Drought-busting 'miracles' in the Colorado River Basin may become less frequent and less powerful under climate warming

Binod Pokharel[1,2,3,*], Kripa Akila Jagannathan[4], S.-Y. Simon Wang[1], Andrew Jones[4], Paul Ulrich[4,5], Lai-Yung Ruby Leung[6], Matthew D. LaPlante[1,7], Smitha Buddhavarapu[4], Krishna Borhara[1], James Eklund[8], Candice Hasenyager[9], Jake Serago[9], James R. Prairie[10], Laurna Kaatz[11], Taylor Winchell[11], Frank Kugel[12]

[1]*Department of Plants, Soils and Climate, Utah State University, Logan, UT, USA*
[2]*Utah Climate Center, Utah State University, Logan, UT, USA*
[3]*Central Department of Hydrology and Meteorology, Tribhuvan University, Kathmandu, Nepal*
[4]*Climate & Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA*
[5]*Department of Land, Air, and Water Resources, University of California, Davis, CA, USA*
[6]*Pacific Northwest National Laboratory, Atmospheric Sciences and Global Change Division, Richland, WA, USA*
[7]*Department of Journalism and Communications, Utah State University, Logan, UT, USA*
[8]*Eklund Hanlon LLC., Denver, CO, USA*
[9]*Utah Department of Natural Resources, Division of Water Resources, Salt Lake City, UT, USA*
[10]*Bureau of Reclamation, Denver, CO, USA*
[11]*Denver Water, Denver, CO, USA*
[12]*Upper Gunnison River Water Conservancy District, Gunnison, USA (retired)*

[*]Corresponding Author: Binod Pokharel (Email: binod.pokharel@usu.edu)

Abstract: Drought-busting events in the Colorado River Basin, such as the “Miracle May” of 2015 that greatly alleviated an unprecedented water shortage, have been observed for more than a century. But while such events are much prayed for in times of drought, they have not been well researched or even characterized. In this study, conducted in collaboration with water managers from across the basin, we propose a definition for “miracle events” that reflects real-world, actionable relevance. The resulting characterization offers a framework by which to quantify the frequency and strength of extreme dry-to-wet springtime transitions. While limited by uncertainties in model simulations and the myriad hydrological futures these simulations seek to project, and thus requiring cautious interpretation, this study finds that such transitions may become less frequent and less powerful under climate warming.

Keywords: Miracle Spring, Colorado River Basin, drought index, climate models, stakeholders, water managers

1. Introduction

In early 2015, the Colorado River Basin (CRB) faced an unprecedented water shortage. In the "Four Corners" states of Utah, Arizona, New Mexico and Colorado, which comprise the majority of the basin's territory, three-quarters of the total landmass were in "abnormally dry" conditions, which had persisted—or became worse—since 2012 without a single month of reprieve. From a near-capacity high of 1,216 feet above sea level in 1998, Lake Mead, the largest reservoir in the United States, had fallen to a historic low, plummeting more than 140 feet. Officials from the U.S. Bureau of Reclamation estimated that Colorado River Compact allocations were deficient in the order of 1.2 million acre-feet per year. And water managers across the region were imposing historic curtailments. But in spring of 2015 a nearly threefold increase in the basin's average precipitation flipped the river system from severe shortage to flooding status in a matter of weeks, and water managers rejoiced at the "Miracle May," which boosted the basin's water storage and alleviated the immediate concerns about shortages.

This wasn't the first "miracle" event, so dubbed because the anomalously strong rainfall had not been predicted during springtime water planning. The term appears to have been coined in 1991, when California was experiencing its worst drought since the Dust Bowl before a "Miracle March" brought record-breaking spring snowfall that tripled the mountain snowpack. Other winter-to-spring, dry-to-wet transitions that replenished the water supply at critical moments of need are reflected in the historical record, including the prodigious precipitation events in 1915, 1945 and 1976.

Facing repeated, prolonged drought events across the West in recent decades (Sullivan et al., 2019; Udall and Overpeck, 2017) alongside growing demand for water that continues to cut away at the CRB's finite supply (Rajagopalan et al., 2009; Woodhouse et al., 2021), water managers may be allured by the opportunity to know whether climate models can project such seemingly abrupt and extreme dry-to-wet springtime transitions, particularly when faced with the prospect of a warming world. Under future warming scenarios, the contribution of Upper Basin snowmelt, which comprises about 92% of the runoff for the entire CRB, could fall by one-third (Lukas and Payton, 2020; Li et al., 2017). A warmer climate is also likely to produce a low-to-no snow future in the CRB, which consequently impacts streamflow and water supply (Siirila-Woodburn et al., 2021; Woodhouse et al., 2021; Lukas and Payton, 2020). As these futures begin to emerge, phenomena that at one time seemed like unforeseeable and wondrous events may be an important part of the scientific process of water management and planning—if, that is, the frequency and intensity of these events can actually be predicted.

Thus far, however, springtime miracle precipitation events in the CRB have not been quantitatively defined nor universally characterized. Thus, to understand the drivers of critical dry-to-wet springtime transitions, how representable they are in climate models, and how they might evolve in response to global climate change, a scientific definition that reflects real-world management relevance must first be developed.

Since a common definition for extreme dry-to-wet transition events does not exist, and no specific criteria have previously been developed, this research tests different metrics with a variety of drought indices to create what we have dubbed the "Miracle Index." Utilizing multiple datasets to evaluate historical dry-to-wet transitions, and the extent to which a warmer climate may impact similar situations in the future, the “Miracle Index” quantifies events that begin with at least four consecutive anomalously dry months followed by at least three consecutive anomalously wet months, hinged at a “month zero,” as shown in Figure 1.

As this index is not just intended for conceptual but also practical use, regional water managers have been involved from the point of conception, and the research questions that drove this study were based on their input during a series of meetings aimed at understanding how miracle events might be relevant to water management (see Section 2.1). These questions include: How can extreme dry-to-wet transitions factor into water management? How often do these events occur? Can climate models predict these miracle events? Would past dry-to-wet transitions have happened without a warmer climate? How will miracle events change in the future? Will projected changes impact water management?

2. Data and Methodology

This study introduces a definition for extreme springtime dry-to-wet transitions (hereafter “miracle events”) using common precipitation and drought indices, with an emphasis on creating a metric that is relevant and useful to water managers in the CRB. To this end, we incorporate the past experiences and future needs of water managers, based on a series of stakeholder discussions, into our analysis of various drought indices, which have been chosen to better understand how miracle events might be differentially characterized, with the intention of arriving at an index that balances scientific value and utility.

2.1. Stakeholders Discussions and Survey Data

Co-production is a process that involves iterative and continual engagement between scientists and decision-makers (in this case water managers) to collaboratively develop actionable science (Jagannathan et al 2020, Kirchhoff et al. 2013). For this research, we used co-production principles and approaches to develop a research plan, finalize research methods, and engage in an iterative process based on feedback about the management relevance of key scientific results. We engaged water managers from five different state and federal agencies located in Colorado and Utah, and seven water management professionals from these agencies, who are also co-authors of this paper, participated in iterative engagements with project scientists throughout the course of the research.

Upon approval from Lawrence Berkeley National Laboratory’s Human Subjects Committee Institutional Review Board for key engagements, three focus group discussions and three surveys were conducted, interspersed by informal conversations and discussions over the course of two years. The first focus group discussion aimed to co-produce the questions, approach and potential outputs of the research. Subsequent focus groups were conducted to elicit iterative feedback on interim results and approach. The surveys were intended to gather written feedback on further directions for the work. Through these discussions and surveys, the managers and scientists co-developed several components of the research, such as the key metrics of interest, the spatial domain that is most decision-relevant, the uncertainty range, and the interpretation of climate model projections. Notably, this feedback resulted in a broadening of the scope of the research from only looking at specific events (such as the "Miracle May" of 2015 and similar "miracle months") to looking at the transitory periods that are centered on such events.

2.2. Observational data

To develop a definition of historical miracle events, we explored datasets including precipitation, Palmer Drought Severity Index (PDSI), Palmer Hydrological Drought Index (PHDI), and Standardized Precipitation Index (SPI, Guenang and Kamga, 2014) to analyze how these indices change due to miracle precipitation in the Upper Basin and Lower Basin (UB and LB, respectively). The observational data used in this study were downloaded from the U.S. National Climatic Data Center for the Colorado Basin (Vose et al., 2014, https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/) and assessed in different timescales (e.g. 1-, 3-, 6-, 12-, 24- month) from 1895 to 2019. Here, SPI3 means a running three month mean of SPI representing the end month, and so forth, as we considered short-term, seasonal, and long-term SPI analyses to see the change in drought in the CRB at different timescales. In this regard, SPI3 depicts semi-persistent moisture conditions and provides a seasonal estimation of precipitation. Note that evaporative effect is not considered here due to the difficulty in deriving the Standardized Precipitation-Evapotranspiration Index (SPEI) from model outputs.

While we initially analyzed both the UB and LB, based on stakeholder feedback we decided to focus on the upper basin, which is the totality of the river network north of Lee's Ferry in northern Arizona, because the vast majority of natural flow of the Colorado River comes from that segment of the CRB (Lukas and Payton, 2020). This decision was reviewed, and affirmed, after it became clear that miracle events are significantly more common in the UB (as discussed below).

2.3 Climate modeling data

Based on feedback from water managers, we used both Coupled Model Intercomparison Project Phases 5 and 6 (CMIP5 and CMIP6) of IPCC global simulation data to investigate modeling relevance and analyze projected miracle events. One limitation to the use of both phases of these climate projections is that the CMIP5 data used here have been bias-corrected and statistically downscaled, with a horizontal resolution of 0.125 degree (produced by the Bureau of Reclamation CMIP5-BCSD; Reclamation, 2013; Maurer et al., 2007), while the CMIP6 data were obtained from http://climexp.knmi.nl/ with the default 1.25-degree horizontal resolution and without statistical downscaling or bias correction (CMIP6 downscaling datasets are not yet available). Thus, comparisons between the two sets of climate projections are limited. However, the stakeholders preferred to have all possible information sources to consider when it comes to future projections.

Each model of CMIP5 used in this study was driven by historical forcings (observations of aerosols, greenhouse gasses, and solar irradiance) from 1950 to 2005, with the follow-on period of 2006-2100 driven by forcings from Representative Concentration Pathway 8.5 (RCP8.5) (Freychet et al., 2015). We used historical precipitation from an ensemble of 81 simulations from 30 global climate models of CMIP5 and an ensemble of 69 simulations from 28 models for CMIP6. The CMIP6 includes shared socio-economic pathway (SSP) projections intended for exploration of future climate conditions under various scenarios of population change, economic growth, urbanization, technological development, and other factors that may influence emissions and other climate-impacting physical processes (Mishra et al. 2020; Zhai et al. 2020). The current study focuses on the SSP585 scenario, which assumes high radiative forcing (8.5 W m^{-2}) by the end of the century. SPI at different timescales was calculated to evaluate the dry, wet and miracle events in both climate models. Historical (1850–2014) and future projected (2015–2100) precipitation under different scenarios were used to derive SPI.

2.4 Regional pseudo-global warming simulation

The Pacific Northwest National Laboratory (PNNL) developed high-resolution pseudo global warming (PGW) simulations using the Weather Research and Forecasting (WRF, Skamarock et al., 2008) model. These simulations (hereafter PNNL-WRF) cover the Western U.S. with a grid spacing of 6-km. The PNNL-WRF output includes a control simulation of 30 years driven by boundary conditions from the North American Regional Reanalysis (NARR) during 1981 to 2020 (Chen et al. 2018). For future projections, five PGW simulations were produced by PNNL-WRF by adding the NARR boundary conditions to the mean monthly perturbations derived from the climate change signals simulated by five CMIP5 models (CanESM2, CESM1-CAM5, GFDL-ESM2M, HadGEM2-ES, and MPI-ESM-MR) for the period of 2041-2070 following a high-end scenario (RCP8.5) relative to the historical simulations for 1981-2010 from the same five CMIP5 models. The PGW simulations provide a direct comparison for how historical climate events may behave under warmer conditions.

3. Characterizing springtime miracle events

Different datasets were used to evaluate and define the extreme dry-to-wet transitions in the CRB. “Month 0” is defined as a month following at least four consecutive winter months of drought conditions and preceding at least three consecutive wet months that reverse the drought situation through the impending summer. For standardized indices like PDSI and SPI, this definition means a persistent sign reversal happening in month 0 as illustrated in Figure 1. Snowpack metrics are not being considered here because the “miracle season” coincides with the snowmelt season, such that even if the increased precipitation added snow on the mountains, it would not last long. (Rainfall in May could accelerate snowmelt; this is discussed later.) Since different drought indices may yield different results, we analyzed many indices and, in collaboration with stakeholders, have chosen to display the results from three: PDSI, SPI3 and SPI6.

The miracle events that are described by each of these indices do reveal some divergence, as shown in Figure 2. Despite these differences, however, there is a 50% overlap between the miracle events identified using the three indices. In the UB, both PDSI and SPI3 produced 11 miracle events (Figures 2a and 2b) while SPI6 (Figure 2c) produced 13 miracle events. Of note, the LB produced fewer than five miracle events regardless of the index used (result not shown).

Based on all the miracle events identified by PDSI, SPI3 and SPI6, we constructed a composite, shown in Figure 3. A notable caveat to this discussion is that there is ongoing debate as to which indices best characterize different types of drought, such as meteorological drought vs.

hydrological drought (Slette et al., 2019), and both PDSI and SPI are meteorological drought indices.

To validate the depiction of these events and examine the long-term behavior of drought with respect to a miracle event, we also plotted a key hydrological index, the PHDI, as well as SPI1 (one month) and SPI24 (two years). While PDSI considers longer-term dryness that will affect streamflow, PHDI offers a mechanism by which to assess how much precipitation is needed to end a drought. The SPI1 histogram reveals the subseasonal behavior of precipitation with respect to month 0, and the result in Fig. 3 suggests a prolonged precipitation change that is of seasonal or longer term. This result indicates that the hydroclimatic change associated with an extreme dry-to-wet transition is a seasonal anomaly that may be part of seasonal-to-interannual or even longer variations. This inference is supported by the PHDI, which shows a more delayed response, suggesting replenished water storage following month 0.

3.1 Relevant climatic anomalies

The CRB has experienced some persistent climate anomalies in recent decades, and we also looked at how these anomalies have changed. In response to stakeholder interest, we analyzed the frequency of "wet-wet" anomalies from a wet winter to a wet spring, based on December-February and March-May seasons, using the SPI3 drought index for the CRB. "Dry-dry" anomalies are also defined similarly. These persistent anomalies ("wet-wet" and "dry-dry") account for most of the historical years, reflecting the lower-frequency nature of hydroclimatic variation in this region (Wang et al. 2018). Figure 4 shows the historical distribution of the tendency in SPI3 based on the count of each type of anomaly within a 15-year bin. Both the UB and LB have experienced an increasing trend in the frequency of dry-dry anomalies, meaning that both winter and spring have become drier in recent years, echoing the worsened drought situation as reported in the literature. The increased dry-dry anomalies and decreased wet-wet anomalies are present in the lower CRB (Figure 4b); however only the trends in dry-dry anomalies are statistically significant ($p<.01$, Figure 4).

By considering all possible combinations of dry-wet, wet-wet, dry-dry, and wet-dry situations shown in Figures 4c and 4d, we found that the UB has more extreme miracle events than the lower basin. This difference is conspicuous in the pie-charts (Figure 4c and 4d) and it is worth noting that this form of graphic depiction was well received by the water managers as an informative piece of climate analysis. We further looked at the historical precipitation and drought strength (PDSI) over the two basins and found that annual precipitation has been decreasing in both basins (Figure S1). Both basins show a similar inter-annual variability of precipitation and drought. Both basins also show a significant decrease in precipitation and, subsequently, PDSI. Note that the decreasing rate of PDSI is more profound than that of precipitation in both basins, reflecting the known compound effect of the declining snowpack and drying soil on precipitation deficit in the CRB (BOR 2013). Figure S2 shows that the wet-wet situation has decreased while the dry-dry anomalies have become more frequent in recent years, consistent with SPI3 (Figure 4).

3.2 Climate projections

We analyzed the CMIP5/6 data to assess the future of extreme dry-to-wet transitions using SPI3 criteria. SPI was found to be preferable to PDSI for model-based analyses as the latter has not been found to be accurately reflected in CMIP projections (Yang, et al., 2020). (The choice of SPI3 is further discussed in Section 4.) As shown in Figure 5, the models produce extreme dry-to-wet transitions in numbers that are similar to observations, with around one event every ten years. The uncertainty among the individual models/ensembles is quite large, as shown by the error bars for both CMIP5 and CMIP6, and the frequency of miracle events is also consistently higher in CMIP5 than CMIP6. This difference could result from the fact that the CMIP5 used in this analysis is a downscaled and bias-corrected dataset and can capture the UB's dry-to-wet spring transitions better than the coarser-CMIP6 data without bias correction.

Both models, however, produce a similarly decreasing frequency of extreme dry-to-wet springtime transitions in a warming climate, with CMIP5 projecting a ~50% decrease and CMIP6 projecting a ~15% decrease from the most recent decade (2009-2019) to the final decade of this century. Notably, both models project relatively steady miracle events through the mid-century, roughly in line with past observations, at which point a gradual decline in these extreme transitions is suggested (Figure 5). The main reason for the decreasing miracle numbers may be twofold. First, while the models project increased annual precipitation as the climate warms, the same models project decreasing May-June precipitation; this may result from the enhanced and poleward shift of the North Pacific Subtropical High during April-June, diverging moisture away from the southwestern US (Song et al. 2018a). Second, CMIP5 projects that the frequency of drought (dry-dry) will mildly decrease in the future (Fig. S3a) while the occurrence of anomalously wet seasons will increase (wet-wet; Fig. S3c). However, CMIP6 suggests a significant decreasing trend in drought frequency (Fig. S3b) in conjunction with a ~50% increase in wet-wet (Fig. S3d). In other words, less drought and more precipitation during the winter-to-spring transition may reduce the possibility of reaching the miracle event criteria, especially in CMIP6, but the reduction in May-June precipitation also can diminish the likelihood of miracle events. This may appear to be contradictory to what some researchers have projected will be a low-to-no snow future in the western United States (Siirila-Woodburn et al. 2021), and the discrepancy speaks to the large uncertainty that still plagues the current generation of climate models. While there are still many questions to answer about the capability of these models to accurately capture the forces that would lead to changes in miracle events, it is intriguing that both sets of models project a declining frequency of miracle events after mid-century in the upper CRB as an integrated effect of the changing characteristics of wet and dry seasons. This has led us to perform the next analysis.

3.3 Pseudo–global warming scenario

Using PNNL-WRF PGW simulations, we assessed the effect of climate warming on miracle events. As shown in Figure 6, the control simulation produces a frequency of dry-to-wet transitions that is similar to observations, with one to two events per decade. Applying the RCP8.5 level of warming to the historical period decreases the frequency of miracle events (Figure 6), a result that is consistent with our CMIP projection analysis.

We further diagnosed the precipitation change in the PGW simulation and found that most of the months during the year would receive more precipitation than the control run, except for May

(Figure S4), again consistent with the CMIP projections. The PGW simulation lends further support to the implication of fewer miracle events under continuously warming climate conditions. The spring (May/June) drying consistently found in CMIP5/6 and the PGW simulations in the UB has been revealed by Gao et al. (2015) based on regional climate simulations and by Song et al. (2018a) from CMIP5 simulations. They attributed the robust spring drying in the southwestern U.S. to increased moisture divergence by the North Pacific Subtropical High (NPSH), which is enhanced by future warming. Song et al. (2018a) found that under global warming, the NPSH is enhanced due to larger land-sea thermal contrast, but more importantly the seasonal march of the subtropical high (and monsoon onset) is delayed and this directly enhances the NPSH in spring more than summer (Song et al., 2018b). Therefore, the seasonally dependent change in the NPSH accentuates the spring drying that contributes to the reduced likelihood of extreme dry-to-wet transition in the UB.

The change in SPI3 between the control and PGW simulations (Figure S5) shows that the strength of dry-to-wet transition is reduced in a warmer climate, compounded by weaker SPI3 before and during month 0. The strength of an extreme dry-to-wet transition can be assessed by averaging SPI3 from the four months before month 0 (dry index) and subtracting the mean SPI3 of the three wet months in and after month 0 (wet index), and the difference between these indices implies a miracle event's strength. With additional warming, miracle strength declines 37% over the historical climate control run (Table 1). Thus, a warmer climate may not only reduce the frequency of extreme springtime dry-to-wet transitions but the strength of such miracle events, too.

3.4 Stakeholder engagement

Stakeholders were essential to formulating the management-relevant research questions upon which this study was centered. At the onset of this research, the water managers indicated a desire to better understand miracle events, as this knowledge could inform reservoir operations, flood control planning, irrigation operations, and municipal use, as well as other water users in the basin. The key stakeholder questions relevant to these desires were: What constitutes a miracle event? What are the metrics of such an event? Can miracle events be predicted? Do different modeling approaches yield different answers? Will the likelihood of miracle events change in the future?

In addition to a specific focus on miracle events, the water managers also suggested that a broader understanding of dry-to-wet winter-to-spring transitions would be additionally relevant for decision-making. Their questions related to a more general understanding of drought-busting spring weather included: To what extent are dry winters and wet springs correlated? What do observations and climate models suggest about how often dry winters are followed by wet springs? How might these conditions change in the future? What are the dynamical drivers at play?

In the initial engagements, water managers identified several miracle events that were of relevance to their regions, with a particular interest in the miracle events that occurred in 1992 and 2015. They also suggested that the UB and LB should be considered separately and informed the decision to focus on the UB, given its dominant role in the Colorado River water supply. In our ongoing discussions, the managers also pointed out that spatial scales play a significant role in defining miracle events, as conditions in one region may be very different from events in another. For example, the managers suggested that while the May 2015 event was significant for most localities within the CRB, other regions, such as the area managed by Denver Water, were not as greatly affected.

Stakeholder input was also key to our decision to examine miracle events using several indices, as their work necessarily incorporates multiple perspectives. The managers expressed a general preference for the indices that showed the "Miracle May" of 2015, as this basin-wide event was immediately and intuitively familiar. This event was reflected in both the PDSI and SPI3 analyses and was one of the factors that helped inform our decision to examine the elements of SPI3 in the CMIP models. Managers also indicated a desire to better understand how and why results differ between CMIP versions, as they have recently begun updating their plans to reflect the relatively recent release of CMIP6 data.

The managers expressed a desire to gain a broader understanding of the patterns of wet-wet, wet-dry, dry-dry, and dry-wet winter-to-spring transitions, and the pie-charts showing these results (Figure 4) were consistently flagged as being most useful for drought planning, reservoir releases, inter- and intra-state water storage management, and demand management programming. The managers noted the utility of knowledge such as the fact that wet winters are generally more likely to be followed by wet springs, and dry winters are generally more likely to be followed by dry springs. These stakeholders further expressed that it was additionally helpful to understand how these patterns might hold up in the future, a question that was answered in part by all three sets of climate projections indicating a decreasing trend of miracle events as the climate warms. As one manager noted, "if we know the miracle spring signal is decreasing, we know that a miracle spring is less likely to save us."

4. Discussion and Summary

It may not be possible to perfectly define the conditions that constitute a "miracle." This is ultimately a phenomenon to which water managers and climate researchers alike might apply Justice Potter Stewart's famous standard of "I know it when I see it." But as "miracle" has become an increasingly common colloquial description of rapidly drought-ending precipitation events, we believe there is great value in a good-faith attempt to define the kinds of conditions that are embraced within that shorthand description.

The principal challenge in this endeavor is selecting the right metrics to define a miracle event. As previously noted, as even the definition of "drought" is subject to broad interpretation, it makes sense that the variables constituting a "drought-busting" event might be similarly rife grounds for debate. Indeed, stakeholders suggested many different ways that one might arrive at a "miracle index," including the application of data related to snow water equivalent calculations, streamflows, and reservoir levels. As these variables were difficult to derive in climate projections, and as stakeholder consensus that a simple-to-assess and relatively easy-to-model equation would offer the broadest potential actionability, SPI3 emerged as the key index upon which to base our analysis, with PDSI and SPI6 playing supporting roles to offer a holistic picture of past and future miracle events. Future work should consider SPEI and other hydrological drought indices.

Thus defined, there is tremendous potential in further exploration of miracle events, most notably in the realms of spatiality and consequentiality. Just like miracles of the unquantifiable sort, after all, a miracle event may not have equal benefits across an entire basin, or even sub-regions of that basin. An extreme dry-to-wet transition during spring may mitigate a given winter drought *in summa*, but the impact of that transition may result in vastly differing effects on agriculture and ecology from place to place, most notably when it comes to fires and floods. This is perhaps best reflected in the "Miracle May" event of 2015, which saved the CRB from a severe water shortage but also resulted in massive flooding in Texas (Wang et al. 2015).

Given that each miracle event affects different watersheds in different ways, every such event will be felt and examined in different ways. This may complicate the path to a holistic analysis. The implication of the presented research, however, offers a starting point for additional examinations of this phenomenon to understand its climatological characteristics and provides valuable clues about the future of extreme dry-to-wet springtime transitions. It may be true, as is often said, that "miracles never cease," but our analysis suggests that, in a warming world, miracle events in the CRB may soon begin to slow down and weaken.

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Open Research

PDSI and SPI data was used in this study can be freely accessed from https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/,CMIP5 downscaled and bias corrected data are freely available at https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Projections:%20Complete%20Archives. CMIP6 data are generated at https://climexp.knmi.nl/selectfield_cmip6.cgi?id=someone@somewhere. The regional climate model (PNNL-WRF) data are available upon request by email to Lai-Yung Ruby Leung (ruby.leung@pnnl.gov).

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FIGURES:

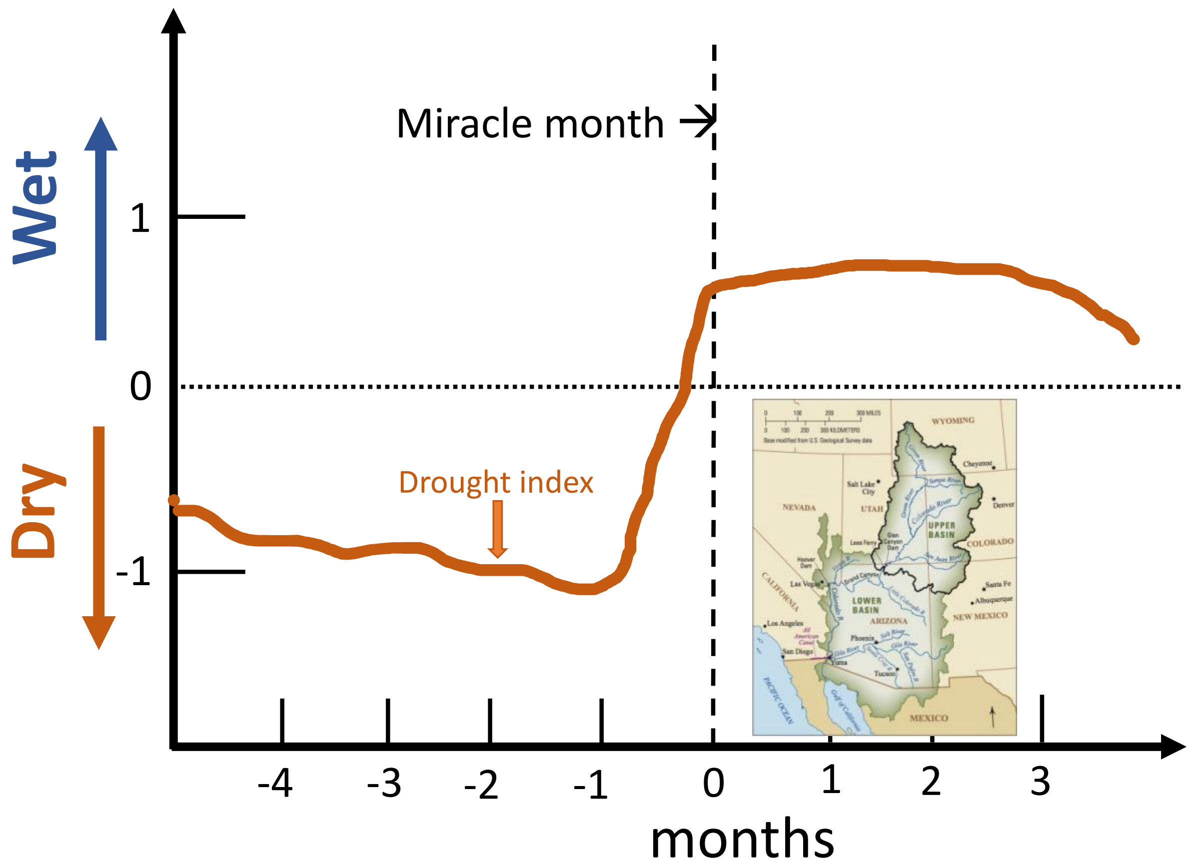

Figure 1: Schematic of miracle spring events with Colorado River Basins map (inserted). ‘Month 0’ represents the miracle month while negative months are dry and positive months are wet months.

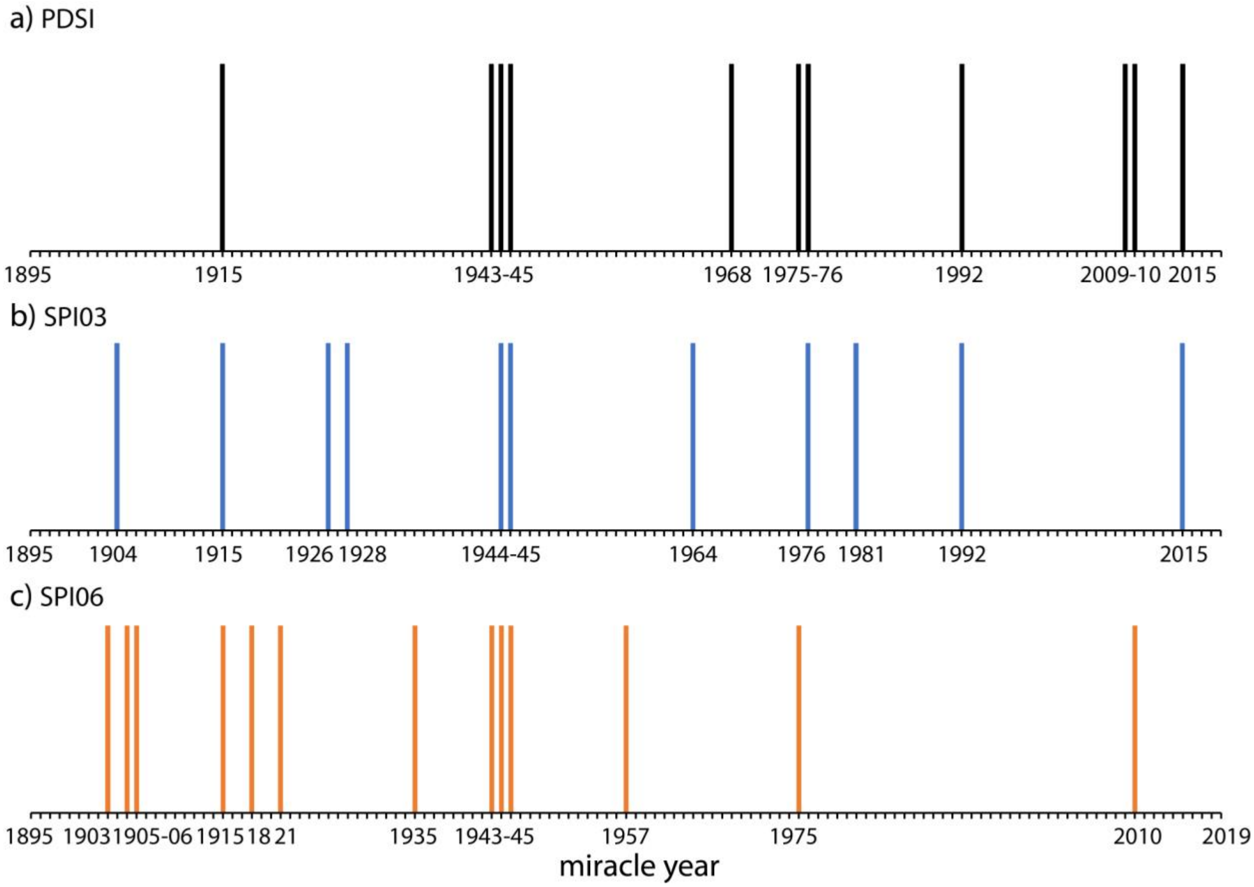

Figure 2: Historical miracle events calculated from different drought indices considering four consecutive negative drought index followed by three consecutive positive drought index. Upper panel (a) shows the miracle years based on PDSI (upper panel), middle panel (b) shows the miracle years based on SPI3, and lower panel (c) based on SPI6.

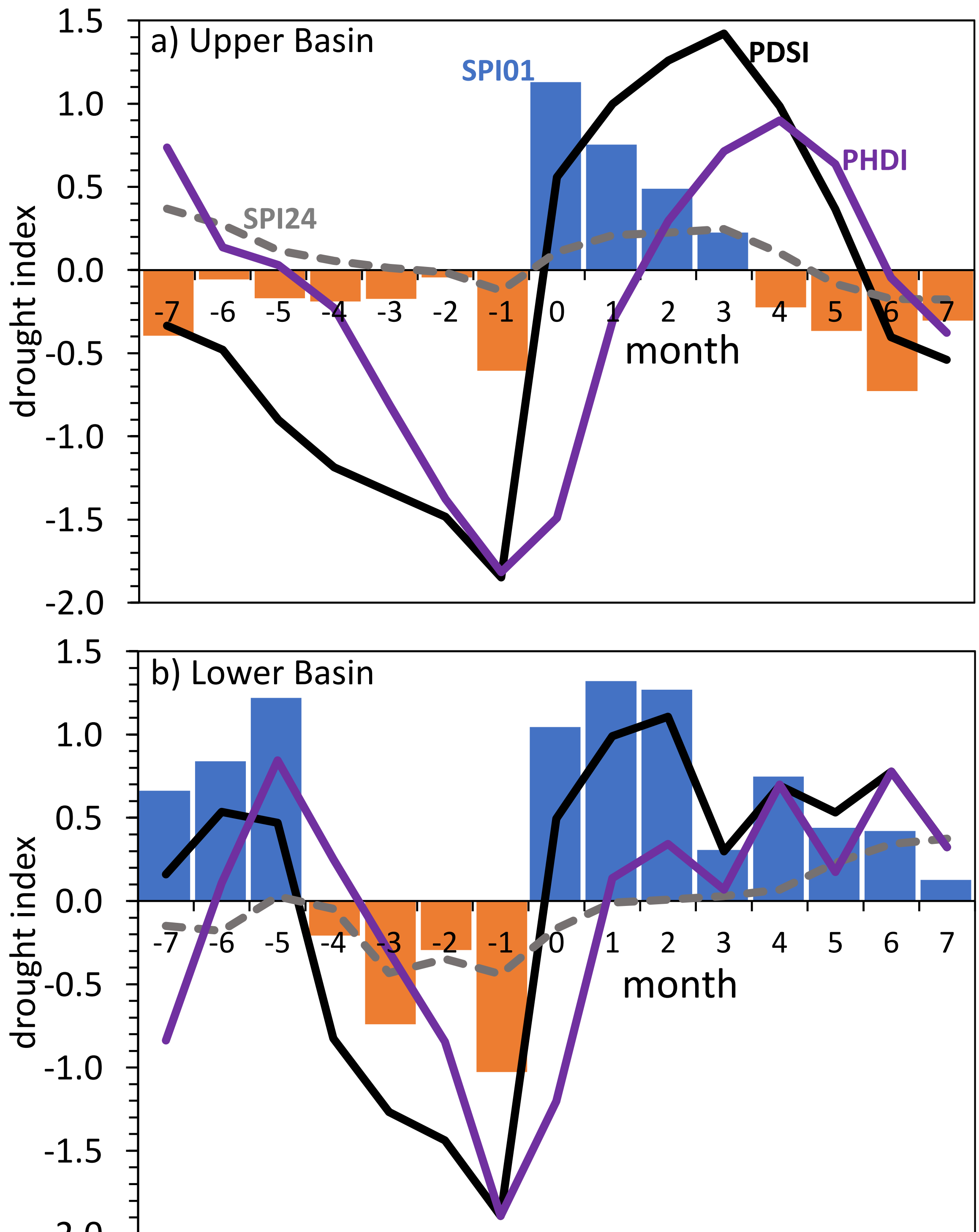

Figure 3: Average drought indices during Miracle years that is calculated based on PDSI for Upper basin a) and lower basin b). Bar plot shows the SPI1, dashed line shows the SPI24, black line shows the PDSI and purple line shows the PHDI. Miracle month is centered at 0 when drought index (PDSI) changed from negative to positive value.

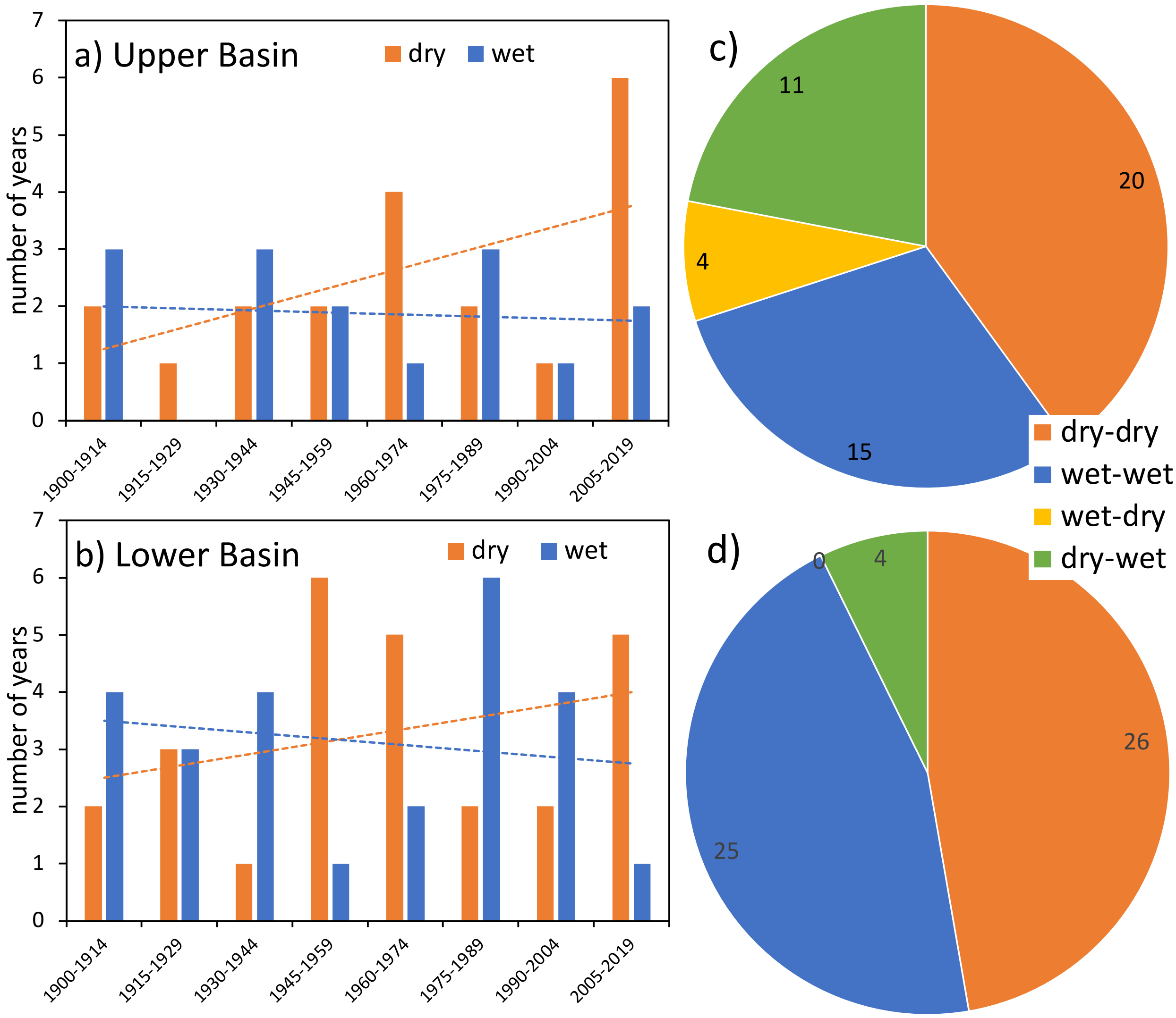

Figure 4: Average dry and wet frequency based on winter and spring SPI3 value considering the months from December to May for a) upper and b) lower basins. The right panel c) and d) show the frequency pie-chart of four different transitions from winter (Dec-Feb) to spring (Mar-May) for upper and lower basins, respectively.

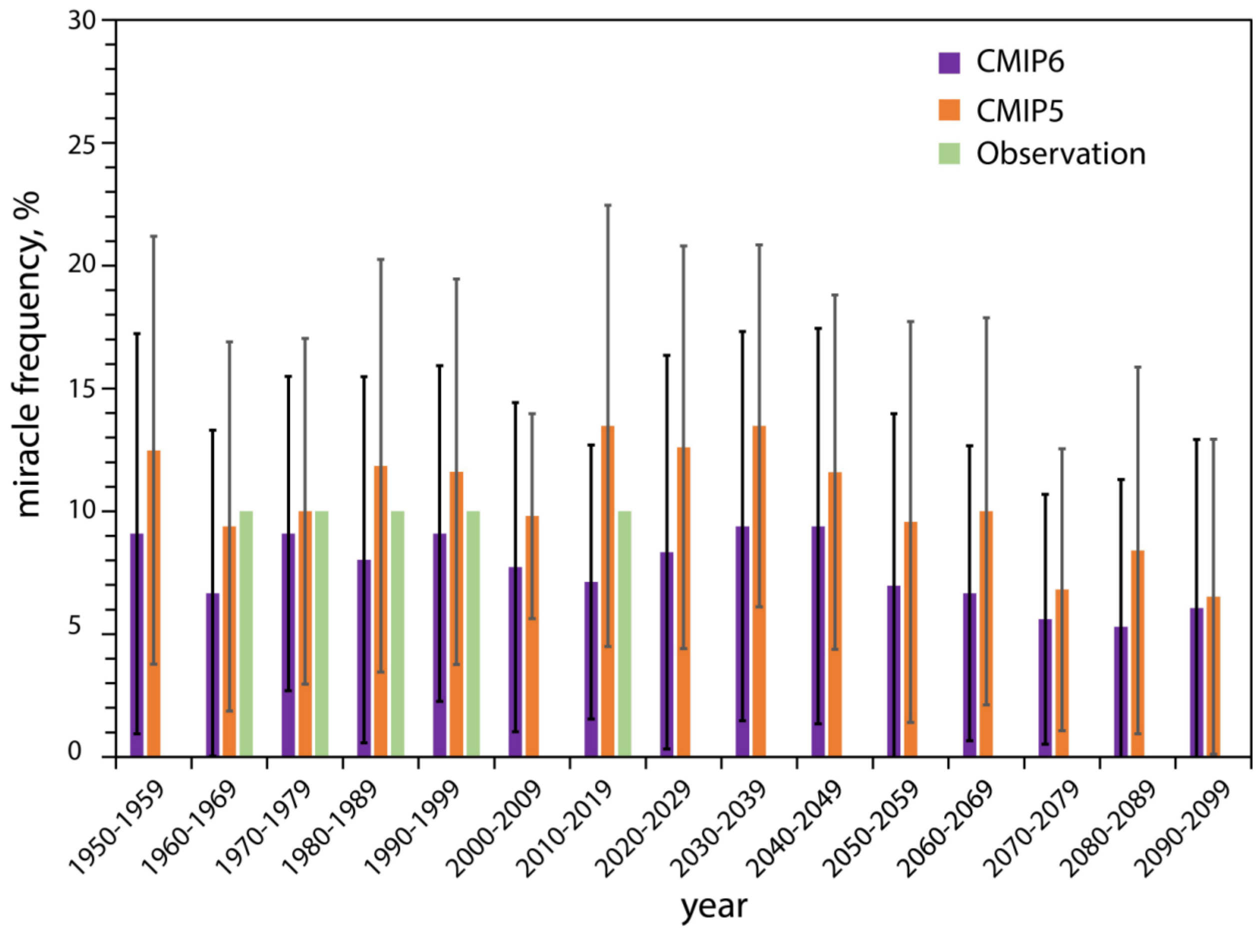

Figure 5: Miracle spring precipitation frequency (per 10 years) based on observational (green bars), CMIP5 (orange bars) and CMIP6 (purple bars). Historical period is considered from 1950 while future projections are considered from 2006 for CMIP5 and from 2015 for CMIP6. Error bars in CMIPs data are based on ±0.8 standard deviation. SPI3 is used to calculate the miracle spring precipitation. There were no miracle events during 2000-2009 in the observation.

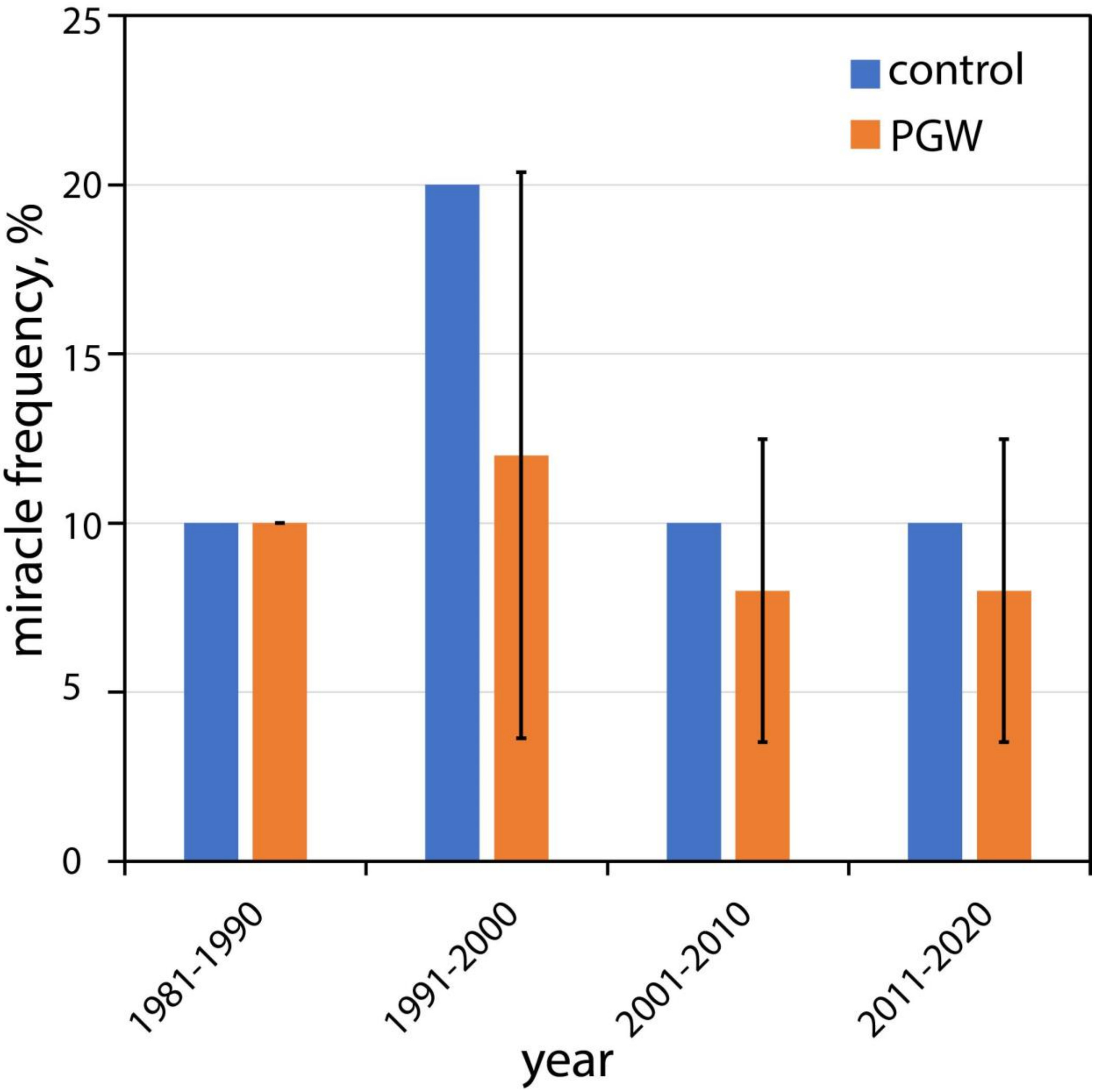

Figure 6: Miracle spring precipitation frequency from regional climate model simulation for the historical control run (blue bars) and pseudo global warming (PGW run, orange bar) that utilized climate change signals from 5 global climate models. Error bars in PGW frequency based on ±0.8 standard deviation.

Table 1: Dry- and wet-indices from average miracle years based on regional climate model simulations (PNNL WRF) from control and PGW runs from (1980-2020). Dry index is the total SPI3 value from four dry months before miracle and wet index is the total SPI3 from following three wet months. Miracle strength is the difference between dry- and wet-indices and change in miracle strength is calculated as control miracle strength/PGW miracle strength *100%.

	control	PGW
dry index	-3.20	-3.36
wet index	2.28	2.10
miracle strenth	-0.92	-1.25
change in miracle strength, %	37	