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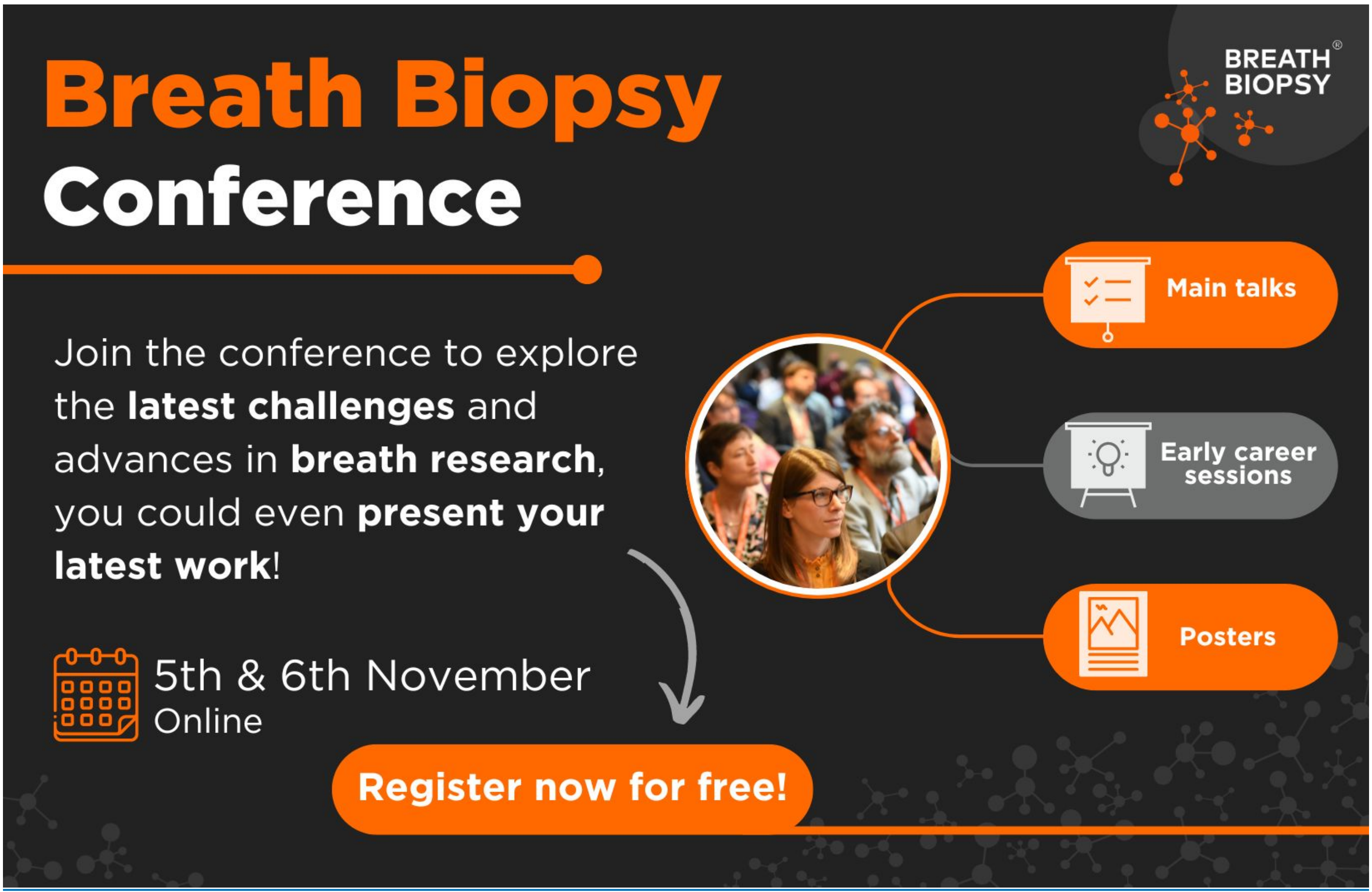

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Characterizing changes in drought risk for the United States from climate change

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Abstract
The effect of climate change on the frequency and intensity of droughts across the contiguous United States over the next century is assessed by applying Standardized Precipitation Indices and the Palmer Drought Severity Index to the full suite of 22 Intergovernmental Panel on Climate Change General Circulation Models for three IPCC-SRES emissions scenarios (B1, A1B, and A2 from the Special Report on Emissions Scenarios (SRES) listed in order of their emissions through 2100 from high to low). The frequency of meteorological drought based on precipitation alone is projected to increase in some parts of the US, for example the southwestern states, and decrease in others. Hydrological drought frequencies based on precipitation and temperature are projected to increase across most of the country, however, with very substantial and almost universally experienced increases in drought risk by 2050. For both measures, the southwestern US and the Rocky Mountain states are projected to experience the largest increases in drought frequency, but these areas may be able to exploit existing excess storage capacity. Drought frequencies and uncertainties in their projection tend to increase considerably over time and show a strong worsening trend along higher greenhouse gas emissions scenarios, suggesting substantial benefits for greenhouse gas emissions reductions.

Keywords: drought, climate change, drought severity indices, uncertainty

S Online supplementary data available from stacks.iop.org/ERL/5/044012/mmedia

1. Introduction

Recurring droughts across the western and southeastern United States over the recent decades have been responsible for significant socioeconomic and ecological consequences [1–3]. In the Colorado River Basin, the longest drought in 100 years left Lakes Mead and Powell at roughly 50% of their capacities in 2007 and threatened electricity generating capacity. Prolonged droughts in the Apalachicola–Chattahoochee–Flint basin have strained water supply negotiations between Georgia, Alabama, and Florida, and low river flows have produced both agricultural water shortages and fish kills in the Upper Klamath River. These and other regional events have gained international attention in large measure because water shortages are being experienced with increasing frequency across the nation [4–6]. The average cost of droughts in the United States is estimated to be \$6–\$8 billion annually [7]. It is widely accepted that water managers and policy makers will face increased planning challenges from drought as future demand for water rises [8].

Climate change could exacerbate these problems by altering the location, timing, frequency, and intensity of future droughts. Projections using Standardized Precipitation Indices

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(SPIs) showed dramatic increases in meteorological drought frequency in western Europe in the late 21st century relative to a 20th century baseline under mid-range climate scenarios [9]. Projections using hydrological Palmer Drought Sensitivity Indices (PDSI) suggested that droughts could affect 30% of worldwide land area by 2100—up from estimates of current global coverage that hover around 1% [10]. Both of these studies relied on different but singular measures of drought, making their results are more relevant to some sectors than to others [2]. Moreover, their reliance on severely limited suites of the available global circulation model (GCM) output may have led their readers to accept a false sense of certainty in interpreting their results. Other estimates also rely on only a single drought measure [11–13], or, where multiple estimates are used, do not rely on a broad set of GCMs or do not use direct GCM output [14].

This letter makes progress in overcoming both shortcomings. It applies both meteorological and hydrological indices to project the spatial and temporal patterns of drought risks across the 99 sub-basins of the contiguous 48 US states in the early, middle, and late 21st century [15]. These projections are offered for manifestations of the B1, A1B, and A2 SRES (Special Report on Emissions Scenarios from the IPCC) greenhouse gas emissions scenarios as reported by the full suite of 22 GCMs deployed for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report [16, 17]; some details are described in section 2.3 below and depictions of representative concentration scenarios are depicted in figure 1S of the supplementary material (available at stacks.iop.org/ERL/5/044012/mmedia; henceforth denoted SM). In addition, while some authors employ a statistical downscaling approach to generate daily data [17], this work uses monthly GCM results at their native spatial scale; no spatial or temporal downscaling is employed, avoiding the introduction of additional uncertainty or error associated with those procedures. The results identify regions within the US where drought is of highest concern and suggest a relationship between higher carbon emissions scenarios and increases in drought frequency. They offer four primary observations about the effects of climate change on drought risk: (i) how climate change affects the frequency of SPI meteorological droughts [18–21], (ii) how climate change affects the frequency and severity of PDSI hydrological droughts [22, 23], (iii) the potential role of current, existing reservoir storage in responding to changes in drought frequency [24], and (iv) how drought frequency might change over time and across alternative SRES scenarios.

Section 2 identifies data sources for the climate scenarios and reviews the methods that were applied to produce various drought indices. Section 3 plus the supplementary material (available at stacks.iop.org/ERL/5/044012/mmedia) presents results and offers some discussion.

2. Methods

The screening analysis described here computes two drought indices for three 21st century time periods along three SRES climate scenarios from 22 global circulation models (GCMs) for the 99 sub-basins that span the contiguous 48 states. The approach involved five steps: (1) selecting appropriate indicators of drought; (2) selecting informative time periods and SRES scenarios, (3) collecting, preparing and translating GCM data into the appropriate spatial scale; (4) using GCM outputs to compute values for various drought indices; and (5) estimating the number of months of drought for each drought index for the current baseline and selected forecast periods so that the change in overall drought duration attributable to climate change could be reported. They are described below.

2.1. Step 1: selecting appropriate indicators of drought

Drought can be defined from a water supply perspective as persistent extreme events that produce significant effects on the hydrological cycle by, for example, decreasing rainfall, lowering stream-flow, reducing reservoir levels, or causing reductions in soil moisture [1, 2]. Drought can also be defined sectorally. Agricultural drought, for example, is defined as the difference between water supply and crop demand. For rain-fed agriculture, a year of normal precipitation may actually be water stressed (i.e., suffering drought conditions) if the growing season is abnormally warm. On the other hand, irrigated crops facing a warmer/drier growing period may be supplied from a reservoir filled to capacity by an above normal snowmelt from winter precipitation, effectively mitigating what would otherwise be a state of drought.

Since climate change has the potential to affect both precipitation and temperature, this analysis included indices that include both of these variables: SPI-5 and SPI-12 [9], and four categories of Palmer Drought Severity Index (PDSI). The SPI is a probability index that measures drought based on the degree to which precipitation in a given time period (e.g., one-month, six-month, two-year) and geographic area (e.g., county, watershed, state) diverges from the historical median. An SPI of zero indicates rainfall is at the median value. The index was first introduced in 1993, and has since been used widely [20, 21]. Given its focus on precipitation, SPI droughts are most relevant for rainfall-dependent activities such as rain-fed agriculture or municipal water supply in certain regions. Runoff, snowmelt, evapotranspiration, and water storage (in snow or reservoirs) are part of any runoff calculation, but are not considered in calculation of the SPI (although snowfall is considered precipitation for purposes of SPI). SPI-5 and SPI-12 droughts occur when the one-month SPI value for an area remains below statistically defined SPI thresholds for longer than five and 12 months, respectively. The steps to calculate the frequency of SPI-5 and SPI-12 droughts are described below.

Unlike the SPI, PDSI [22–24] uses precipitation and temperature data in a formula to estimate the relative changes in soil moisture in a particular region. PDSI is generally calculated on a monthly time scale, and considers the meteorological conditions of both the current month and those of past months so that it can accommodate the cumulative nature of drought. A PDSI value of zero is considered normal, minus one is a mild drought, minus two is a moderate drought, minus three is a severe drought, and minus four is an extreme drought. Positive PDSI numbers, on the other hand, reflect wetness in excess of normal conditions. Because of its focus on soil moisture as a primary indicator of drought, PDSI is particularly appropriate for agricultural droughts. Like SPI, PDSI does not consider runoff, snowmelt, or water storage and therefore may not forecast water supply effectively.

One of the drawbacks to PDSI is that the index is based on conditions at Palmer's reference sites in Kansas and Iowa and thus the absolute values of the index have little scientific meaning [3]. SPI, on the other hand, defines drought statistically with reference to local conditions and can therefore be more relevant on a local or regional level [6, 24].

2.2. Step 2: selecting climate scenarios and GCMs

Three SRES scenarios were employed to reflect a range of future climate change scenarios and atmospheric carbon concentrations [16]:

- *B1: low-end emissions scenario*. This scenario represents a world where population peaks in the middle of the 21st century, economic structures rapidly move toward a service and information economy, and resource-efficient technologies are introduced with commensurate reductions in material intensity.
- *A1B: moderate emissions scenario*. Part of the broader A1 family of scenarios, A1B population peaks mid-century, economic growth occurs rapidly, efficient technologies are introduced, and a mix of fossil and non-fossil fuels are adopted.
- *A2: high-end emissions scenario*. Under A2, global population continually increases and economic growth is regional and slower than in other scenarios.

Future drought frequency and intensity under each of the SRES scenarios for all of the drought indices were projected early, middle, and late 21st century periods of 30 years (2006–35, 2036–65, and 2066–95) and compared with drought frequency and intensity during a 20th century baseline period (1961–90). Figure 1S in the supplementary material (available at stacks.iop.org/ERL/5/044012/mmedia; as indicated by the S after the figure number) displays representative trajectories of projected carbon dioxide concentrations for the three SRES scenarios between 2000 and 2100.

2.3. Step 3: working with multiple GCMs

Previous research on drought impacts has evaluated the effects of drought based on the outputs of very few GCMs. Because the outputs of GCMs vary widely within the same SRES scenarios [10], the use of GCM ensemble means with some acknowledgment of the uncertainty in ensemble outputs has become standard practice in climate science research. Although research has suggested that a subset of the models may have higher skill in specific regions, some find that good model performance during one time period does not necessarily translate to good performance in subsequent periods [25, 26]. We therefore use IPCC outputs from the full range of available model runs for the B1, A1B, and A2 SRES scenarios (17, 22, and 17 GCMs, respectively, for a total of 56 GCM–SRES combinations—the 22 models represent efforts of 14 climate modeling institutions from around the world). GCM runs available for each of the three selected SRES scenarios are displayed in table 1S (available at stacks.iop.org/ERL/5/044012/mmedia). For each GCM, we used monthly temperature and precipitation data for three time periods: early 21st Century—2016–35; Middle 21st Century—2036–65; and Late 21st Century—2066–95.

Watersheds are the most appropriate geographic units for analyses of the spatial patterns of drought. Within the United States, watersheds are generally classified based on the US geological survey's (USGS) hydrologic unit codes (HUCs). They divide the country into drainage basins of four nested size categories. The first category divides the lower 48 states into 18 regions (e.g., the Missouri region, the Texas-Gulf region, called 2-digit HUCs); this differentiation was too coarse for the purposes of this analysis. A second category for the lower 48 states contains 208 sub-regions (called 4-digit HUCs) that are nested within the 18 2-digit HUCs [20]. These 4-digit HUCs provide too much resolution given the relatively coarse scale of the GCM output data. Intermediate and therefore appropriate geographic resolution was provided by the US Watershed Council's 99 watershed regions for the lower 48 states; each watershed there spans several 4-digit HUCs and are nested within the 2-digit HUCs [5]. Figure 2S (available at stacks.iop.org/ERL/5/044012/mmedia) in the SM displays a map that locates the 99 watershed regions within the coarser 18 2-digit HUC basins.

Because GCM grid cells do not fall on watershed boundaries, it was necessary interpolate GCM output data (e.g., precipitation, temperature) down to the watershed level. Outputs from the 22 GCMs were first aligned to a common 0.5° by 0.5° grid pattern for the continental United States by replicating their native resolutions (typically 2.5° by 2.5°, where a degree is roughly 111 km at the equator; at 35° north or south, 111 km north-south and 91 km east-west) at a smaller scale. For example, the output for each cell of a GCM with 2.5° by 2.5° resolution was applied to 25 smaller 0.5° by 0.5° cells. Average values from these smaller cells (including interpolated values for cells that spanned watershed boundaries) were then computed for each of the 99 watershed regions. Figure 3S in the SM (available at stacks.iop.org/ERL/5/044012/mmedia) overlays the 0.5 by 0.5 GCM grid cells over the 99 watershed regions identified in figure 2S (available at stacks.iop.org/ERL/5/044012/mmedia). The resulting dataset for each GCM output was therefore a matrix of 99 watershed values for each of the 56 GCM–SRES scenario combinations.

2.4. Step 4: computing drought risk indicators

Estimates of the number of months a region would experience an SPI-5 or SPI-12 drought for a given GCM for a particular time slice along an SRES scenario involved several tasks:

- *Task SPI1: Assign SPI values to baseline and projected data*. As described above, the SPI is a probability index that measures drought based on the degree to which precipitation has diverged from the historical median. The statistical approach outlined below [4]:
  - * *Task 1a*. First, create a separate gamma probability density function (PDF), which has been shown to be

an appropriate function to model rainfall [28, 29], for each month of the year across the selected 30-year dataset. For example, in the baseline period, a gamma PDF was prepared for January using the 30 January precipitation values between 1961 and 1990, and so on.

* *Task 1b*. Second, these 12 probability density functions were translated into 12 cumulative density functions (CDFs).
* *Task 1c*. Third, this new CDF was transformed into a standard normal distribution (i.e., with median zero and standard deviation of one). The SPI value for any one of the 360 months during the period is simply its position on the standard normal for that month.

If, for example, precipitation in a southwestern sub-basin during January of 1983 were 0.6 inches and this value were 1.5 standard deviations below the median on the standard normal distribution for January between 1961 and 1990, the SPI for January 1983 would be −1.5 [4].

- *Task SPI2: identify SPI-5 and SPI-12 drought months*. SPI-5 and SPI-12 droughts occur when the one-month SPI value for an area remains below given SPI thresholds (−1.81 and −1.42 for SPI-5 and SPI-12) for five or more and 12 or more months, respectively [27, 28]. For example, if the SPI for May through September remained below −1.81 but then rose above −1.42 in October, then a SPI-5 drought would have occurred but not an SPI-12 drought. On the other hand, if the SPI from March through February (i.e., one full year) remained below −1.42 but greater than −1.81, an SPI-12 drought would be recorded instead of a SPI-5 drought (or a series of SPI-5 droughts). The SPI-5 and SPI-12 drought month counts are the number of months falling into the five- and 12-month droughts. For instance, if an SPI-5 drought lasted from May to November, it would count for seven 'SPI-5 drought months'.

Generating PDSI values for each month in a given 360-month time period for a GCM and SRES scenario involved a different process. Values between −1 and −2 were deemed to indicate mild droughts; between −2 and −3 were moderate droughts; between −3 and −4 were severe droughts; and lower than −4 were extreme droughts. Positive PDSI numbers, on the other hand, reflect wetness in excess of normal conditions. PSDI drought month estimates were the result of a similar approach:

- *Task PDSI1: generate potential evapotranspiration data*. GCM outputs were transformed into monthly potential evapotranspiration data using the modified Hargreaves Method [21].
- *Task PDSI2: generate PDSI values*. Potential evapotranspiration data were then employed to generate PDSI values, following procedures outlined by Palmer [22, 23].
- *Task PDSI3: assign PDSI drought severity levels*. Four subsets of monthly PDSI values corresponding to drought severity levels were identified as described above.

Unlike SPI, PDSI is a drought indicator that uses soil characteristics, precipitation, and potential evapotranspiration (based on temperature) data in a formula to determine the water balance of a particular region [22, 23]. PDSI is generally calculated on a monthly time scale, and considers the meteorological conditions of both the current month and those of past months, accommodating the cumulative nature of drought [23]. Because of its focus on soil moisture as a primary indicator of drought, PDSI is particularly appropriate for agricultural droughts. Like SPI, PDSI does not consider runoff, snowmelt, or water storage and therefore may not forecast water supply effectively, particularly west of the Continental Divide.

2.5. Step 5: estimating differences between baseline and future drought months

The procedures described produced estimates of the number of drought months in the 99 US regions during the 360-month (i.e., 30-year) baseline period and during each of the 360-month 21st century time-slices. Subtracting the number of drought months in the baseline period from the projected values in each of the three alternative future scenarios for three time-slices produced the final multi-dimensional dataset of differences in drought months based on outputs from 22 different GCMs.

3. Results and discussion

Analyses of the SPI-5 and SPI-12 indices indicated that meteorological drought frequency based only on changes in precipitation patterns generally show increases in certain sub-basins and decreases in others [30][5]. This point clearly emerged when spatial patterns of projected mean changes in SPI-5 and SPI-12 indices calculated for 22 GCMs were depicted on a map of the contiguous 48 states (e.g., Panel A of figure 1 with complete coverage provided by Panels A and B in figure 4S of the SM available at stacks.iop.org/ERL/5/044012/mmedia). Projected changes in precipitation-based drought frequencies varied widely across GCMs, however, and so it is important to note that at least some fraction of each set of GCMs projected decreases in drought frequency nearly everywhere (e.g., Panel B of figure 1 with complete coverage in Panels A and B of figure 5S of the SM available at stacks.iop.org/ERL/5/044012/mmedia).

In contrast to meteorological drought, hydrological droughts as measured by PDSI were projected to increase in frequency and severity across nearly all of the 99 sub-basins (e.g., Panel A of figure 2 with complete coverage provided by Panels C through F in figure 4S of the SM available at stacks.iop.org/ERL/5/044012/mmedia). This result differs from the SPI-12 projections because PDSI considers temperature in calculating the index value. Increased temperatures drive higher rates of evapotranspiration that, in turn, cause reductions in soil moisture [31]. Projected changes in drought frequency still varied widely across GCMs, but

[5] SPI-5 and SPI-12 droughts occur when the one-month SPI value for an area remains below statistically defined SPI thresholds for longer than five and 12 months, respectively.

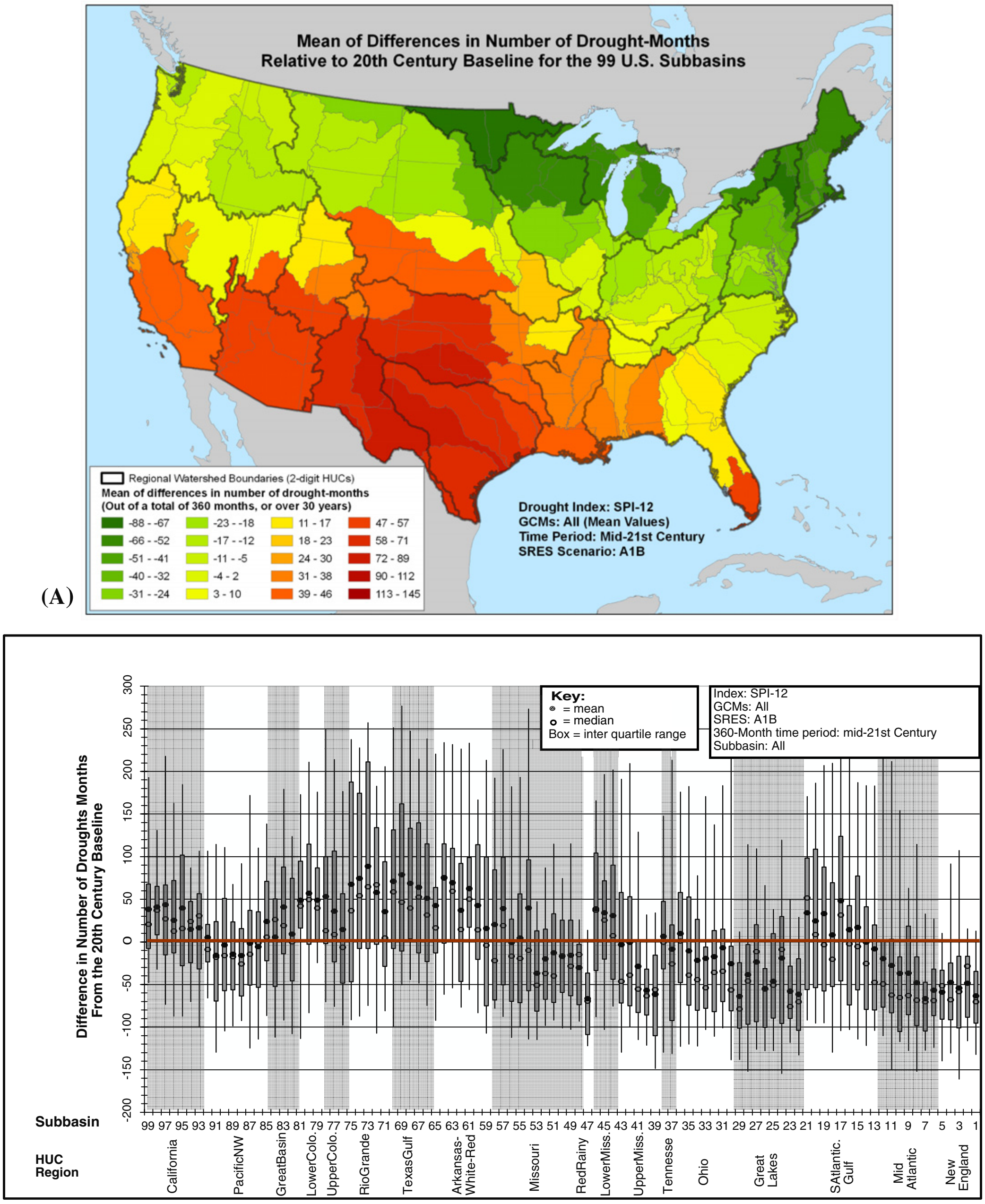

Figure 1. (A) Mean changes in the number of drought months (SPI-12 meteorological drought index) across 22 GCMs relative to the 20th century baseline for the middle 30-year period of this century along the A1B scenario. Frequency increases in the Southwest (up to 89 additional drought months over the 360-month period); frequency decreases in the Northeast by up to 67 drought months. The Southeast, Central Midwest, and Northwest show relatively modest changes. (B) Box and whisker diagrams for the full set of 99 sub-basins for the same future period. Western and eastern sub-basins (i.e., California and New England) generally correspond to the left and right sides of the graph, respectively. Droughts increase in the Southwest and decrease in the Northeast, but the distributions of changes in drought frequency across all of the GCMs all include zero (i.e., no change); for the definition of drought embodied in the SPI-12 index, therefore, many of the possible futures associated with respected climate models include the possibility that frequency declines even when most suggest that frequency increases.

now the inner-quartile ranges projected increased drought frequency for nearly every sub-basin. Moreover, variability across climate models was smallest for sub-basins where changes in mean frequency were close to zero. Projected changes in the frequency of lower severity PDSI droughts were smaller and displayed less clearly defined spatial patterns. It follows that climate change tends to turn events that might currently be mild PDSI droughts into long periods of severe or even extreme drought (e.g., Panel B of figure 2 with complete coverage in Panels C through F of figure 5S of the SM available at stacks.iop.org/ERL/5/044012/mmedia).

Differences in projected changes in mild, moderate, severe, and extreme PDSI droughts could be critical as residents of specific sub-basins plan to respond to their consequences. The San Joaquin Valley sub-basin in California, for example, is an agricultural area that has recently

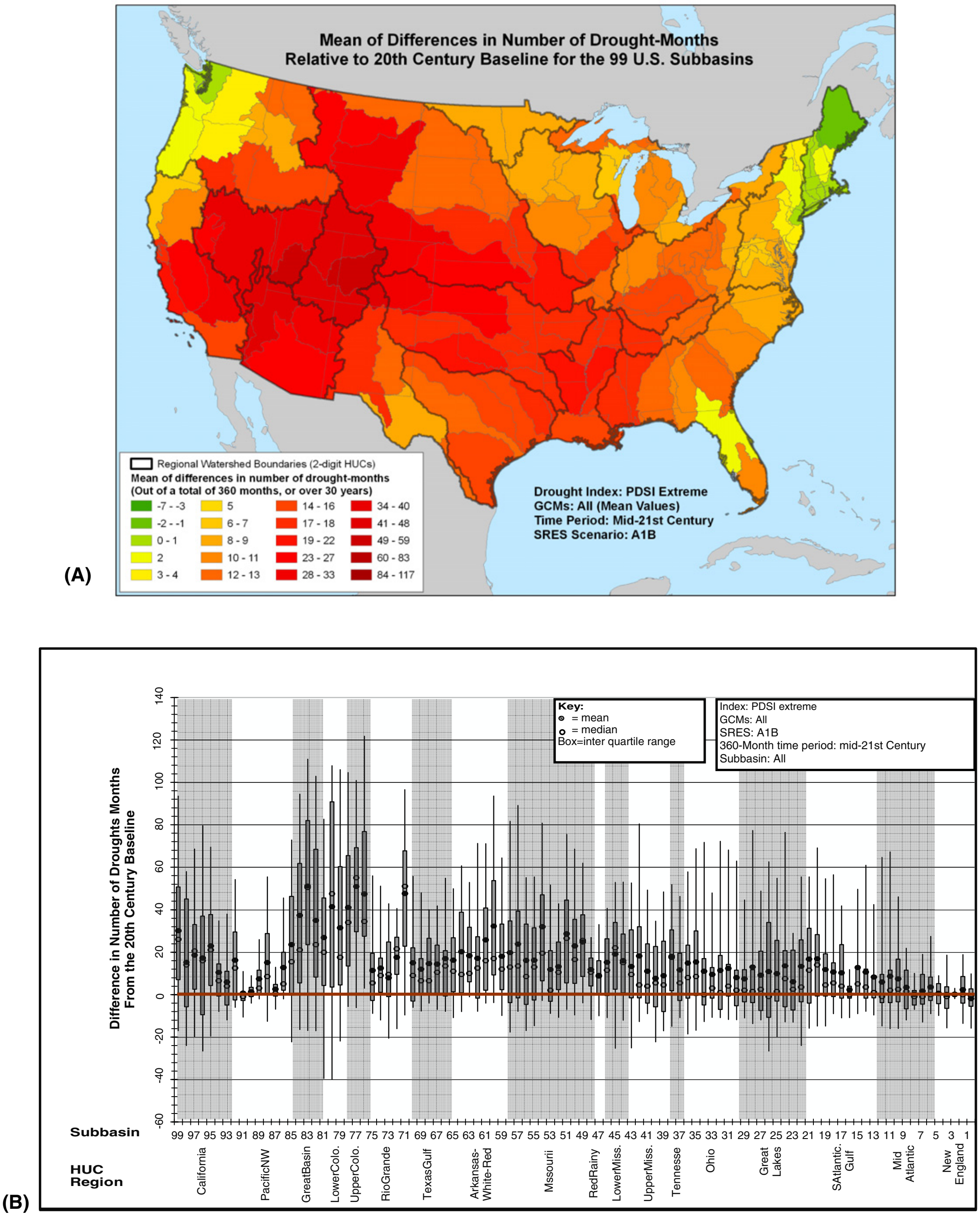

Figure 2. (A) Mean changes in extreme PDSI drought frequency across 22 GCMs relative to the 20th century baseline for the middle 30-year period of this century along the A1B scenario. The spatial pattern of projected droughts differs from the SPI-12 pattern in two notable ways. First, the location of the largest increases in drought frequency (up to 51 additional months in the 360-month period) shifted northward to the Rocky Mountain States rather than the Southwest. Second, almost every sub-basin in the lower 48 states shows a projected increase in drought frequency. (B) Box and whisker diagrams showing the variability of changes in PDSI extreme drought frequency across the 22 GCMs show means and medians that are almost uniformly greater than zero. Sub-basins that have mean changes in drought frequency nearest zero display the lowest variability across climate models.

experienced several years of relatively severe drought. Severe PDSI droughts are, however, not very common in the Valley; that is to say, mild or moderate droughts are more the norm and adaptive responses have come to anticipate coping with their more modest impacts. If the future portends moving from this baseline into a 21st century that is projected to include more frequent episodes of severe and extreme droughts, then these responses could easily be overwhelmed. Unfortunately, this is the future that has been projected by most of the GCMs; and it is a dangerous pattern that would likely be exaggerated along the highest emission SRES scenario (A2) for which extreme droughts are projected to increase sharply in the second half of the century (figure 6S of the SM available at stacks.iop.org/ERL/5/044012/mmedia).

The impacts of drought could, however, be buffered by existing or potential storage capacity if it were possible to

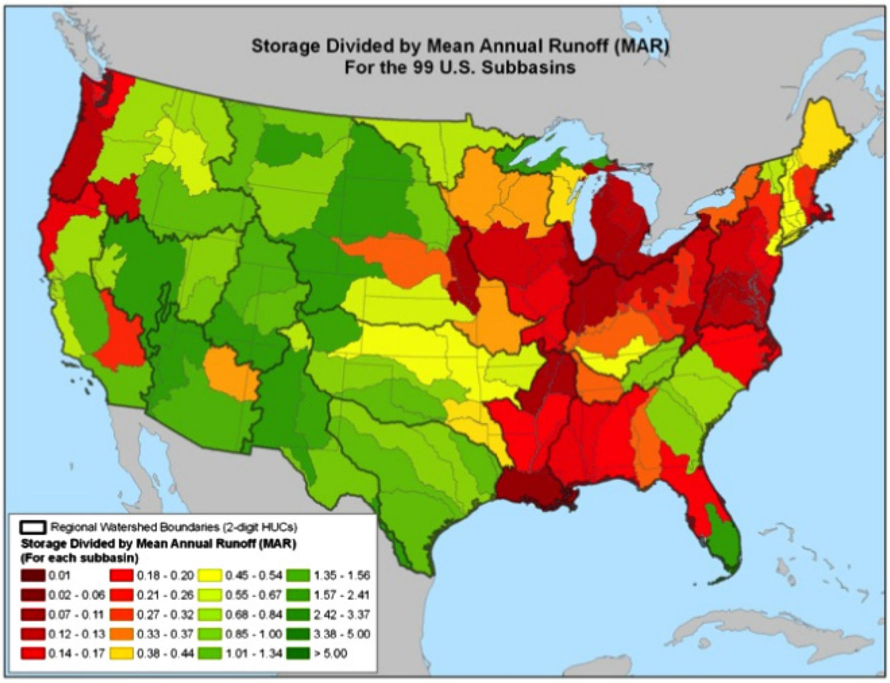

Figure 3. Total water storage divided by the current mean annual runoff (MAR) for all 99 sub-basins in the contiguous US are depicted; this ratio is a measure of the relative resilience of a particular basin to droughts. Notice that the majority of non-coastal western sub-basins have relatively high ratios while eastern sub-basins have relatively low ratios. Sources: MAR data from US Water Resources Council, 1978, The Nation's water resources 1975–2000, Second National Water Assessment: Washington, DC, US Government Printing Office; Reservoir storage data from US Army Corps of Engineers, 2009. National Inventory of Dams, National Atlas of the United States, http://www.nationalatlas.gov/mld/dams00x.html.

use that capacity to transfer water from wet seasons to dry seasons [19]. In the more mountainous regions of the western US, for example, a significant percentage of annual runoff currently comes from snowmelt; it is captured during the spring and withdrawn throughout the high demand summer and fall months to a degree indicated by the ratio of total storage capacity divided by mean annual runoff (MAR). If, for example, runoff in a sub-basin were to total four million acre-feet per year and total storage were eight million acre-feet, then the storage to MAR ratio would be a very favorable two. Many of the areas where significant increases in drought frequency are likely (e.g., the Southwest) to also have large volumes of storage capacity (high existing storage to MAR ratios) that might be employed to manage short- and long-term droughts (figure 3). Storage capacity is not enough to allay fears and diminish risk if there is little water to store, of course; but results derived from modeling entire river basins suggest that it may indeed be possible to use existing capacity to ameliorate some of the impacts of some droughts in some places. The devil will be in the details, to be sure, and so this observation does little more than highlight an area in which further research could be extremely productive.

Changes in climate will also affect reservoir yield (i.e., the expected amount of water that can be sustainably withdrawn from a reservoir each year; see figure 7S (available at stacks.iop.org/ERL/5/044012/mmedia) of the SM for further explanation of the storage–yield relationship) by altering the timing and magnitude of runoff in any particular sub-basin. Drought frequency tells us about the tails of water supply, but it is important to recognize that climate change can increase both drought frequency and overall runoff over longer periods of time. If reservoir storage–yield increases in areas that are likely to experience increased drought frequency, existing water infrastructure would be able to offset some of the drought impacts to managed systems. Identifying the basins where such opportunities might exist would require a runoff and reservoir yield model that carefully accounts for complex issues such as changes in flood frequency and intensity, evaporation, evapotranspiration, and soil moisture; this would be a valuable avenue for future research.

This analysis did not explicitly consider scenarios that are based on carbon control policies or stabilization targets, but the emissions levels in the SRES scenario vary widely to support several conjectures about relationships between changes in drought frequency and CO_2 emissions (figure 4). Meteorological SPI drought measures showed increasing drought frequency over time and with higher emissions for areas that were prone to more drought but decreasing frequency for areas that were getting wetter; put another way, higher emissions tended to magnify projected regional precipitation-based drought trends. Hydrological PDSI measures showed increasing drought frequency over time and with higher emissions across most of the country. Finally, changes in the number of drought months in the late 21st century were far less certain (as measured by dispersion across the 22 GCMs) under the higher emissions SRES scenarios for both drought measures (figure 5S of the SM available at stacks.iop.org/ERL/5/044012/mmedia).

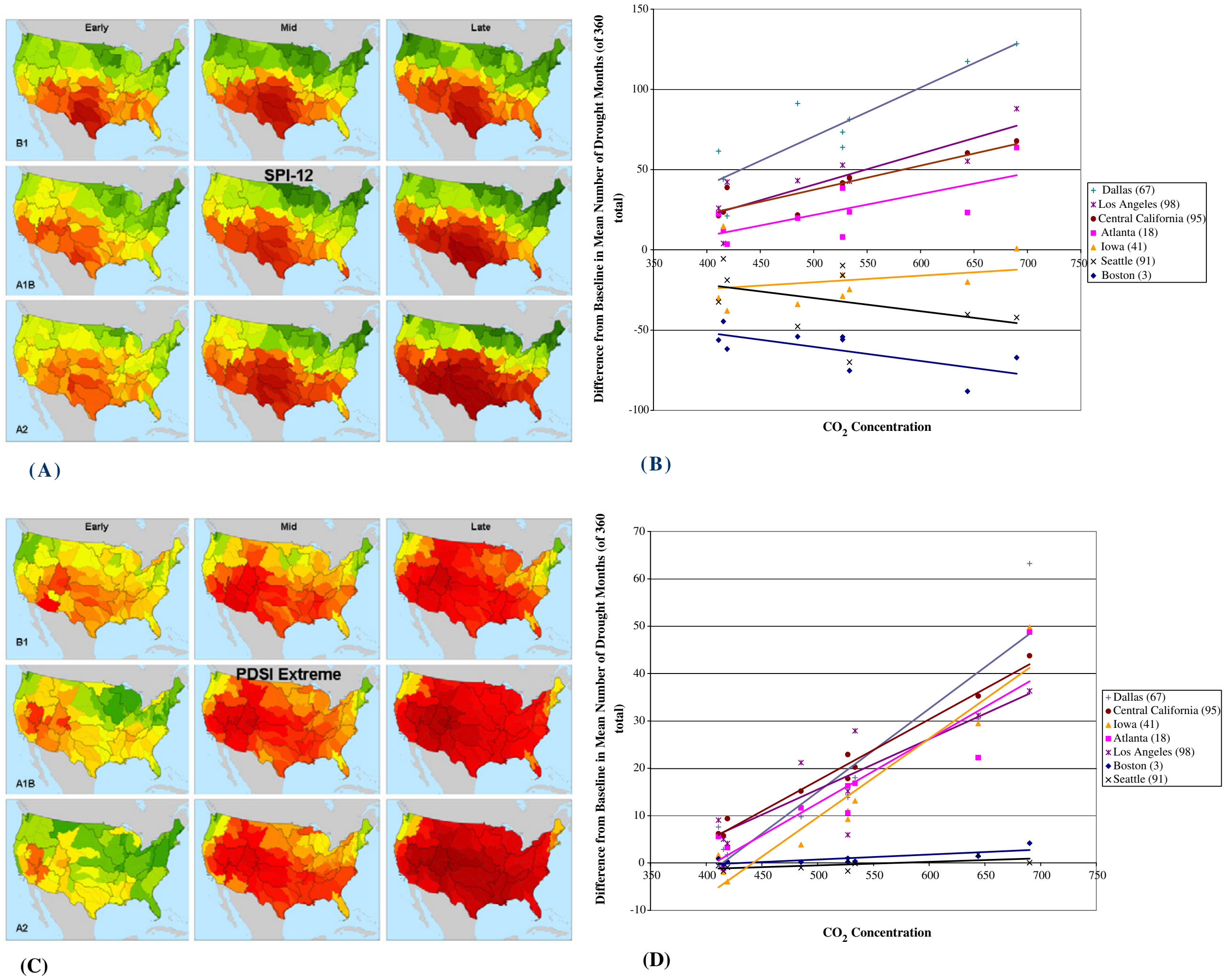

Figure 4. (A) Mean changes in SPI-12 drought frequency relative to the 20th century baseline across the SRES scenarios (the vertical axis) and 21st century time periods (the horizontal axis); color scale as in figure 1(A). The area of increasing drought frequency expands, and the region of lessening frequency contracts over time and with higher emissions. Little changes over time along B1, but nearly the entire southern half of the lower 48 states shows significant increases in drought frequency along A2. (B) Atmospheric CO_2 concentrations implicit in the IPCC scenarios are plotted against changes in SPI-12 drought frequency for seven representative cities or regions across the US. Regions initially experiencing increases in droughts show further increases, and most areas with reductions in droughts reduce further as CO_2 concentration increases. (C) Mean changes in PDSI extreme drought months relative to the 20th century baseline; color scale as in figure 2(A). Sharp increases in the geographic extent and frequency of PDSI extreme droughts from the mid- to late 21st century are seen for A1B and A2 scenarios, as are significant differences between B1 and A2; color scale as in figure 1(A). (D) Atmospheric CO_2 concentrations plotted against changes in PDSI extreme drought months. Trend-lines are all upward sloping when the hydrologic definition of drought depends on changes in precipitation and temperature.

4. Conclusions and future research

These findings provide an important first step in a more comprehensive evaluation of the geographically disparate implications of changes in drought frequency under climate change. They show clearly that different definitions of drought generate different distributions of frequency and point to the importance of using multiple indices when studying drought risk.

Secondly, GCMs vary widely in their drought frequency projections, particularly in later periods and under higher emissions SRES scenarios. This uncertainty must be reflected in micro-scale analyses of local and regional water management issues, particularly in 'hot spots' that can now be identified by overlaying significant changes in drought frequencies and/or widening disagreement of those changes across climate projections over geographically explicit distributions of water sensitive sectors and population centers.

Tracing the geographic distribution over time along alternative climate scenarios of a runoff-based drought index like the Standardized Runoff Index (SRI) could also provide more relevant indications of drought risk for irrigated agriculture or municipalities that depend on rivers for drinking water [19]. SRI distributions would depend not only on precipitation and temperature, but also on storage (i.e., reservoirs and snowpack) and inflows/outflows from/to adjacent areas. As a result, pictures of future drought conditions taken through an SRI lens could be enormously different from those supported by either SPI or PDSI indices.

Finally, although this work did not assess drought risk under CO_2 stabilization scenarios, comparisons of SPI and PDSI results across emissions scenarios strongly suggest that lower CO_2 concentrations are associated with lower drought risk throughout the United States. This work therefore lays the foundation for tracing geographically distributed measures of the social and economic value of alternative mitigation strategies as it offers preliminary support of the hypothesis that mitigation could reduce drought risk. When and where those reductions might occur first and/or most significantly along which alternative mitigation pathway are questions yet to be answered.

Acknowledgments

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