within the
136 field-of-view of the DSCOVR instrument, and this convolution is area-averaged to produce
137 global fluxes.

138

139 We focus on observational datasets from 2017-2018, and frequency analysis is conducted
140 on detrended flux time-series using fast Fourier Transforms. We perform discrete Fast
141 Fourier Transforms on RSR time-series and display power spectral density (PSD) functions.
142 For cross PSD, we use a Welch's averaged, modified periodogram method of spectral
143 estimation (Matlab's cpsd function). Uncertainty in frequency analysis is developed using
144 bootstrap methods, wherein we selectively remove data and determine statistical
145 distributions for the range in power at a given frequency, assuming that spectral density
146 power is a normally-distributed random variable [Hall *et al*, 2004].

147

148 **Results:**

149 We first present the three time-series of observationally-derived reflected shortwave
150 radiation (RSR) from CERES SYN, EPIC, and NISTAR, shown in Figure 1(a). These data
151 show a seasonal cycle and numerous sub-seasonal modes of variability across a wide range
152 of time-scales, indicating that frequency analysis of these observations is warranted.

153 Figure 1(b) presents a difference plot between the NISTAR or EPIC and CERES SYN and
154 shows negligible differences between the EPIC and CERES SYN RSR time-series ($+1.1 \pm 3.9$
155 (1σ) W/m^2), though there are much more significant differences in fluxes between them
156 and those from the NISTAR instrument ($+11.9 \pm 7.9$ (1σ) W/m^2). RSR from EPIC and
157 NISTAR are highly correlated with the RSR from CERES SYN [Su *et al*, 2018; 2020].

158

159 The DSCOVR Science Team has investigated this RSR discrepancy and found that some of
160 this discrepancy can be due to uncertainty in the transmission function of the filter wheel,
161 as elaborated in Su *et al* [2020]. The differences between CERES SYN/EPIC and CERES
162 SYN/NISTAR are plotted in Figure 1(b).

163

164 There are a number of periodic features in the RSR datasets. We will start by discussing
165 the prominent features in observed PSDs. First, the diurnal cycle of RSR is a major feature
166 of the time-series. It arises primarily due to the large difference in surface reflectivity
167 between the Earth when Africa and Europe are illuminated vs. when the Pacific Ocean is
168 illuminated. The diurnal cycles of RSR as determined from EPIC and CERES SYN fluxes are
169 similar, as shown in Figure 1(c), while those from NISTAR are systematically higher than
170 the other datasets due to the issues discussed above. All three datasets show similar
171 diurnal variations. The PSDs of the three estimates of RSR are shown in Figure 1(d),
172 normalized by the maximum power at any period, and indicate that there is substantial
173 agreement in relative strength in modes of variability in the three time-series. There are
174 major sources of variability at diurnal time-scales, but also secondary sources of variability
175 at shorter periods, including at 6, 8, and 12 hours. There are also non-prominent features
176 at periods longer than one day, for which CERES and EPIC have slightly larger

177 disagreement. The upward slope of the PSD with period length indicates that there are a
178 number of processes that occur at irregular intervals that contribute to variability in RSR.
179

180 Building off of the substantial agreement in the modes of variability in all-sky RSR fluxes
181 from CERES, EPIC, and NISTAR, it is reasonable to explore the modes of variability in RSR in
182 more detail to understand the impact of clouds on that quantity. The panels in Figure 2
183 indicate the contribution of clouds to the variability in RSR. Figure 2(a) shows the power
184 spectral density function of both clear-sky and all-sky CERES SYN fluxes, where the former
185 is estimated by calculating fluxes based on measurements of the atmospheric state,
186 including surface albedo, aerosols, and water vapor, largely based on data from other,
187 collocated satellites [*Rutan et al*, 2015], whereas the latter is derived from CERES radiance
188 measurements directly. Figure 2(b) shows the cross spectral density function of clear-sky
189 and all-sky CERES SYN fluxes and reveals, at periods of 2 hours and longer, the most
190 prominent power at 1 day, and potentially power at seasonal time-scales. These features
191 indicate that clouds tend to modulate and suppress the variability in RSR that would
192 otherwise exist in the absence of clouds. That is, the more frequent occurrence of clouds
193 over dark ocean areas reduces the albedo difference between marine and bright, relatively
194 cloud-free land surfaces. Below seasonal time-scales, most of the modulation in variability
195 occurs at 1-day periods, but there are non-negligible effects at sub-diurnal periods. These
196 features are impacted by the contrast between RSR over the portion of the daylit Earth that
197 has more land vs. RSR with more ocean. Surface albedo plays a prominent role in these
198 sub-diurnal features, but again clouds modulate the stronger variability associated
199 primarily with surface reflection under clear-sky conditions.

200

201 The means and 95% confidence intervals of clear- and all-sky CERES SYN PSDs, derived
202 from observational data spanning 2001-2019, are shown in Figures 2(c) and 2(d). These
203 plots indicate that the prominent diurnal feature of clear- and all-sky PSDs is stationary and
204 nearly invariant over nearly 2 decades of observations. There is limited variability in sub-
205 diurnal prominent features at 4-, 8-, and 12-hour periods of these PSDs.

206 Also, there are other features, such as the distribution of power between one day and
207 several months that have an upward slope with little relative uncertainty in its upper

208 bound, but with no prominent features. These super-diurnal features indicate that there
209 are a large number of interacting processes operating irregularly on super-diurnal time-
210 scales that contribute to RSR time-series. The small level of uncertainty in features that are
211 both super-diurnal and sub-annual suggests that these processes are stationary over time.
212 Together, these findings indicate that there is a relatively small uncertainty in prominent
213 features of RSR PSDs, and therefore, that comparisons between observations and model
214 fields over a limited time-window will be meaningful and reveal underlying model skill, or
215 lack thereof, in achieving longer-term RSR stability.

216
217 Building off of the results in Figure 2, we undertake a comparison of clear-sky and all-sky
218 RSR PSDs between observations and models, and some results of this comparison are
219 shown in the panels of Figure 3. They indicate that there are similarities and differences to
220 be explored. First, the clear-sky RSR PSDs from CNRM-CM5 and HadGEM2-ES have varying
221 levels of concurrence in their apportionment of power at diurnal and sub-diurnal 1-day
222 periods with the CERES SYN flux product. Where models are greater than observations for
223 sub-diurnal periods, this means that these models exhibit too much zonal contrast in RSR,
224 and vice versa. For super-diurnal periods, the cause(s) of excessive model apportionment
225 of power are not attributable to a single period, since the modeled power at all periods
226 greater than one day and less than one year is greater than the observed power.

227
228 The three primary surface-atmosphere constituents that lead to clear-sky RSR variability
229 are surface albedo, aerosols, and water vapor. Surface albedo is generally variable at
230 super-diurnal periods, driven by changes in snow and sea-ice coverage, and to a lesser
231 extent, changes in albedo from seasonal vegetation and surface wetness, while aerosols and
232 water vapor can exhibit variability at sub-diurnal and super-diurnal periods. Biases in
233 surface albedo may be due to differences in frozen surface extent and snow/ice reflectivity,
234 but biases have also been found in modeled snow-free surface albedo [*Levine and Boos,*
235 2017]. However, a closer investigation regarding how these three factors interact to
236 produce model biases is warranted to determine if the origin(s) of biases are structural, in
237 terms of radiative transfer code issues, or parametric.

238

239 Figures 3(b) and 3(d) compare the cross-spectral density of observations and models.
240 These figures indicate that models generally overestimate power at prominent diurnal and
241 sub-diurnal frequencies, indicating that the variability in RSR is overly correlated between
242 clear- and all-sky conditions in models relative to observations. That is, models
243 overestimate how clouds modulate all-sky RSR variability relative to clear-sky RSR.

244

245 We summarize the findings of total power for clear-sky and all-sky RSR in Tables 1 and 2,
246 respectively. The primary result that is shown by these tables is that at periods greater
247 than 1 day but less than 1 year, models apportion too much power, indicating that they
248 overestimate the variability in the sum of processes that contribute to albedo but have
249 irregular periods. These findings suggest that a closer investigation into the causes of bias
250 in the variability in modeled RSR over the range of periods from greater than 1 day to less
251 than 1 year is warranted.

252

253 **Discussion and Conclusions:**

254 Here, we have undertaken frequency analysis of high-frequency RSR observational time-
255 series from CERES SYN, EPIC, and NISTAR. From these observations, we have developed
256 several findings. First, frequency analysis reveals that there are prominent sub-diurnal and
257 diurnal features due to a zonal contrast in surface and cloud reflection, and there are no
258 prominent features over periods greater than 1 day but less than one year, though these
259 super-diurnal features indicate that most of the variability in RSR is contributed from a set
260 of processes that occur at irregular intervals.

261

262 Second, we have tested whether we can use CERES SYN observations to confront Earth
263 System Models at a range of frequencies ranging from sub-diurnal to annual. Because
264 CERES observations at the top-of-atmosphere have few data points across the diurnal cycle,
265 the process chain for filling in the diurnal cycle relies on geostationary products with
266 calibration tied to MODIS. Here, we have shown that the diurnal-filling process chain,
267 which is a key component of the development of TOA energy-balance estimates from
268 observations, does not exhibit discernible biases, and is stationary over nearly 2 decades,
269 so it may be considered robust for model confrontation.

270
271 More specifically, we have found that there is broad concurrence between different
272 observational datasets, including CERES SYN, EPIC, and NISTAR on the modes of variability
273 in the Earth's RSR. That being said, these are all predicated on radiance-to-flux conversion
274 algorithms that have been built based on low-earth observations. It may be difficult to
275 directly assess errors incurred in the use of these angular distribution models with such
276 different viewing geometries, though efforts to do so have been outlined in *Su et al* [2020].
277 Nevertheless, where radiative transfer models indicate there is the most potential for bias
278 in extrapolating radiance-to-flux conversion from low-earth orbit viewing geometries to
279 those associated with L-1 orbit, targeted rotating azimuthal scans from CERES or a CERES-
280 like instrument can be developed to constrain this conversion.

281
282 When we compare frequency features of RSR between CMIP5 models and observations, the
283 most significant differences occur over periods ranging from greater than 1 day to less than
284 1 year. Both observations and models concur that there are no isolated sources of
285 variability at regular intervals over this range of periods, but rather a number of processes
286 that are not insignificant for RSR but occur at irregular intervals. However, the
287 contribution to total variability over this range of periods is overestimated by models, both
288 for clear-sky and all-sky RSR.

289
290 We also explore how clouds modulate the variability in RSR on time-scales ranging from
291 sub-diurnal to annual, and find that over diurnal and sub-diurnal periods, models
292 reasonably concur with observations, but, as with clear-sky RSR, models overestimate the
293 contribution of super-diurnal frequencies to total RSR variability.

294
295 Together, these findings show that there is an uneven path by which models achieve their
296 tuning requirement for long-term stability in reflected shortwave radiation. These high-
297 frequency observations of shortwave flux therefore provide the model development
298 community the opportunity to consider time-varying constraints on shortwave radiation
299 that capture the processes by which the Earth system achieves long-term stability in
300 albedo, and not just the long-term number. While there is no debate about the paramount

301 importance of using tuning to ensure a model achieves TOA radiation balance in principle,
302 the specific approaches that modeling centers have taken differ in practice. The choices in
303 tuning this balance, which largely focus on adjusting cloud parameters, can have different
304 temporal signatures.

305

306 We show here that there is concurrence in observational datasets in how the temporal and
307 spatial variability of cloud systems realizes longer-term features in planetary albedo. We
308 also show that there are significant differences between observations and models in this
309 metric, which is disquieting. Longer-term TOA radiation balance is enforced, and therefore
310 achieved by tuning, but there would be greater confidence in modeled radiative processes,
311 particularly with respect to clouds, if they would substantially concur with the
312 observations that form the basis for this radiation balance.

313

314 Especially given recent work that finds that the parametric tuning constraints, developed
315 from perturbed-physics ensemble model simulations of 3 days, improve long-term model
316 performance [*Qian et al, 2018*], modeling centers should, at the very least, consider using
317 high temporal frequency features of TOA radiation as constraints in their approaches to
318 tuning.

319 **Acknowledgements:**

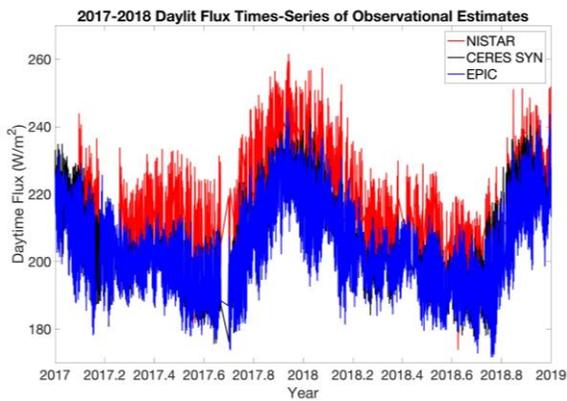
320 This research was supported by NASA Grant NNL16AA05C. The research depended
321 critically on NISTAR and EPIC products development made possible by the following
322 individuals: Steve Lorentz, Alan Schwarz Yinan Yu, and Allan Smith of L-1 Standards and
323 Technology, Inc., and David P. Duda, Konstantin Khlopenkov, and Mandana M. Thieman and
324 Lusheng Liang of SSAI. CERES SYN data are available at [https://ceres-](https://ceres-tool.larc.nasa.gov/ord-tool/jsp/SYN1degEd41Selection.jsp)
325 [tool.larc.nasa.gov/ord-tool/jsp/SYN1degEd41Selection.jsp](https://ceres-tool.larc.nasa.gov/ord-tool/jsp/SYN1degEd41Selection.jsp). AMIP are available from
326 <https://esgf-node.llnl.gov/search/cmip5/> and EPIC and NISTAR data are available at
327 <https://tinyurl.com/yastzeo5>.

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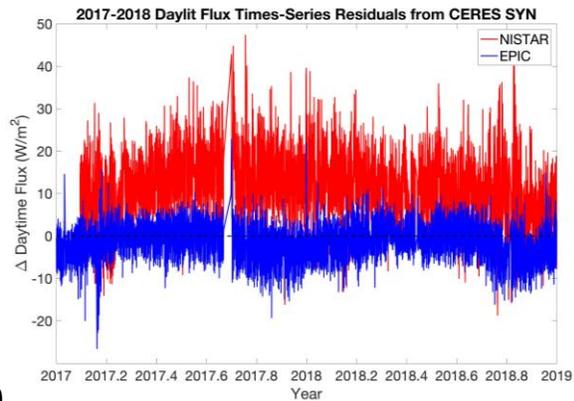


329 **Figures and Tables:**

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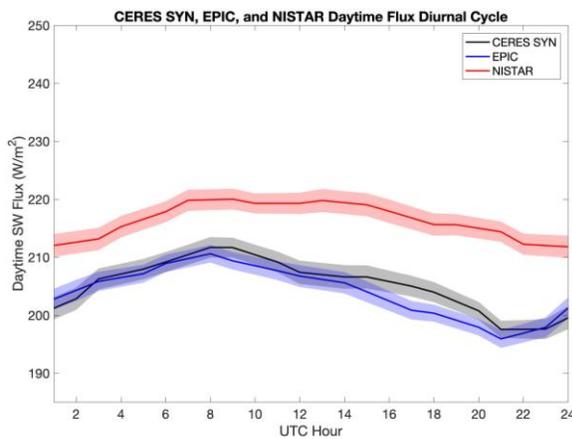


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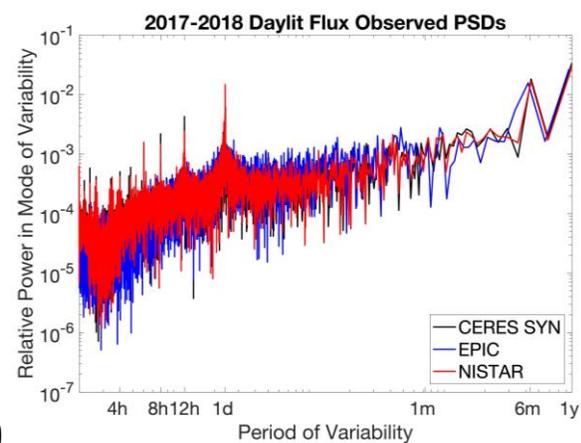


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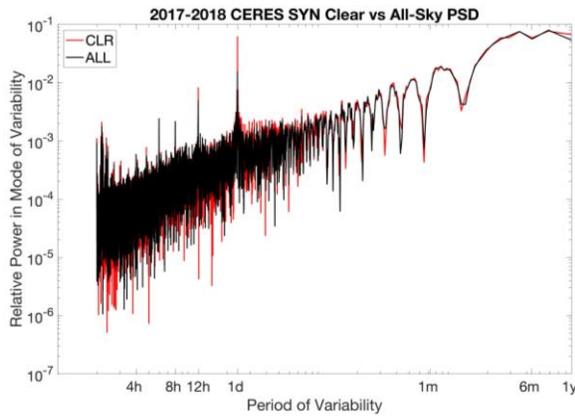


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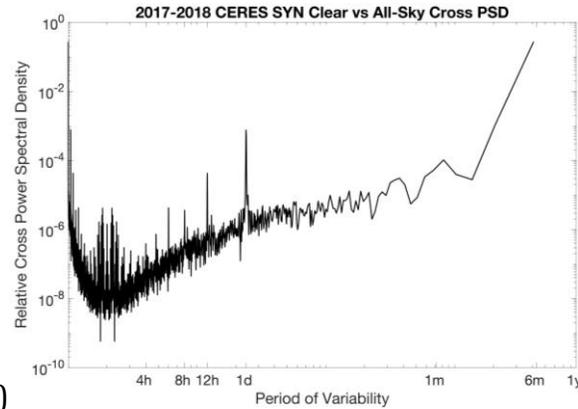


(d)

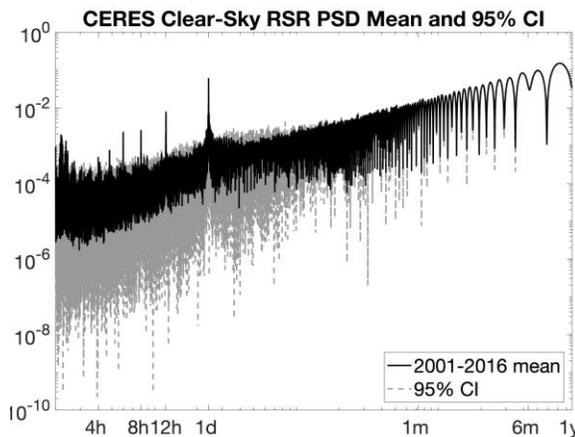
332 Figure 1: (a) Time-series from 2017-2019 of the daylit portion of the Earth's reflected
 333 shortwave radiation (RSR) as determined from NISTAR and EPIC Level-2 data and from the
 334 CERES SYN product. (b) Difference time-series between NISTAR or EPIC and CERES SYN
 335 RSR. (c) Diurnal cycle and 95% confidence interval from the 3 RSR data sources (d) Power
 336 spectral density of the 3 detrended RSR data sources.



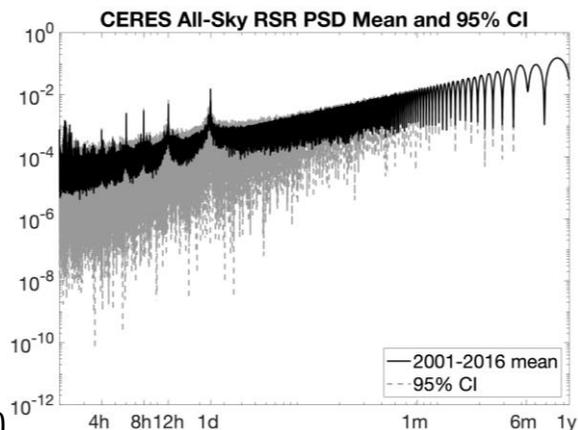
(a)



(b)



(c)

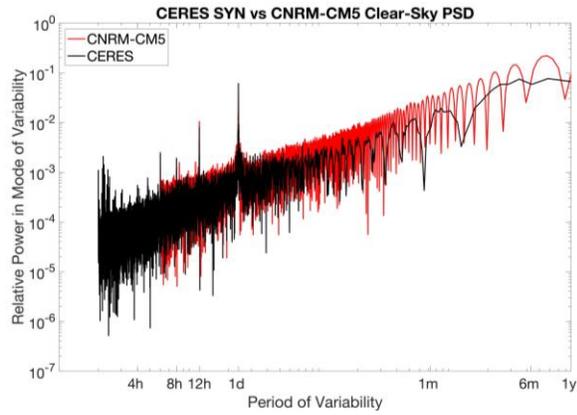


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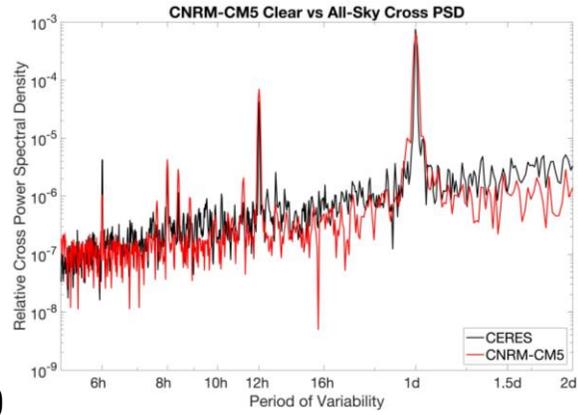
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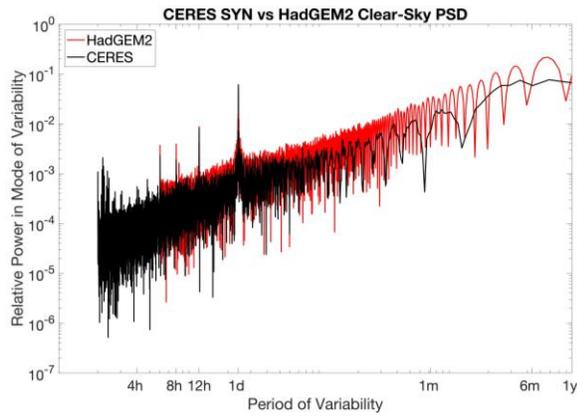
339 Figure 2: (a) Clear-sky (red) and all-sky (black) PSD functions of CERES SYN RSR fluxes
 340 covering 2017-2018. (b) Cross PSD function for clear-sky and all-sky CERES SYN RSR
 341 fluxes. (c) Mean and 95% confidence interval of PSD for clear-sky CERES SYN RSR fluxes
 342 derived from two-year intervals from 2001-2019. (d) Same as (c) but for all-sky CERES SYN
 343 RSR fluxes.



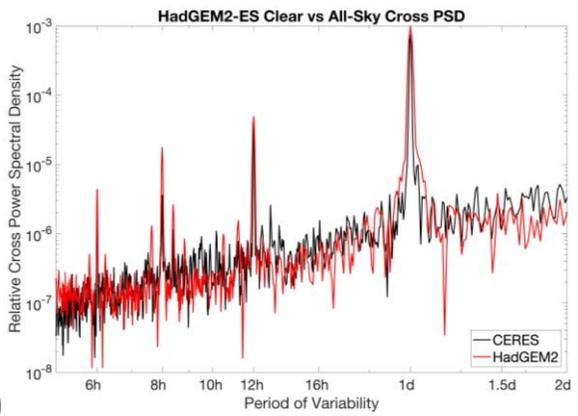
(a)



(b)



(c)



(d)

344

345

346 Figure 3: (a) Clear-sky RSR PSD for CERES SYN fluxes and fluxes reported by the CNRM-
 347 CM5 model. (b) Same as (a) but for clear vs all-sky cross PSD. (c) Same as (a) but for the
 348 HadGEM2-ES model.

	>1day, <1year	1 day	12 hours	8 hours
CERES SYN	0.7092 ± 0.003	$0.0277 \pm 1 \times 10^{-3}$	$0.0088 \pm 4 \times 10^{-4}$	$0.005 \pm 1 \times 10^{-4}$
CanAM4	0.7548	0.0328	0.0111	0.0070
CNRM-CM5	0.8020	0.0215	0.0108	0.0040
HadGEM2-ES	0.7920	0.0308	0.0096	0.0059
MRI-CGCM3	0.7781	0.0322	0.0087	0.0040

349

350 Table 1: Fraction of total power for a given period or range of periods for clear-sky daylit
351 RSR fluxes from CERES and several AMIP models. Mean of CERES SYN represents values
352 for 2017-2018, while uncertainty is 95% confidence interval derived all two-year intervals
353 from 2001-2019.

354

	>1day, <1year	1 day	12 hours	8 hours
CERES SYN	$0.5042 \pm 5 \times 10^{-3}$	$0.0173 \pm 7 \times 10^{-4}$	$0.0080 \pm 2 \times 10^{-3}$	$0.0070 \pm 5 \times 10^{-4}$
EPIC	0.4964	0.0168	0.0118	0.0082
NISTAR	0.5879	0.0118	0.0080	0.0068
CanAM4	0.7988	0.0089	0.0066	0.0075
CNRM-CM5	0.7950	0.0101	0.0085	0.0062
HadGEM2-ES	0.8028	0.0107	0.0055	0.0072
MRI-CGCM3	0.7951	0.0128	0.0092	0.0052

355

356 Table 2: Same as Table 1, but for all-sky conditions, and including EPIC and NISTAR
357 observations for 2017-2018.

358 **References:**

359 Bergman, J.W. and M.L. Salby, (1997) The Role of Cloud Diurnal Variations in the Time-
360 Mean Energy Budget. *J. Climate*, **10**, 1114–1124, doi:[10.1175/1520-](https://doi.org/10.1175/1520-0442(1997)010<1114:TROCDV>2.0.CO;2)

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