

RESEARCH LETTER

10.1029/2018GL079408

Key Points:

- In 2013–2016, the Caribbean experienced its worst drought since 1950, which we named the Pan-Caribbean drought
- Enhanced evaporative demand due to anthropogenic warming contributed to 15–17% of Pan-Caribbean drought severity
- Anthropogenic climate change has likely already enhanced drought risk in the Caribbean

Supporting Information:

- Supporting Information S1
- Data Set S1
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Citation:

Herrera, D. A., Ault, T. R., Fasullo, J. T., Coats, S. J., Carrillo, C. M., Cook, B. I., & Williams, A. P. (2018). Exacerbation of the 2013–2016 Pan-Caribbean drought by anthropogenic warming. *Geophysical Research Letters*, 45, 10,619–10,626. <https://doi.org/10.1029/2018GL079408>

Received 29 JUN 2018

Accepted 15 SEP 2018

Accepted article online 21 SEP 2018

Published online 7 OCT 2018

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Exacerbation of the 2013–2016 Pan-Caribbean Drought by Anthropogenic Warming

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Abstract The Caribbean islands are expected to see more frequent and severe droughts from reduced precipitation and increased evaporative demand due to anthropogenic climate change. Between 2013 and 2016, the Caribbean experienced a widespread drought due in part to El Niño in 2015–2016, but it is unknown whether its severity was exacerbated by anthropogenic warming. This work examines the role of recent warming on this drought, using a recently developed high-resolution self-calibrating Palmer Drought Severity Index data set. The resulting analysis suggest that anthropogenic warming accounted for ~15–17% of the drought’s severity and ~7% of its spatial extent. These findings strongly suggest that climate model projected anthropogenic drying in the Caribbean is already underway, with major implications for the more than 43 million people currently living in this region.

Plain Language Summary Climate models project significant drying for the Caribbean as a consequence of increased anthropogenic greenhouse-gas concentrations. Between 2013 and 2016, virtually, the entire region experienced a *Pan-Caribbean* drought, which was unprecedented since at least 1950. We find that human-caused warming contributed to ~15–17% of drought severity by increasing evapotranspiration rates and accounted for ~7% of land area under drought across the Caribbean. Our results therefore suggest that anthropogenic warming has already increased drought risk in the Caribbean.

1. Introduction

Since 1950, the Caribbean has seen a gradual drying trend (e.g., -0.09 self-calibrating Palmer Drought Severity Index [scPDSI] units per decade; Dai, 2011; Herrera & Ault, 2017; Neelin et al., 2006; Sheffield et al., 2012) with several multiyear droughts, the most severe and widespread of which occurred between 2013 and 2016 (Herrera & Ault, 2017). Given its extensive spatial scale, we refer to this event as the *Pan-Caribbean Drought* (Figure 1). This drought affected the entire region and pushed more than two million people into food insecurity (OCHA, 2015). The effects were particularly acute in Haiti, where one million people (~10% of its population) were severely affected by food insecurity and required immediate assistance (OCHA, 2015), and over 50% of crop were lost due to the drought (FAO, 2016).

In addition to significant precipitation deficits, which were driven in part by the strong El Niño in 2015–2016 (Blunden & Arndt, 2016; OCHA, 2015), the Pan-Caribbean drought occurred in conjunction with some of the highest temperature and potential evapotranspiration (PET) anomalies observed in the region (Herrera & Ault, 2017). As compared to previous droughts that also occurred during strong El Niño events (e.g., in 1997–1998), the Pan-Caribbean drought was considerably more severe (Herrera & Ault, 2017), and it affected regions usually associated with wet conditions during El Niño, such as western Cuba (Jury et al., 2007).

Previous studies using climate model simulations have projected increased aridity and freshwater stress for the Caribbean in the near future as a result of anthropogenic climate change (Hayhoe, 2013; IPCC, 2014; Karnauskas et al., 2016). In fact, Lehner et al. (2017) suggested that drought risk in the Caribbean is highly sensitive to even relatively small increases in global mean temperature. The authors indicate that both the severity and duration of drought in the region will increase with global mean temperatures of 1.5 and 2 °C above historical averages. Similarly, Karnauskas et al. (2018) suggest that 2 °C higher global mean

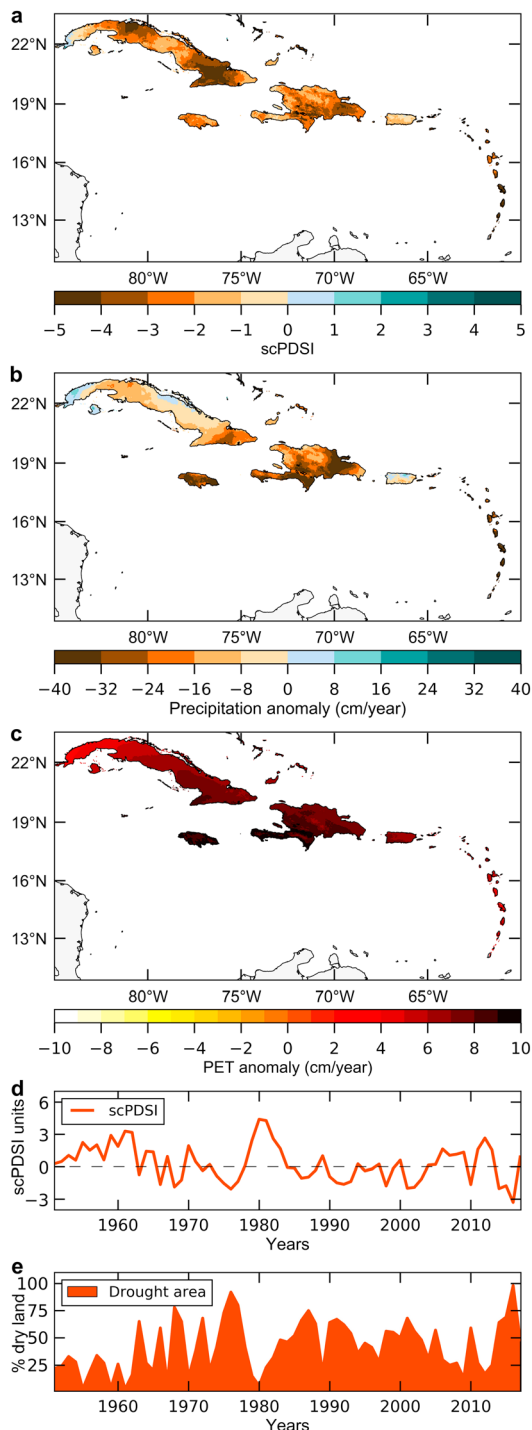


Figure 1. Spatial and temporal characteristics of the Pan-Caribbean drought: (a) scPDSI composite between July 2013 and October 2016, (b) and (c) are the same as (a) but with precipitation and Penman-Monteith potential evapotranspiration (PET) anomalies, respectively. Both precipitation and PET anomalies are calculated as departures from the 1950–1980 climatology. The Caribbean averaged scPDSI time series is plotted in (d). Negative scPDSI values indicate drought, while positive values are pluvials. Finally, the drought area index between 1950 and 2016 across the Caribbean is plotted in (e). The Pan-Caribbean drought affected ~98% of land area of the region. scPDSI = self-calibrating Palmer Drought Severity Index.

temperature will increase freshwater stress in the Caribbean by ~25% by the end of the 21st century. Although the projected drying is mostly due to a significant decrease of precipitation rates (30% to 50% in most areas of the Caribbean across most models; IPCC, 2014), future changes in precipitation are less certain than those projected for temperature (IPCC, 2014).

Given the warming and drying projected for the Caribbean over the coming decades (Dai, 2011; Hayhoe, 2013; IPCC, 2014) and because of the observed warming in the Caribbean since 1950 (Herrera & Ault, 2017; Stephenson et al., 2014), assessing the contribution of anthropogenic warming to drought is critical for better understanding drought risks in the region. Along these lines, we estimate the contribution of anthropogenic warming to the Pan-Caribbean drought using climate data from observations and model simulations to calculate the scPDSI for the period 1950–2016, which we used as a proxy for surface soil moisture balance given the data limitation of the Caribbean. To address the inherent limitations of coarse resolution data sets for characterizing drought on the Caribbean Islands—many of them with substantial topographic variability over small scales—the observed gridded products are statistically down-scaled following Herrera and Ault (2017).

2. Data and Methods

2.1. Climate Data

The observationally based and simulated gridded climate products we used to calculate PET and scPDSI are listed in Tables S1 and S2 and described in Supporting Information S1. Because of the relatively coarse horizontal resolution of state-of-the-art gridded observationally based climate products, which varies from 0.5° to 2.5° (~55 to ~280 km, respectively) and thus fails to resolve many of the Lesser Antilles (Dai, 2011; Jury et al., 2007; van der Schrier et al., 2013), we used statistically down-scaled observed monthly precipitation and temperature (T_{min} , T_{mean} , and T_{max}) data from the Global Precipitation Climatology Centre (Schneider, Becker, Finger, Meyer-Christoffer, Rudolf, et al., 2015; Schneider, Becker, Finger, Meyer-Christoffer, & Ziese, 2015) and Berkeley Earth Surface Temperature (Rohde et al., 2013), respectively. The validation of down-scaled products and further details of the downscaling and bias-correction procedures are described in Supporting Information S1 and in Herrera and Ault (2017). Wind speed and net radiation data were obtained from various reanalysis products and were bilinearly interpolated to a common resolution of 4 km. We also computed alternate PET and scPDSI records using data from the Climatic Research Unit version TS4.01 (Harris et al., 2014) and other observationally based gridded products to help characterize uncertainties in the anthropogenic contribution to the Pan-Caribbean drought (Supporting Information S1), but they were not down-scaled. Finally, the climate model outputs we used came from the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al., 2012).

2.2. The scPDSI as a Soil Moisture Indicator

Since it was introduced in the mid-1960s, PDSI (Palmer, 1965), and more recently scPDSI (Wells et al., 2004), has been widely used in North America for drought monitoring and research (Cook, Seager, et al., 2015; Dai, 2013; Sheffield et al., 2012; van der Schrier et al., 2013). PDSI has been also used as a metric in hydroclimate reconstructions over the last thousand years

in North America, southern Asia, and Europe (Cook et al., 2004; Cook, Seager, et al., 2015) and for assessing observed and projected changes in hydroclimate as a result of anthropogenic climate change (e.g., Ault et al., 2014, 2016; Lehner et al., 2017; Williams et al., 2015). Although PDSI has been criticized as a soil moisture indicator due to its relatively simple water balance formulation, limitations in long-term and quality-controlled climate data across the Caribbean precluded the use of a more sophisticated model like the Variable Infiltration Capacity Model (Liang et al., 1994). Criticism of PDSI has also arisen because the index does not account for the effect of increased atmospheric CO₂ concentration on plant physiology, which is projected by earth system models to moderate drought impacts on plant water demand (e.g., Swann et al., 2016). However, as shown in Figure S1 and further discussed in section 4, soil moisture and scPDSI calculated over the Caribbean using data from NASA's Global Land Data Assimilation Systems (Rodell et al., 2004) are consistent in terms of long-term trends and variability during the period 1979–2017 ($r = 0.65$). We further selected scPDSI as the main drought metric for comparison to previous work in California that used a similar methodology (e.g., Williams et al., 2015). A comprehensive description of how PDSI and scPDSI are formulated is included in Supporting Information S1 and in Palmer (1965) and Wells et al. (2004).

We used the UN Food and Agriculture Organization (FAO) PET formulation (Allen et al., 1998) because it is more physically realistic than the Thornthwaite (1948) equation used in the original PDSI calculation (Palmer, 1965). A key drawback of the Thornthwaite approach—especially for climate change applications—is the use of temperature as the only climate variable forcing PET, which leads to an exacerbation of the sensitivity of PET to temperature variations (Abatzoglou & Williams, 2016; Smerdon et al., 2015; Williams et al., 2015). The FAO formulation for PET, in contrast, is calculated using temperature, vapor pressure, wind speed, and net radiation.

2.3. Estimation of Anthropogenic Contribution

We estimated the contributions of anthropogenic warming to the Pan-Caribbean drought using our down-scaled precipitation and temperature products. Alternatively, we used other observationally based gridded climate products that were combined to validate the consistency of our findings (see Supporting Information S1). We compared the observed record of PET and scPDSI to an alternate record calculated after removal of anthropogenic warming trends since 1950, following a similar approach as in Williams et al. (2015). We refer to the alternate PET and scPDSI records that do not include warming trends as “adjusted” records. In both calculations, we used unadjusted records of precipitation, net radiation, and wind speed. The anthropogenic contribution to drought was estimated as the difference between PET anomalies and scPDSI calculated using adjusted temperature (T_{\min} , T_{mean} , and T_{\max}) against PET anomalies and scPDSI using unadjusted temperature. Results were compared to the same estimates calculated using multimodel ensembles of T_{\min} , T_{\max} , and net radiation from CMIP5.

We approximated the anthropogenic trends as the difference between naturally only and fully forced ensemble means of temperature anomalies from 28 CMIP5 models during 1950–2016 (see Supporting Information S1). Since most CMIP5 historical simulations end in December 2005, we appended the difference between the RCP8.5 scenario and the preindustrial control temperature anomalies from 2006 to 2016. We then smoothed these trends of simulated temperature anomalies using a 30-year low-pass filter. To calculate the adjusted temperature record, we subtracted the anthropogenic trends from observationally based gridded temperature products. Despite its simplicity, we used this approach because we aimed to specifically quantify the anthropogenic warming trend, which models are likely to accurately characterize. However, we did not attempt to identify the anthropogenic component of other variables used in the calculation of PET and scPDSI (such as precipitation) because of the difficulty of separating forced and internal variability in these variables (Cook et al., 2014; Deser et al., 2012; Williams et al., 2015).

To assess the robustness of results using the methodology described above, alternate approaches to characterize the anthropogenic warming effect on the Pan-Caribbean drought were also taken. For example, we evaluated temperature and net radiation data from 14 CMIP5 models to determine the change in the Pan-Caribbean drought severity due to the $\sim 2\text{-Wm}^{-2}$ anthropogenic radiative forcing after the preindustrial era. To do so, we compared PET and scPDSI calculated with historical outputs of temperature and net radiation from CMIP5, against PET and scPDSI using preindustrial control outputs of the same variables. As we did

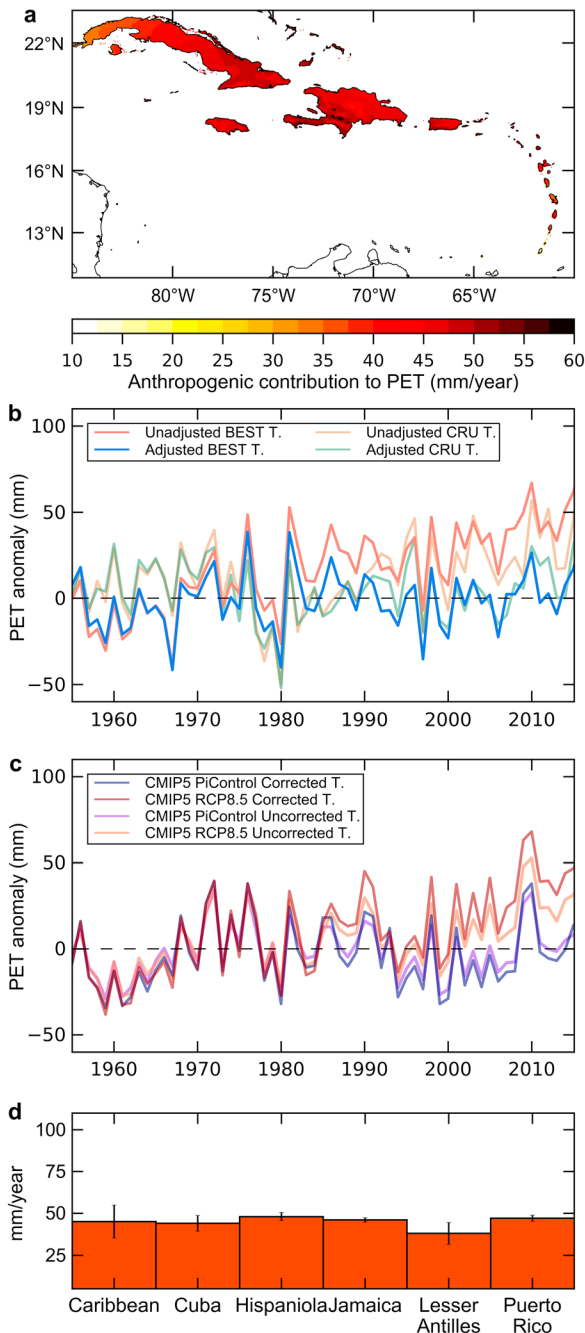


Figure 2. Anthropogenic contributions to potential evapotranspiration (PET): (a) geographic distribution of anthropogenic contributions to observed PET anomalies in the Caribbean between 2013 and 2016. (b) PET-anomaly time series estimated using observationally based temperature data. Reddish colors are PET anomalies calculated with unadjusted temperatures, while bluish colors group those calculated with adjusted temperatures (e.g., after the removal of the anthropogenic signal using a 30 low-pass filter). (c) As in (b) but from CMIP5 outputs of bias-corrected and not bias-corrected temperatures using preindustrial control (bluish colors) and historical plus RCP8.5 (reddish colors), and (d) contributions to PET by island and the Lesser Antilles from observations. Differences between PET anomalies with and without the anthropogenic signal in (b) and (c) are statistically significant ($p < 0.05$) as evaluated using a two-tailed t test. CRU = Climatic Research Unit; CMIP5 = Coupled Model Intercomparison Project phase 5.

from observed records, in these calculations, we used observed unadjusted precipitation and wind speed data. Modeled temperatures were bias-corrected, so that the variance and mean match with observed temperature records.

2.4. Statistical Hypothesis Test and Significance

Given the relatively small size of our sample ($n = 48$ months from January 2013 to December 2016) and because the data are not normally distributed, we implemented a resampling (10,000 samples with replacement), or *bootstrap*, method to estimate the statistical significance of our findings following Wilks (2011). Here the null hypothesis states that “anthropogenic warming did not increase the Pan-Caribbean drought severity,” while the alternative hypothesis states that “anthropogenic warming has intensified the drought.” We selected the mean as the statistic to test using the unadjusted-temperature PET and scPDSI records to contrast them against the adjusted-temperature version of the same metrics during the Pan-Caribbean drought. Using this approach, we considered as significant anthropogenic contributions those with p values ≤ 0.05 at the 95% confidence level. Additionally, we used a two-tailed t test to evaluate whether anthropogenic warming has significantly increased the overall drought risk in the Caribbean during the 1980–2016 period.

3. Results

Observed annual PET anomalies during 2013–2016 were significantly higher than PET anomalies with the adjusted temperatures, increasing PET rates from 27 to 72 mm/year in the Caribbean on average (Figure 2). The CMIP5 multimodel ensemble supports a similar contribution of higher temperatures to these PET anomalies, increasing from 15 mm/year with the preindustrial control to 51 mm/year with the RCP8.5 scenario with bias-corrected temperatures and from 9 mm/year to 36 mm/year with uncorrected modeled temperatures (Figure 2c). However, the magnitude of simulated PET anomalies estimated with not bias-corrected CMIP5 temperatures was lower than that from observations, because multimodel ensemble temperatures were also lower in the Caribbean. Changes in PET anomalies on each island were comparable to those observed in the Caribbean as a whole, with the lowest change in the Lesser Antilles (38 mm/year) and the highest in Hispaniola Island (48 mm/year; Figure 2d).

Anthropogenic warming accounted for $\sim 15 \pm 2\%$ regional average of the Pan-Caribbean drought severity across the region, which was significant against the null hypothesis that these trends in scPDSI were random (see section 2 and Supporting Information S1; Figure 3). Consistent with observations, estimations from the CMIP5 multimodel ensemble indicated a $\sim 17 \pm 4\%$ ($p < 0.05$) contribution to drought severity with the RCP8.5 scenario during this period as compared to the preindustrial control. However, there was substantial geographic variability in these contributions across the Caribbean (Figure 3a). For example, the greatest changes in scPDSI were observed in Cuba, where there was a $32 \pm 7\%$ ($p < 0.05$) contribution of anthropogenic warming to the drought severity, while in the Lesser Antilles, it was only $6 \pm 4\%$ and not statistically significant. The contribution of anthropogenic warming to drought severity in Hispaniola Island was $13 \pm 4\%$ ($p < 0.05$), yet drought severity changes were only statistically significant on parts of the island (Figure 3a). In

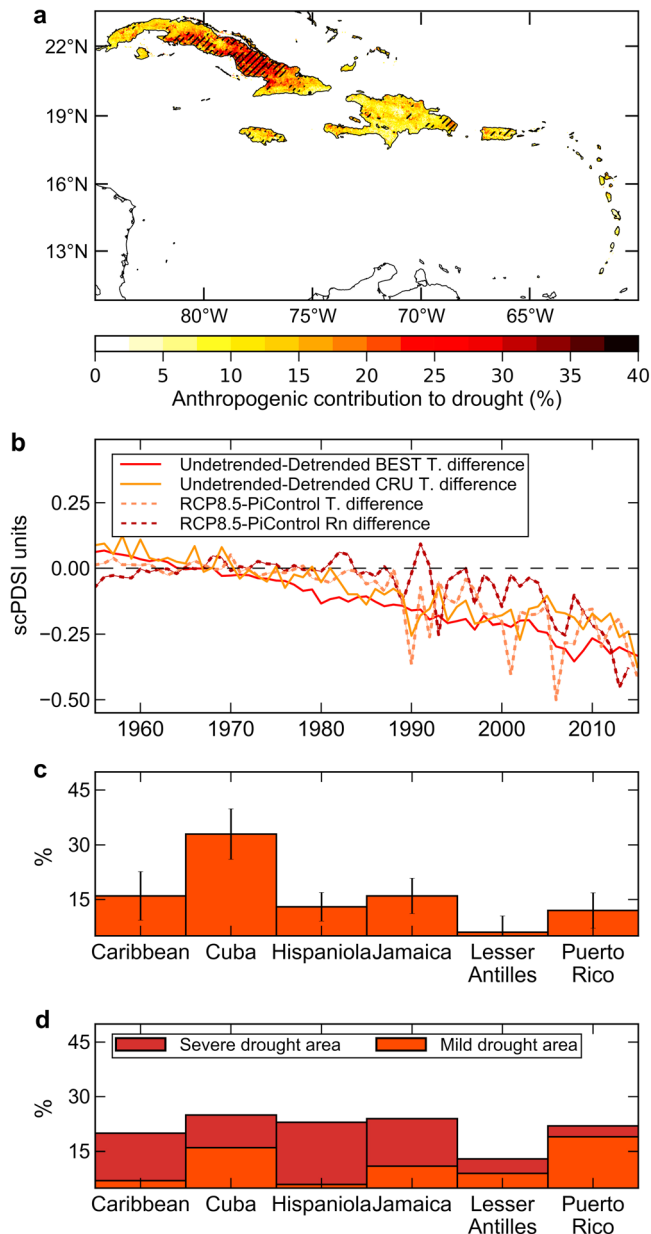


Figure 3. The contribution of anthropogenic warming to drought severity (scPDSI): (a) across the Caribbean. Hatching corresponds to statistically significant contributions at the 95% confidence level. (b) Changes in drought severity as estimated with scPDSI. The negative trend is the drying contribution from anthropogenic warming. (c) Anthropogenic contributions (in percentage) to drought severity on each of the Greater Antilles and the Lesser Antilles. (d) Contribution of anthropogenic warming to areas under mild (scPDSI between -1.0 and -1.9) and severe drought (scPDSI between -3.9 and -3.0). Drought areas were calculated as the number of grid cells equal or below the scPDSI thresholds of mild and severe drought, over the number of total grid cells included in the Caribbean Islands. CRU = Climatic Research Unit; scPDSI = self-calibrating Palmer Drought Severity Index.

Jamaica, anthropogenic warming contributed to $\sim 16 \pm 5\%$ of drought severity ($p < 0.05$), while in Puerto Rico, the contribution was $12 \pm 5\%$ and not statistically significant ($p > 0.05$; Figure 3c). Anthropogenic warming also increased the probability of occurrence of the Pan-Caribbean drought from 4% to 7% (two-tailed t test $p < 0.05$). This result was primarily due to higher-temperature effects on PET, shifting scPDSI mean toward drier conditions during the Pan-Caribbean drought. Finally, the averaged contributions estimated from various combinations of observationally based climate products were $\sim 14.5\%$, with the highest contributions ($\sim 16\%$) from Global Precipitation Climatology Centre and Berkeley Earth Surface Temperature and the lowest ($\sim 13\%$) from Climatic Research Unit (Supporting Information S1).

Higher temperatures also enhanced the geographic extent of the drought (Figure 3d). In the Caribbean, for example, anthropogenic warming accounted for $\sim 7\%$ of the area affected by mild drought (scPDSI values between -1.9 and -1.0) and for $\sim 20\%$ of the area under severe drought (scPDSI values between -3.9 and -2.0 ; Table S3). These changes encompassed areas of nearly 16,000 and 13,000 km^2 , respectively. Consistent with changes in drought severity, the greatest change in dry area was observed over Cuba, where the warming trend accounted for 16% and 25% of areas under mild and severe drought, respectively (Figure 3d). For comparison, a 16% contribution to drought area in Cuba corresponds to $\sim 10,400 \text{ km}^2$ more land under mild drought, which roughly comprises 10% of the total area of the country (109,820 km^2 ; CIA, 2013; Table S3). In Hispaniola Island, Puerto Rico, Jamaica, and the Lesser Antilles, contributions to mild-drought area ranged from approximately 6% to 19% (Table S3).

We found that the contribution of anthropogenic warming to drought severity, as estimated with scPDSI, does not respond linearly to changes in PET anomalies at local scales. By comparing Figure 2a with Figure 3a, for example, this nonlinearity is noticeable in southern Hispaniola Island and parts of central-eastern Cuba, where the largest contributions of anthropogenic warming to PET anomalies were observed. These areas, however, did not correspond to those with the highest contributions of anthropogenic warming to scPDSI. This apparent discrepancy is likely related to how scPDSI is calibrated. For example, the scPDSI's sensitivity to both precipitation and PET varies across the region because it is calibrated to local climate conditions. Consequently, relative contributions of precipitation and PET to scPDSI vary depending on the climate of a specific location. During the Pan-Caribbean drought, we found that areas with the lowest coefficients of variation in precipitation anomalies coincided with those where there was the largest contribution of anthropogenic warming to drought (Figure S2). This result suggests that the effect of anthropogenic warming on drought severity is stronger in areas where precipitation is less variable.

4. Discussion

Our estimates of the contribution of anthropogenic warming to the Pan-Caribbean did not consider anthropogenic effects on precipitation trends and variability nor how these affected the Pan-Caribbean drought, as these effects are likely too complex to be approximated by calculating empirical trends (Abatzoglou & Williams, 2016; Deser et al., 2012; Williams et al., 2015). Notably, climate models consistently simulate significant decreases in precipitation in the Caribbean as anthropogenic greenhouse-gas concentrations increase in the future (IPCC, 2014;

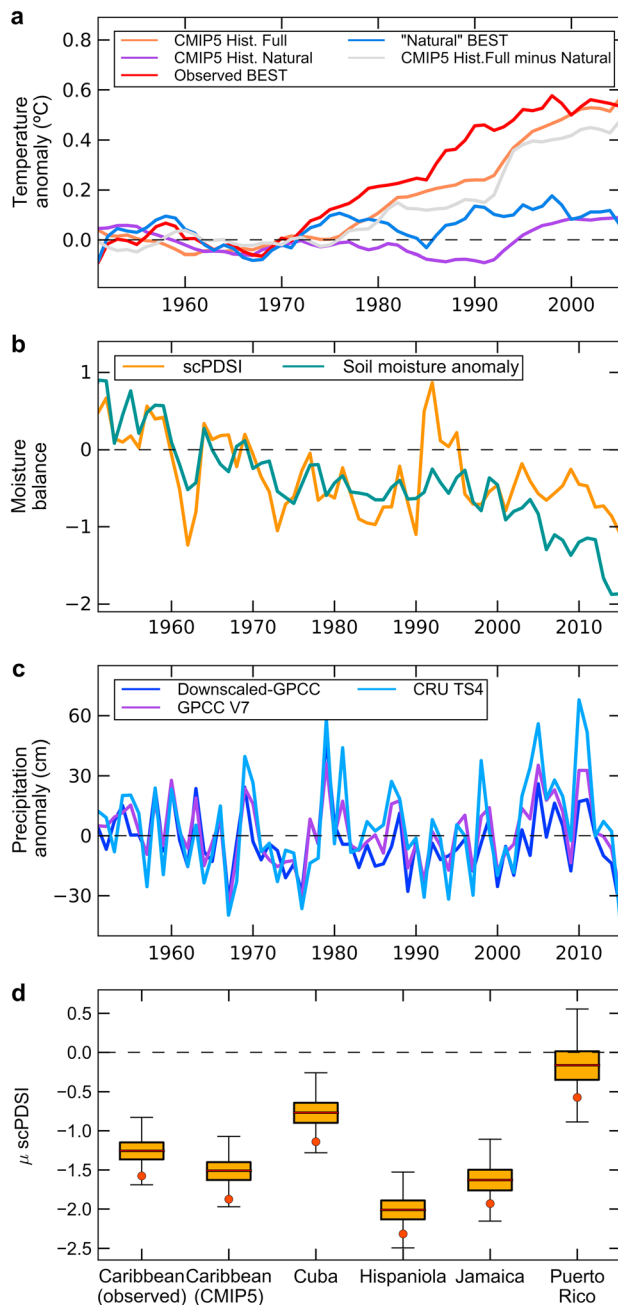


Figure 4. (a) Instrumental and simulated 10-year running mean of temperature anomalies in the Caribbean. Instrumental temperatures come from our statistically downscaled temperature estimates. Simulated temperatures come from a 15-member ensemble of CMIP5 using fully forced and natural-only forced historical simulations between 1950 and 2006. (b) Multimodel mean ensemble of simulated scPDSI and soil moisture anomalies during 1950–2016 from CMIP5. (c) Annual precipitation anomalies regionally averaged in the Caribbean. (d) The distribution of means from the 10,000 scPDSI resamples. scPDSI is calculated with adjusted temperatures for the Caribbean (using observed and simulated temperatures), for each of the Greater Antilles and the Lesser Antilles (using observed temperatures). The red dots represent the mean of the observed scPDSI for the Pan-Caribbean drought. CMIP5 = Coupled Model Intercomparison Project phase 5; CRU = Climatic Research Unit; scPDSI = self-calibrating Palmer Drought Severity Index; GPCC = Global Precipitation Climatology Centre.

Neelin et al., 2006), and if those trends are already underway, then the total contribution of anthropogenic climate change would be greater than that estimated here.

Uncertainties in our results arise from intrinsic limitations of scPDSI as a soil moisture indicator. However, we compared observational (Global Land Data Assimilation Systems) and modeled (CMIP5) soil moisture anomalies against scPDSI and found consistency in their trends and variability (Figure S1). Although further uncertainties in our results also arise from our statistical downscaling method, the paucity of long-term high-quality weather station data and the low resolution of CMIP5 data relative to the size of the Caribbean Islands precluded a more accurate evaluation. Nevertheless, we validated our downscaled products with station data from the Global Historical Climatology Network before computing scPDSI (Supporting Information S1). As shown in Figure S3, our products correlated well with independent Global Historical Climatology Network stations in the Caribbean and northern South America. We also included a combination of various observational data sets in our analysis, obtaining similar results as those reported from our downscaled climate products (Supporting Information S1). Collectively, our results indicate that anthropogenic warming almost certainly increased drought severity and the area experiencing record-breaking drought during the Pan-Caribbean drought, which is similar to what was found for California during the 2012–2014 drought (Williams et al., 2015).

ScPDSI does not account for the effect of increased atmospheric CO₂ concentration on plant physiology, which is hypothesized to diminish PET-induced soil drying by increasing water use efficiency of plants (Cook et al., 2016; Mankin et al., 2018; Swann et al., 2016). We thus compared scPDSI from CMIP5 with soil moisture from CMIP5 during 1950–2016 over the Caribbean as in Cook, Ault, and Smerdon (2015). Simulated soil moisture in the coupled land surface models of CMIP5 is a more explicit and physically based representation of the surface moisture balance than the simple bucket model used in scPDSI and includes responses of vegetation to climate and CO₂. If CO₂ effects on water use efficiency have a large water savings effect, we would expect the model soil moisture to show substantially less drying than scPDSI. For each CMIP5 model considered in the Caribbean (Table S2), there was a significant correlation between scPDSI and soil moisture anomalies (ranging from $r = 0.23$ to $r = 0.85$, $p < 0.05$), with an average correlation of $r = 0.69$ ($p < 0.01$; Figures 4b and S4), and drying trends in scPDSI were not systematically more severe than in soil moisture (Supporting Information S1). This suggests that scPDSI accurately reflects surface moisture balance in these models, in spite of the simple water balance formulation it uses, and that CO₂ effects on plant physiology and PET-induced drying trends were small in the Caribbean over the analysis period.

During the Pan-Caribbean drought, precipitation anomalies were not the lowest on record in the Caribbean. By comparing precipitation anomalies of some of the worst droughts in the region (Figure 4c), we found that the 1974–1977 and 1968–1969 droughts had larger rainfall deficits. However, drought rankings calculated with scPDSI (Figure S5) indicate the Pan-Caribbean drought was the most severe drought in ~32% of the Caribbean Islands, but when removing the warming trend, this area changed to 21% (Figure S5).

5. Conclusions

The Pan-Caribbean drought of 2013–2016 was appreciably more severe as a result of anthropogenic warming, a finding that is robust across a range of models and observationally based data sets. This result supports the idea that anthropogenic climate change is already impacting the Caribbean through temperature effects on PET and that the recent drought is likely to be a prelude to future drought events under anthropogenic climate change. That is, we expect future droughts in the region to be increasingly severe because of higher temperatures alone, regardless of changes in precipitation.

As is the case for many of the Small Island Developing States around the world (Holding et al., 2016; Karnauskas et al., 2016, 2018), freshwater resources in the Caribbean are already facing a growing number of pressures ranging from saltwater intrusion from sea level rise to demands from the municipal, energy, agricultural, and tourism sectors. Importantly, in the Caribbean Islands, freshwater cannot be moved around at large scales as it can in continental locations like the U.S. southwest. Although, new technologies such as desalination have recently provided relief in some Caribbean Islands, particularly in the Lesser Antilles and the Bahamas (UNESCO, 2006), the operational cost of desalination plants often outweighs their benefits. Moreover, the economic limitations of many Caribbean nations preclude the implementation of such an option (UNESCO, 2006). Finally, though the 2013–2016 Pan-Caribbean drought was unprecedented in an historical context, our work suggests that it might be a good analog for future droughts because of the important role temperature played in exacerbating its severity and extent. Further study of the 2013–2016 drought can help inform strategic policy and water management decisions across the region.

Acknowledgments

We thank the Advanced Study Program (ASP) of the National Center for Atmospheric Research (NCAR) for partially supporting this research through the ASP Graduate Visitor Program. This material is partially supported by a National Science Foundation (NSF) EaSM2 grant AGS-1243125, and NSF grant AGS-1602564. J. T. F. and S. C. participation in this work is supported through NSF grant AGS-1243107, NASA Award NNN11ZDA001N, and DOE Award ID DE-SC0012711. B. I. C. and A. P. W. are supported by the NASA Modeling, Analysis, and Prediction Program, and A. P. W. is supported by the National Science Foundation grant AGS-1703029. The downscaled climate data used to calculate scPDSI and PET are available at <https://ecommons.cornell.edu/handle/1813/58763>. Gridded temperature and precipitation data were obtained from <http://berkeleyearth.org> and <https://www.esrl.noaa.gov/psd/data/gridded/data.gpcp.html>, respectively; while CRU data were obtained from <http://www.cru.uea.ac.uk/data>. The CMIP5 models data were obtained from <https://esgf-node.llnl.gov/>. The codes used to calculate PET and scPDSI are available at <https://bitbucket.org/ecl/scpdsi/src/master/>. The authors declare no conflict of interests.

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