

Trends in Daily Solar Radiation and Precipitation Coefficients of Variation since 1984

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ABSTRACT

This study investigates the possibility of changes in daily scale solar radiation and precipitation variability. Coefficients of variation (CVs) were computed for the daily downward surface solar radiation product from the International Satellite Cloud Climatology Project and the daily precipitation product from the Global Precipitation Climatology Project. Regression analysis was used to identify trends in CVs. Statistically significant changes in solar radiation variability were found for 35% of the globe, and particularly large increases were found for tropical Africa and the Maritime Continent. These increases in solar radiation variability were correlated with increases in precipitation variability and increases in deep convective cloud amount. The changes in high-frequency climate variability identified here have consequences for any process depending nonlinearly on climate, including solar energy production and terrestrial ecosystem photosynthesis. To assess these consequences, additional work is needed to understand how high-frequency climate variability will change in the coming decades.

1. Introduction

Strategies for adaptation to climate change hinge on the expected changes in the distribution functions of climate variables. Contemporary climate studies have overwhelmingly focused on two properties of the distribution functions: the mean and the tails (i.e., extreme events) (Trenberth et al. 2007). While these statistics are clearly important, other statistics are also relevant to humans, ecosystem structure and functioning, and physical and chemical processes. In general, any process that depends nonlinearly on a climate variable will be sensitive to the variance of that climate variable. To illustrate the range of processes satisfying this requirement, note that photosynthesis (Sinclair et al. 1976), terrestrial ecosystems (Medvigy et al. 2010), and properties of solar cells (Gupta et al. 2002; Rahman et al. 2007; Boettcher et al. 2010) all depend nonlinearly on

downward solar radiation at the earth's surface ("solar radiation"), and that runoff and soil moisture (Marani et al. 1997; Margulis and Entekhabi 2001), mosquito populations (Koenraadt and Harrington 2008), and microbial respiration (Lee et al. 2004) all depend nonlinearly on precipitation. Thus, we expect changes in climate variances to impact energy production, sequestration of carbon by the terrestrial biosphere, and disease outbreaks.

Previous studies have typically considered changes in surface climate variances only in the context of extreme events (e.g., Wettstein and Mearns 2002; Goswami et al. 2006). One exception is Vinnikov et al. (2002), who investigated changes in temperature variance at local meteorological stations. However, changes in variances and changes in extremes are likely to have distinct impacts. Taking the example of carbon budgets, high-frequency variability of precipitation affects photosynthesis (Medvigy et al. 2010) and respiration (Lee et al. 2004) in ways that are totally different from the impacts of low-frequency extreme storms (Dupigny-Giroux et al. 2003) or droughts. The potential consequences of changes in high-frequency variability in the twenty-first century may be large, potentially

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impacting some terrestrial ecosystems as strongly as anticipated changes in mean climate (Medvigy et al. 2010). To our knowledge, there have been no global-scale studies of historical changes in variances of surface climate variables. In this work, we seek to address this knowledge gap by using satellite datasets to obtain the high-frequency, long-term measurements of climate variables needed for global analysis. We focus on solar radiation and precipitation.

We describe the relevant datasets in section 2 and our analysis methods in section 3. In section 4, we first present a case study that illustrates our analysis and then identify locations that have experienced statistically significant changes in solar radiation and precipitation variability, and where these changes are related to changes in cloudiness. We present our conclusions in section 5.

2. Datasets

Our analysis used 24 yr (1984–2007) of International Satellite Cloud Climatology Project (ISCCP) radiative flux (FD) and cloud products available on a 280-km equal-area grid (Zhang et al. 2004). The FD estimates of the downward surface flux of total solar radiation were derived using ISCCP clouds and other meteorological data in conjunction with radiative transfer code (Zhang et al. 2004, 2007). The solar radiation estimates, obtained eight times daily, have been used to construct time-averaged solar radiation values over 3-hourly intervals that account for variation in solar zenith angle (Zhang et al. 1995). Daily averages are obtained by averaging the 3-hourly values for each day. This approach is designed to yield accurate values of daily-averaged solar radiation and has been evaluated in previous work (Zhang et al. 1995). Other solar radiation datasets that span similar time periods exist, but they incorporate the same ISCCP cloud data (e.g., Gupta et al. 2006).

Previous studies have carefully quantified uncertainties in ISCCP solar radiation estimates (Whitlock et al. 1995; Zhang et al. 1995, 2004, 2007, 2010). A substantial portion of the uncertainty arises from errors in the input data, including aerosol information, cloud properties, and atmospheric conditions, rather than errors in the radiative transfer model (Zhang et al. 2004, 2010). In clear-sky cases, much of the mismatch between surface observations and ISCCP FD solar radiation can be attributed to mismatches in aerosol optical depths (Zhang et al. 2010). Uncertainties in daily mean solar radiation can also arise from nonuniform sampling (the number of daytime samples varies with season and latitude, and the samples were collected with some variation in their temporal separation). Furthermore, for any 3-hourly

period, about 15% of the globe has missing data. Zhang et al. (1995) tested several filling methodologies and found that filling physical properties using a nearby value in time at the same location (as done in the ISCCP dataset) produced lower rms errors than direct filling of fluxes in the calculated solar radiation. Further evaluation of uncertainties in solar radiation arising from sampling and from the filling of missing data can be found in Zhang et al. (1995, 2004, 2010). Efforts to ensure constant and common calibration among ISCCP satellites have also been described (Rossow and Schiffer 1991; Desormeaux et al. 1993; Brest et al. 1997).

Our ability to accurately detect significant trends in solar radiation variability may be compromised if the sources of error exhibit strong heteroscedasticity (i.e., time-varying error variances), in which case trends in the error can potentially be mistaken for trends in variability. There are several regions of particular concern. One is the Indian Ocean sector, which lacked good geostationary satellite coverage until ~1998. We have therefore omitted this region from our 1984–2007 analyses. We are also cautious about the latitude band near 60°N/S because this is approximately the transition region between geostationary and polar-orbiting satellites. Finally, Evan et al. (2007) argued that changes in satellite viewing geometry can give the appearance of a trend in ISCCP cloud amount where a trend does not necessarily exist. However, this effect was limited to relatively few regions of the world, including the central Pacific, western Atlantic, and tropical Indian Oceans. In particular, little tropical land was biased by this effect.

Values of daily precipitation were derived from the Global Precipitation Climatology Project (GPCP) 1°-daily combination (1DD) product, version 1.1, which consists of the daily sum of precipitation amount (mm day^{-1} ; Huffman et al. 1997). The GPCP 1DD product is the longest-running global daily precipitation dataset (since October 1996) and has been extensively validated (Adler et al. 2001, 2003; Yin et al. 2004). The 1DD product is a merge of rain gauge data and measurements from geostationary and polar-orbiting satellites. These different data streams have different strengths and weaknesses. Rain gauges provide accurate local estimates of precipitation, but their spatial coverage is sparse in many regions and point measurements are statistically noisy (Petty 1995). Infrared sensors on board geosynchronous satellites provide cloud-top temperatures for the entire 40°N–40°S latitude band; however, these measurements must be related to rainfall rates using empirical formulas, which can perform poorly (Joyce et al. 2004). The GPCP 1DD also includes information from polar-orbiting satellites, but such satellites have limited spatial and temporal sampling

resolution. McPhee and Margulis (2005) compared the GPCP 1DD to measurements from the dense network of rain gauges across the continental United States and found rms error values of $\sim 5 \text{ mm day}^{-1}$. Bolvin et al. (2009) compared the GPCP 1DD to rain gauge measurements from Finland and found that precipitation occurrence was better captured by the GPCP 1DD than corresponding precipitation event amounts.

3. Analysis

We computed annual, seasonal, and monthly coefficients of variation (CVs) for solar radiation and precipitation. The CV is a dimensionless metric of variability. The annual CV consisted of the annual standard deviation of daily data divided by the multidecadal mean. We computed seasonal and monthly CVs in the same way except that we only used data corresponding to the eponymous season or month. For solar radiation, each CV time series consisted of 24 points, one for each of the years 1984–2007. For precipitation, each CV time series consisted of 11 points, corresponding to the years 1997–2007. In all cases, the time variation of CV is attributable solely to time variation in the standard deviation because the denominator is a multidecadal mean.

Because we did not have prior knowledge of how to parameterize the CV time dependence, we applied a number of simple regression models to each grid cell's CV. These included 1) first- to fourth-degree polynomial regressions, where the time is the independent variable; 2) an exponential; and 3) a logarithm. All models for which the Fisher test of the overall fit was significant at the 95% confidence level were preserved for further consideration, while the others were excluded (throughout this paper, the 95% confidence level is used as the threshold for statistical significance). In addition, for the polynomial fits we required that the coefficient of the highest-order term be significantly different from zero. We note that the determination of confidence intervals in ordinary regression analysis requires that fit residuals be normally distributed, independent (i.e., not temporally autocorrelated), and homoscedastic (i.e., the characteristic magnitude of a residual is the same for different subpopulations of residuals). Various statistical tests have been developed to test these requirements. Here, we use the Shapiro–Wilk test (Royston 1982) to evaluate the null hypothesis of normality, the Ljung–Box test (Ljung and Box 1978) to evaluate the null hypothesis of independence, and the Breusch–Pagan test (Breusch and Pagan 1979) to evaluate the null hypothesis of homoscedasticity. All statistical tests are conducted in R (R Development Core Team 2008).

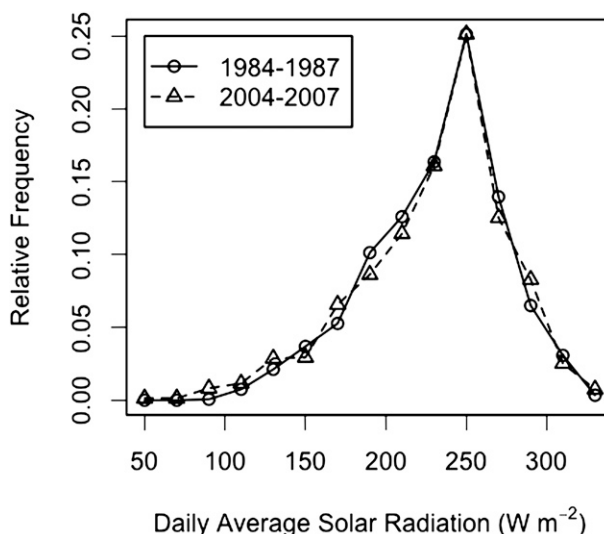


FIG. 1. Distributions of daily solar radiation for a single grid cell centered at 6.25°S, 23.75°E. The distributions are shown for two periods: 1984–87 and 2004–07.

Of the significant models, we selected the one with the smallest Akaike information criterion with second-order bias correction (AIC_c) (Akaike 1974; Burnham and Anderson 2004). This selection criterion leads to the selection of the most likely model but with a penalty for the number of parameters. Under the assumption that the model errors are independent and identically distributed according to a normal distribution, the AIC_c can be expressed by

$$AIC_c = n \log\left(\frac{1}{n}RSS\right) + n(\log 2\pi + 1) + 2k + \frac{2k(k+1)}{n-k-1}, \quad (1)$$

where n is the number of observations, k is the number of model parameters to be estimated, and RSS is the residual sum of squares. The AIC_c should be preferred over ordinary AIC unless $n/k > 40$ so as to avoid overfitting (Burnham and Anderson 2004).

4. Results

a. Single-gridcell case study

To illustrate our statistical analysis, we first make a detailed investigation of annual solar radiation for a single ISCCP grid cell centered at 6.25°S, 23.75°E. We find that the distribution of average daily solar radiation changes over time, as depicted in Fig. 1. Here, we see that the solar radiation distribution corresponding to the 2004–07 period has more support in the tails (solar

radiation in the ranges 50–135 and 285–325 W m^{-2}) than the distribution corresponding to the 1984–87 period. Moreover, the 2004–07 distribution is more sharply peaked (solar radiation in the range 200–260 W m^{-2}) than the 1984–87 distribution. Overall, the standard deviation of daily solar radiation increases from 41.8 W m^{-2} in 1984–87 to 46.0 W m^{-2} in 2004–07.

Then we calculated the standard deviation of daily solar radiation for each year in the 1984–2007 period and converted this to a CV by dividing by the 1984–2007 mean solar radiation, 230.7 W m^{-2} . This time series of CV (Fig. 2a) suggests an increase in CV over time. To test this, we carried out polynomial, exponential, and logarithmic ordinary least squares fits to these data. The number of degrees of freedom is defined by the difference between the number of observations and the number of parameters to be estimated in each model. For example, linear, exponential, and logarithmic fits had 22 degrees of freedom. The linear fit (also shown in Fig. 2a) minimized the AIC_c and had a p value less than 2×10^{-4} . This can be interpreted as a statistically significant fit at the 95% confidence level if the fit residuals are normally distributed, independent, and homoscedastic. Visual inspection of the residuals (shown in Fig. 2b as a time series and in Fig. 2c as a histogram) suggests that this may be the case, and indeed our statistical tests indicated that the null hypotheses of normality, independence, and homoscedasticity could not be rejected. This demonstrates that our methodology and underlying assumptions are appropriate and supports the interpretation of the fit in Fig. 2a as “statistically significant.” We note that this interpretation is contingent only upon the statistics of the residuals (Fig. 2) and, in particular, it does not depend on the shape of the underlying solar radiation distribution (Fig. 1).

b. Changes in solar radiation coefficient of variation

We then repeated our analysis for every ISCCP grid cell. For 34% of the globe, at least one of the regressions had a p value less than 0.05 (Fig. 3; note that this excludes the Indian Ocean sector, which lacked geostationary satellite coverage prior to 1998). Of models with $p < 0.05$, the linear model was most commonly selected as AIC_c minimizing (13% of the globe), but higher degree polynomials (5%–10% of the globe) and the exponential model (2% of the globe) were also occasionally selected. The logarithmic model was selected for less than 1% of the globe. For each grid cell, the residuals of the selected model were examined to test the null hypotheses of normality, homoscedasticity, and independence. These hypotheses were rejected for 3%, 2%, and 3% of the globe, respectively. The smallness of these percentages

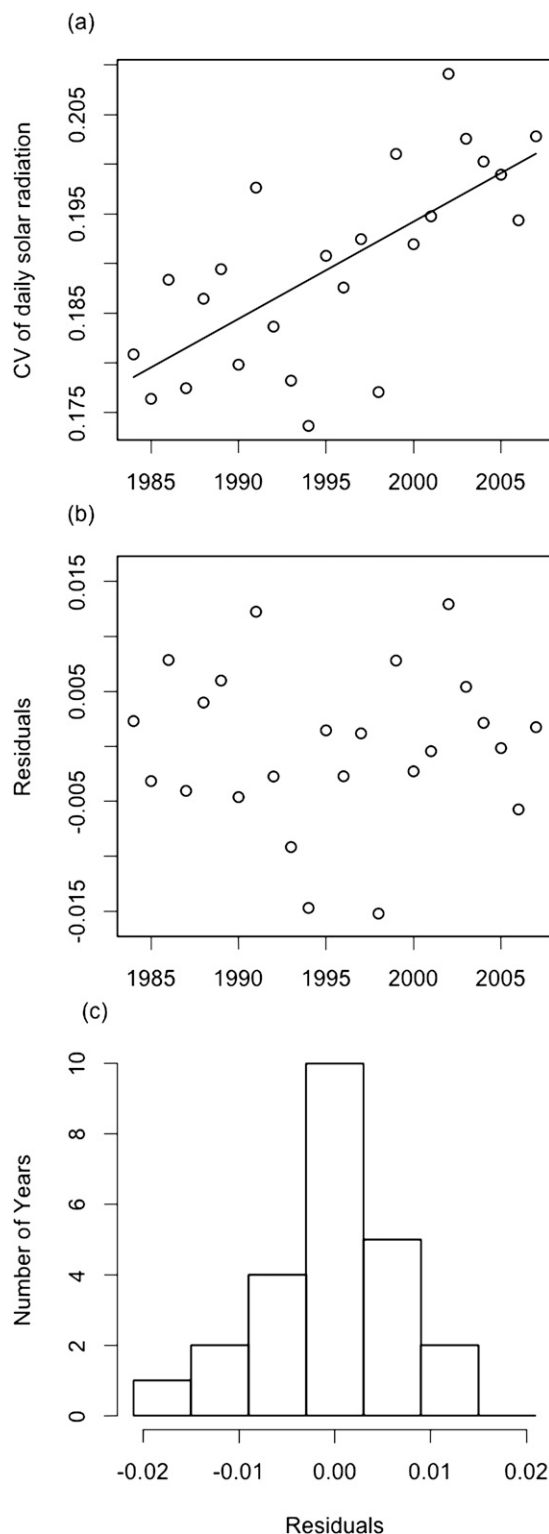


FIG. 2. Analysis of daily solar radiation CV for a single grid cell centered at 6.25°S, 23.75°E. (a) Open circles indicate the daily solar radiation CV from the ISCCP dataset; the line is a linear regression. (b) Time series of the residuals of the regression. (c) Histogram of the residuals of the regression.

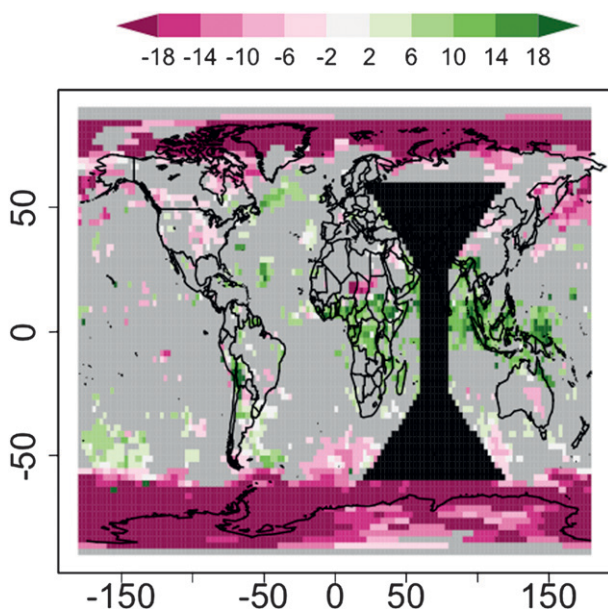


FIG. 3. Percentage changes in the annual coefficient of variation (CV) of solar radiation between 1984 and 2007: grid cells without a statistically significant change are shown in gray and the Indian Ocean sector is blacked out because data were not available for much of this period.

relative to the amount of total significant area (35%, Fig. 3) shows that our fits are appropriate and that their associated p values are reliable to ascertain statistical significance.

We calculated the change in solar radiation CV over the whole 24-yr period using the significant AIC_c -minimizing model assigned to each grid cell (Fig. 3). The Maritime Continent and tropical Africa experienced large CV increases, while changes in Western Hemisphere tropical land were small. The central United States experienced CV decreases. Decreases were also evident at high latitudes. Overall, it was more common to see changes over land than changes over ocean.

We repeated our analysis for seasonal CV to identify the time of year that CV changes were occurring. For each grid cell and each season, we determined which models gave significant fits to the data and then selected the model that minimized the AIC_c . In December–February, there were large, positive CV changes in tropical land regions including the Maritime Continent, southern tropical Africa, and the southwestern Amazon (Fig. 4a). While these were all apparent in the annual CV change, in December–February there was also a positive CV change in northeastern North America and a negative CV change in the Sahel. In June–August, there were particularly large CV increases in the Maritime Continent and northern Africa (Fig. 4b). A previous study has also identified multidecadal climate variability in the

Maritime Continent during June–August (Wang et al. 2008). Relatively smaller CV changes were found in March–May (Fig. 4c) or September–November (Fig. 4d).

c. Changes in precipitation coefficient of variation

We fit models to precipitation CV time series over the period 1997–2007 using a similar procedure as for annual solar radiation. Again, the number of degrees of freedom was equal to the number of years minus the number of parameters to be estimated. We rejected both the null hypotheses of normality and homoscedasticity for 5% of the area with a significant model fit. However, we rejected the null hypothesis of independence for 16% of the area with a significant model fit. Because this percentage seemed large, we repeated our analysis using generalized least squares under the assumption of a first-order autoregressive process for the regression errors. This increases the number of parameters to estimate by one. In this case, we found that 40% of the globe had a significant fit (Fig. 5). The Maritime Continent, tropical Africa, and parts of tropical South America exhibited increases in annual precipitation CV. There were large negative changes in the eastern tropical Pacific. The linear feature around 60°S is likely an artifact of merging data from geostationary and polar-orbiting satellites.

Despite being computed for different time periods, changes in annual solar radiation CV and annual precipitation CV exhibited similarities in locations, including tropical Africa and the Maritime Continent. We used the Spearman rank correlation test to test for monotonic association. This is a nonparametric test that does not assume any functional form (e.g., linear) for the correlation. Our analysis was limited to 1997–2007, the period of overlap between GPCP and ISCCP datasets. Prior to the analysis, solar radiation (original dataset available at $2.5^\circ \times 2.5^\circ$ resolution) and precipitation (original dataset available at $1^\circ \times 1^\circ$ resolution) data were regridded to a common $5^\circ \times 5^\circ$ grid. The analysis was carried out for annual and all monthly CV time series.

For the annual CV, we rejected the null hypothesis (no correlation) for 21% of the globe. For monthly CV, we rejected the null hypothesis (no correlation) for 29%–38% of the globe, depending on the month. To illustrate the spatial and seasonal variability, we computed the fraction of the globe with significant positive correlations and with significant negative correlations for each latitude band and each month (Fig. 6). Positive correlations were strongest (typically 50%–80% of surface area) near the equator and decreased toward the poles (Fig. 6a). There was also a seasonal cycle, with less surface area exhibiting positive correlations in June–August than at other times. Much less surface area exhibited a negative correlation (Fig. 6b).

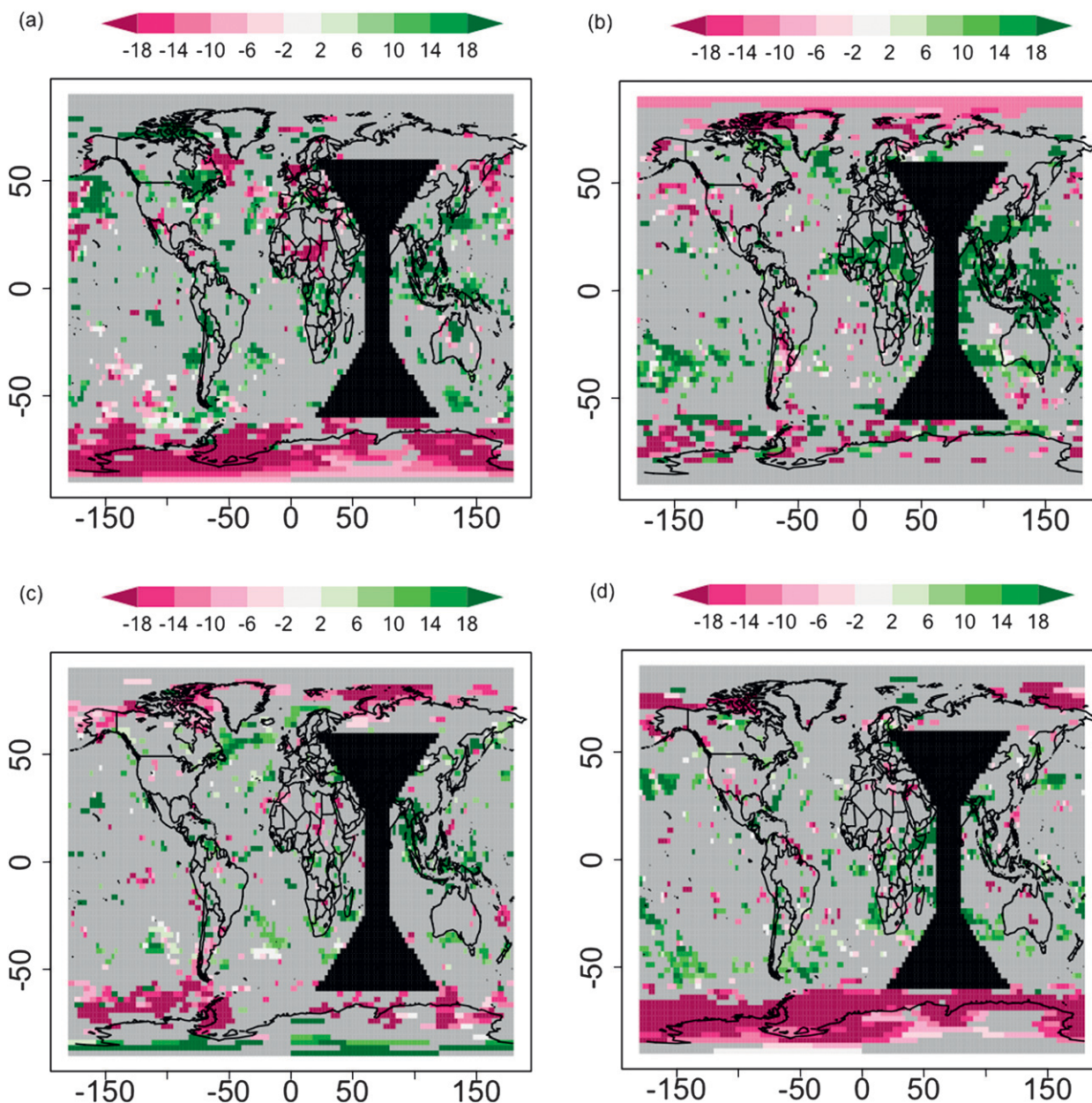


FIG. 4. Percentage change in the seasonal coefficient of variation of solar radiation between 1984 and 2007 for the seasons (a) December–February, (b) June–August, (c) March–May, and (d) September–November: grid cells without a statistically significant change are shown in gray and the Indian Ocean sector is blacked out because data were not available for much of this period.

d. Correlations between solar radiation CV and cloud properties

Finally, we sought to assess whether changes in cloud properties accompanied changes in solar radiation CV. Three critical cloud properties available in the ISCCP FD dataset include cloud amount, cloud-top height, and cloud optical depth. Following Hahn et al. (2001), we defined nine types of clouds on the basis of cloud-top

height and cloud optical depth. For each grid cell and cloud type, we temporally averaged the cloud amount, weighted by 3-hourly clear-sky solar radiation values. This weighted averaging allowed us to minimize the impact of nighttime clouds without having to do a complicated diurnal analysis.

We used the Spearman rank correlation test to evaluate the 1984–2007 correlation between annual solar radiation CV and the mean annual cloud amounts of

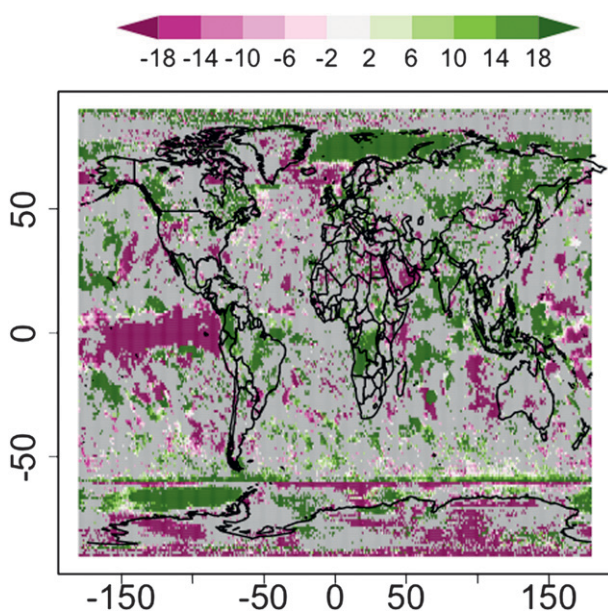


FIG. 5. Percentage changes in the annual coefficient of variation of precipitation between 1997 and 2007: grid cells without a statistically significant change are shown in gray.

different cloud types. For deep convective clouds, the correlation was significant for 42% of the globe (Fig. 7). Except for the central and western Amazon, correlations were positive and strong throughout the tropics. We also tested for correlations between other cloud types and annual solar radiation CV. These were significant for much smaller amounts of surface area, ranging from 11% to 23% of the globe.

We fit polynomial, exponential, and logarithmic regression models to the deep convective cloud amount time series, following the same protocol as in section 4a. Consistent with the increases in solar radiation CV (Fig. 3), we found significant increases in deep convective cloud amount for tropical Africa and the Maritime Continent (Fig. 8a). Increases in tropical convection during the 1990s have also been reported by Tselioudis et al. (2010). It has been previously hypothesized that temperature increases can cause increased convective intensity over tropical land as a result of upward shifts in the freezing level (Del Genio et al. 2007). If this is so and if the correlation between deep convective clouds and solar radiation CV is preserved, future warming may act to increase solar radiation CV. Such a mechanism requires more detailed study.

Unlike other tropical land areas, tropical South America generally experienced decreases in deep convective cloud fraction (Fig. 8a). We found that these decreases were linked to a sudden change in deep convective cloud amount that occurred in the Amazon around 1995 (Fig. 8b). We

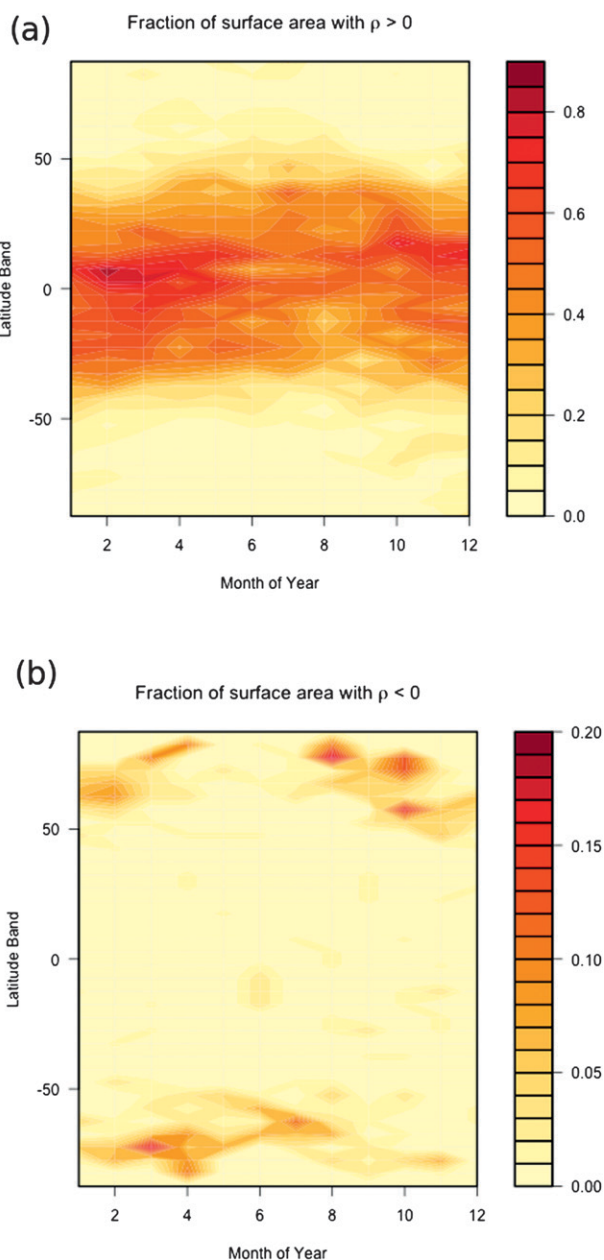


FIG. 6. Correlation between the monthly coefficient of variation of precipitation and of solar radiation using 1997–2007 data: fractional area for each latitude band and month with (a) significant positive correlation and (b) significant negative correlation. Note that the two panels use different scales.

do not know of any artifacts in the ISCCP dataset that could have led to this persistent change (although *Meteosat-3* substituted for the *Geostationary Operational Environmental Satellite (GOES)-East* in the year or two prior to 1995, the periods before and after have similar GOES coverage). We investigated whether annual solar radiation CV also changed at this time, but t

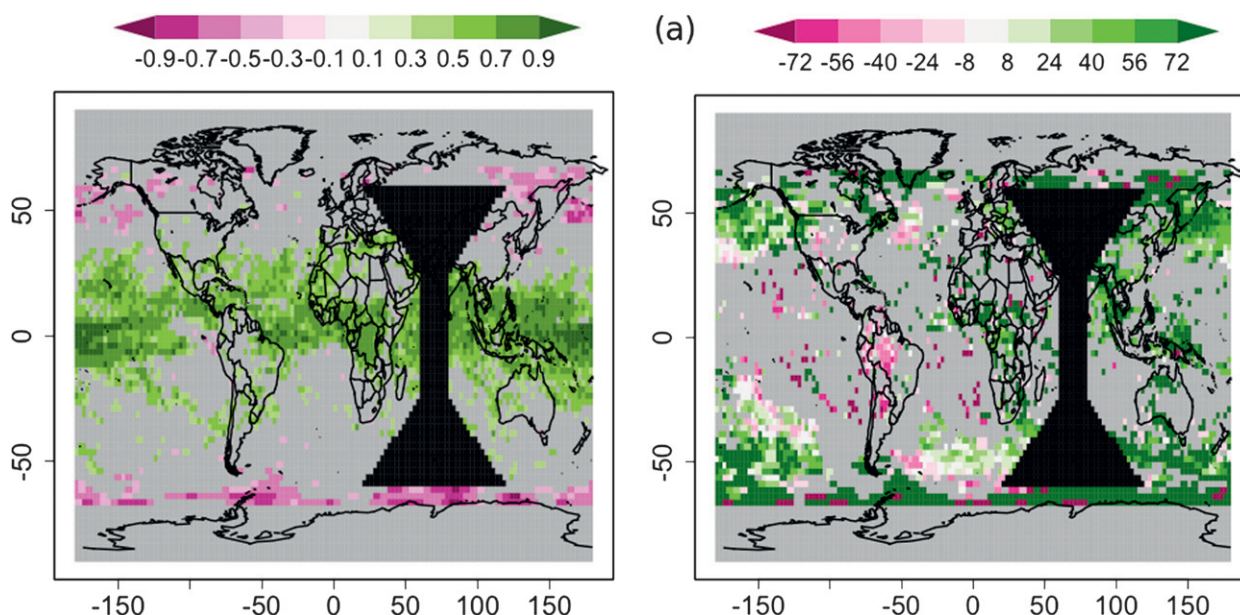


FIG. 7. The Spearman rank correlation coefficient for annual deep convective cloud amount and annual solar radiation coefficient of variation: grid cells without a statistically significant change are shown in gray and the Indian Ocean sector is blacked out because data were not available for much of this period.

tests indicated no significant difference between pre-1995 and post-1995 CVs in most Amazon grid cells. This change in deep convective cloud amount is contemporaneous with a phase change of the Atlantic multidecadal oscillation (Goldenberg et al. 2001), which may impact South American rainfall (Chiessi et al. 2009).

5. Conclusions

We conclude that there have been detectable changes in high-frequency solar radiation and precipitation variability over the past few decades. Changes in solar radiation CV were large and positive for tropical Africa and the Maritime Continent (Fig. 3). Interestingly, correspondingly large changes in tropical South America mainly occurred only during December–February (Fig. 4). These continental locations where we detected changes do not overlap with the mainly oceanic regions where trend detection is sensitive to long-term changes in satellite geometry (Evan et al. 2007). Although we also detected negative trends in solar radiation CV at high latitudes (Fig. 3), these high-latitude trends should be regarded with caution because sampling errors and cloud detection errors are much larger there than at lower latitudes.

The solar radiation CV was correlated with precipitation CV and deep convective cloud amount throughout

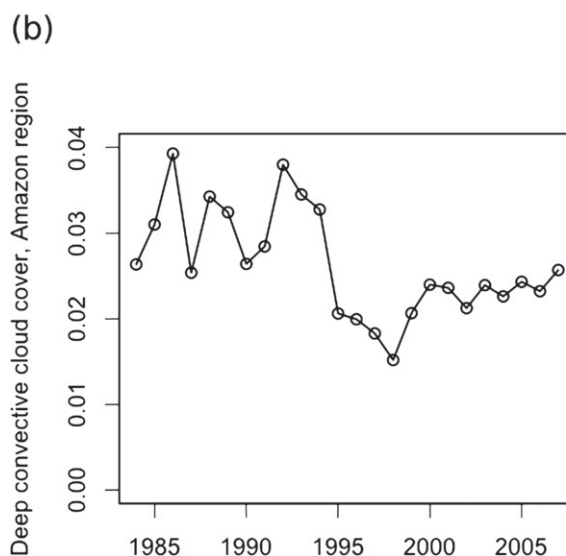


FIG. 8. Changes in deep convective cloud amount. (a) Percentage change over the period 1984–2007: grid cells without a statistically significant change are shown in gray and the Indian Ocean sector is blacked out because data were not available for much of this period. (b) Time series of annual-average deep convective cloud amount for the Amazon region.

much of the tropics. In particular, the Maritime Continent and tropical Africa had significant increases in all three quantities. Links between convective activity over continents and temperature have already been suggested (Del Genio et al. 2007). It is notable that changes in deep convective cloud amount (and solar radiation CV) were much lower over tropical oceans than tropical land. Because marine tropical lapse rates are expected to be

nearly moist adiabatic under climate change (Held and Soden 2006), we would not necessarily expect surface warming to cause increases in deep convective cloud amount. The possibility of a causal relationship between deep convective cloud amount and solar radiation CV and precipitation CV requires further study.

We expect that increased solar radiation CV will decrease the productivity of terrestrial ecosystems (Medvigy et al. 2010). Photosynthesis increases with insolation, up to a critical point, and then the response saturates. An increase in the number of low insolation days will therefore reduce photosynthesis, while an increase in the number of high insolation days will have little effect. Quantifying the future capacity of the terrestrial biosphere to sequester carbon should take into account changes in high frequency variability. Furthermore, increases in solar radiation CV can make solar energy conversion systems less efficient (Janetz et al. 2000) and impact the thermal properties of buildings (Matiasovsky 1996). Finally, increased deep convective cloud amount may result in increases in diffuse radiation. While this can have a positive effect on terrestrial ecosystems (Gu et al. 2003), it can also make it more difficult to effectively orient solar cells.

There are several key aspects of high-frequency variability that require further investigation. First, the physical mechanisms that ultimately control the degree of high-frequency variability require further investigation. Climate models can also be used to understand current and potential future changes, but this is challenging because high-frequency variances are seldom reported in model output, and thus are rarely validated. In addition, the higher order statistics of solar radiation and precipitation are likely to be sensitive to some of the most uncertain model parameterizations, including those for clouds. Another area requiring further investigation is the analysis of CV trends in other climate variables, including temperature (Vinnikov et al. 2002). Finally, at least in the case of precipitation, variances can be sensitive to extreme event frequency and intensity (Goswami et al. 2006). Analysis of this connection would be greatly aided by additional weather station data from tropical land areas. Given the large number of processes that are nonlinearly sensitive to climate, improving our understanding of current and future high-frequency variability should be a high-priority area of research.

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