Increased air temperature has the greatest contribution to projected ET₀ increases. Extreme ET₀-based wildfire potential and 3-year droughts based on precipitation minus ET₀ become much more frequent in the future.

Key Points:
- All climate models show increasing reference evapotranspiration (ET₀) through the end of the century.
- Increased air temperature has the greatest contribution to projected ET₀ increases.
- Extreme ET₀-based wildfire potential and 3-year droughts based on precipitation minus ET₀ become much more frequent in the future.

Supporting Information:
- Supporting Information S1

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Projected Changes in Reference Evapotranspiration in California and Nevada: Implications for Drought and Wildland Fire Danger

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Abstract
Recent high impact wildfires and droughts in California and Nevada have been linked to extremes in the Evaporative Demand Drought Index (EDDI) and Standardized Precipitation Evapotranspiration Index (SPEI), respectively. Both indices are dependent on reference evapotranspiration (ET₀). Future changes in ET₀ for California and Nevada are examined, calculated from global climate model simulations downscaled by Localized Constructed Analogs (LOCA). ET₀ increases of 13–18% at seasonal timescales are projected by late century (2070–2099), with greatest relative increases in winter and spring. Seasonal ET₀ increases are most strongly driven by warmer temperatures, with increasing specific humidity having a smaller, but noteworthy, counter tendency. Extreme (95th percentile) EDDI values on the 2-week timescale have coincided with recent large wildfires in the area. Two-week EDDI extremes are projected to increase by 6–10 times during summer and 4–6 times during autumn by the end of the century. On multiyear timescales, the occurrence of extreme droughts based on 3-year SPEI below the historical fifth percentile, similar to that experienced during the 2012–2016 drought across the region, is projected to increase 3–15 times by late century. Positive trends in extreme multiyear droughts will further increase seasonal fire potential through degraded forests and increased fuel loads and flammability. Understanding how these drought metrics change on various climate timescales at the local level can provide fundamental information to support the development of long-term adaptation strategies for wildland fire and water resource management.

Plain Language Summary
Since the start of the 21st century, California and Nevada have observed extreme wildland fires and droughts that have caused devastating impacts to ecosystems and society. A common feature of these events has been very high atmospheric evaporative demand—the “thirst” of the atmosphere—which has largely been driven by increased air temperatures caused by anthropogenic climate change. This study examines projected changes in evaporative demand, which of the input variables are causing those changes and how the frequency of extreme wildfire potential and multiyear droughts will change. Evaporative demand is found to increase during all seasons, and increased temperatures drive most of that change. The likelihood of extreme wildfire potential based on 2-week periods of elevated evaporative demand during summer and autumn increases substantially. A climatic water balance based on precipitation and evaporative demand indicates extreme 3-year droughts that hold potential to deplete regional-scale water supply also become much more likely. Future adaptation planning efforts for wildland fire management agencies, forest management, and water resource managers should account for a greater likelihood of more extreme events.

1. Introduction
Wildland fires and droughts in California and Nevada have had devastating impacts on natural resources, ecosystems, and society. In the last decade, extreme events with unprecedented impacts have occurred including the 2012–2016 drought (e.g., Griffin & Anchukaitis, 2014; Lund et al., 2018; Shukla et al., 2015; Swain, 2015; Williams et al., 2015) and a series of catastrophic wildfires in 2017 and 2018 (Brown et al., 2020; Nauslar et al., 2018, 2019). A common thread in these recent events is the increased likelihood of exacerbated drought impacts and heightened fire potential due to increased air temperatures and...
Evaporative demand \((E_o)\)—including that associated with anthropogenic climate change (e.g., Griffin & Anchukaitis, 2014; Goss et al., 2020; Shukla et al., 2015; Williams et al., 2015, 2019).

Evaporative demand \((E_o)\)—the upper limit of actual evapotranspiration \((ET)\) that could occur given unlimited surface water supply (Hobkins et al., 2017)—has a strong connection to drought and wildfire potential in the western United States (e.g., Abatzoglou & Kolden, 2013; Abatzoglou & Williams, 2016; Littell et al., 2016; McEvoy et al., 2016) and globally (e.g., Dai, 2011; Vicente-Serrano et al., 2010). In California and Nevada, elevated \(E_o\) contributed to the 2012–2016 drought’s severity (Hobkins et al., 2016; McEvoy et al., 2016; Shukla et al., 2015; Williams et al., 2015) and to wildfire potential (Brown et al., 2020; McEvoy et al., 2019; Nauslar et al., 2019). Although \(E_o\) is sometimes calculated from temperature alone, a physically based \(E_o\) formulation is critical to obtaining realistic estimates that include not only temperature changes but also the wind speed, humidity, and incoming shortwave radiation components that drive land surface-atmosphere interactions and drying (Hidalgo et al., 2005; Hobkins et al., 2017). Reference \(ET\) \((ET_o)\) calculated using the Penman-Monteith equation (Monteith, 1965) is a physically based formulation of \(E_o\) that serves as the basis for the Evaporative Demand Drought Index (EDDI; Hobkins et al., 2016; McEvoy et al., 2016) and has been recommended as the \(E_o\) component of the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010). While Hobkins (2016) has demonstrated that the historical (1981–2010) sensitivity of \(ET_o\) to the drivers can vary regionally and seasonally, assessments that examine the sensitivity of \(ET_o\) based on projected changes in the drivers are lacking.

A number of studies have looked at projected changes in \(ET_o\) and drought indices that use \(ET_o\) at global or Contiguous United States (CONUS) scale based on coarse resolution Global climate model (GCM) output (e.g., Cook et al., 2014; Dewes et al., 2017; Ficklin et al., 2016; Schef & Frierson, 2014). More localized studies in portions of California and Nevada for specific basins or counties using downscaled GCM data have also been conducted (Huntington et al., 2015; Oakely et al., 2019). Using downscaled GCM data to develop \(ET_o\) projections provides localized information about future fire potential and droughts that can highlight regional differences that are less apparent using coarser scale GCM data.

Extreme EDDI values (greater than 95th percentile) have been found to occur simultaneously with start dates of recent large and destructive wildfires in California (Brown et al., 2020; McEvoy et al., 2019; Nauslar et al., 2019) and has been put into use by fire management agencies (McEvoy et al., 2019). In addition to the aforementioned case studies, McEvoy et al. (2019) compared EDDI to seasonally averaged fire danger indices (ERC, 100-, and 1,000-hour fuel moisture) across California and Nevada for 1979–2015, and results show EDDI strongly reflects the buildup of antecedent drought conditions also found in dead fuel moisture. The multi‐scalar nature of EDDI (Hobkins et al., 2016) and ability to decompose into individual weather drivers is appealing to fire managers who found added value when used in combination with traditional fire danger metrics (McEvoy et al., 2019). Abatzoglou and Kolden (2013) found \(ET_o\) to have good interannual relationships to fire season total burned area in California. Several studies have examined climate change impacts on fire weather and fire danger indices in the region (Abatzoglou et al., 2019; Brown et al., 2004; Goss et al., 2020), but thus far, no studies have evaluated projected changes in extreme EDDI days for fire danger applications.

Multiyear droughts, particularly those lasting three or more years, have the greatest impact on California and Nevada water resources as even the larger reservoirs can become depleted causing water shortages for agriculture and public use (Lund et al., 2018) with the most devastating impacts to rural communities that rely on groundwater (Swain, 2015). Multi‐scalar drought indices that incorporate both precipitation and \(ET_o\) are better correlated to reservoir levels during droughts than indices only using precipitation, and levels in large reservoirs are best correlated at timescales of 3–4 years (McEvoy et al., 2012). While changes in annual SPEI have been examined globally (Cook et al., 2014), the occurrence of multiyear extreme droughts has not been examined using SPEI. Previous studies on changes in multiyear droughts have found increases in duration of soil moisture droughts in the Southwest United States (Cayan et al., 2010) and increased frequency of snow droughts in the western United States (Marshall et al., 2019).

This paper aims to build our understanding of how future changes in \(ET_o\) can impact wildland fire potential and multiyear droughts in California and Nevada based on an ensemble of downscaled GCMs. Specifically, we seek to quantify changes in extreme \(ET_o\) at short timescales for fire potential (2-week EDDI) and long timescales for sustained droughts (3-year SPEI). We first examine seasonal changes in precipitation, \(ET_o\), and multiyear droughts in California and Nevada based on an ensemble of downscaled GCMs. Specifi-
and the drivers of ET0. Second, we look at changes in extreme EDDI days as a metric of changes in wildfire potential. Finally, changes in multiyear droughts are assessed based on the 3-year SPEI and Standardized Precipitation Index (SPI).

2. Data and Methods
2.1. Daily Reference Evapotranspiration

To characterize historical changes in frequency of extreme EDDI days, daily ET0 data were obtained from gridMET (Abatzoglou, 2013), which combines the North American Land Data Assimilation System version 2 and the Parameter Regression on Independent Slopes Model (PRISM) to produce continually updated daily data at 4 km spatial resolution over CONUS beginning in 1979. ET0 is computed using gridMET temperature, wind speed, specific humidity, and incoming shortwave radiation following the ASCE Penman-Monteith procedure (Walter et al., 2000).

Four Predictive Service Areas (PSAs), a management unit used by the National Interagency Fire Center and Predictive Services for monitoring and forecasting fire danger as well as allocating resources for fire suppression, were used as spatial averaging domains to investigate both historical and future changes in ET0 and precipitation. South Coast, Mid Coast to Mendocino (hereafter Mid Coast), and Northern Sierra PSAs were used in California and Humboldt Basin PSA for Nevada (Figure 1a). All four PSAs have experienced large

Figure 1. Seasonal LOCA RCP 8.5 ensemble median percent change in ET0 for the late century period (2070–2099) relative to the base period (1950–2019) in (a) winter, (b) spring, (c) summer, and (d) autumn. Blue boundaries in (a) show Predictive Service Areas used in the study including (1) South Coast, (2) Mid Coast to Mendocino, (3) Northern Sierra in California, and (4) Humboldt Basin in Nevada.
and destructive wildfires both historically and recently (McEvoy et al., 2019). These regions also provide surface water to large populations and/or major regional agricultural areas, making them ideal for studying long-term hydrologic drought. Daily gridMET $ET_0$ spatially averaged to each PSA for the period 1979–2019 was extracted using Climate Engine (Huntington et al., 2017).

### 2.2. Monthly Reference Evapotranspiration and Precipitation

Historical multiyear droughts are characterized using monthly $ET_0$ and $Pr$ from Williams et al. (2020) covering the period 1901–2018. This data set merges a number of observation-based and reanalysis products to produce a continuous timeseries over North America at 1/4° spatial resolution. For further details, see Williams et al. (2020) supplemental material. Monthly data were spatially averaged over each PSA.

### 2.3. LOCA Projections

GCM simulations from the Climate Model Intercomparison Project version 5 (CMIP5; Taylor et al., 2012) statistically downscaled using Localized Constructed Analogs (LOCA; Pierce et al., 2014; Pierce et al., 2015) were obtained for California and Nevada from the LOCA database (http://loca.ucsd.edu). Daily data at 6 km spatial resolution from historical (1950–2005) and future (2006–2099) LOCA runs for Representative Concentration Pathway (RCP) 4.5 (supplemental material) and 8.5 were used. Climate variables of maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), specific humidity ($q$; Pierce & Cayan, 2016), wind speed ($u$), incoming shortwave radiation ($R_d$), and precipitation ($Pr$) were examined. The full suite of LOCA GCMs includes 32 models of which 10 were selected in previous studies as best suited to studies in California and Nevada on the basis of performance over the historical era and independence in model lineage (Cayan & Tyree, 2015; Pierce et al., 2018). The performance measures that were evaluated included accuracy in the global representation of air temperature, pressure, wind, and solar radiation patterns; western U.S. regional evaluations of temperature, precipitation, sea level pressure, and (due to their teleconnected importance to regional climate) El Niño/Southern Oscillation variability; and California state evaluation of dry and wet regimes, heat waves, and cold snaps (Cayan & Tyree, 2015). Seven of the 10 GCMs retained daily $q$, $u$, and $R_d$ necessary to calculate $ET_0$ and were used in this study: ACCESS1-0, CanESM2, CNRM-CM5, GFDL-CM3, HadGEM2-CC, HadGEM2-ES, and MIROC5. Gridded daily $ET_0$ covering California and Nevada was calculated using the ASCE Penman-Monteith method (Walter et al., 2000) and archived for both RCPs and historical and future periods. All future changes were calculated relative to a base period of 1950–2019 and classified by early (2020–2039), mid (2040–2069), and late (2070–2099) 21st century. A comparison of LOCA seasonal $ET_0$ totals with gridMET shows that LOCA does well in capturing the seasonal cycles and variability (supporting information Figures S1 and S2).

Seasonal changes relative to the base period for LOCA $P$, mean temperature ($T_{\text{mean}}$), $q$, $u$, $R_d$, and $ET_0$ were computed for early, mid, and late century. Changes are expressed as the percent difference from the base period for $ET_0$ and $Pr$ and absolute difference for other variables, for each future year and then averaged over each of the three future periods. Seasonal timeseries (three-month average for each year) for each of the four PSAs described in section 2 were spatially averaged from the LOCA grids to examine the seven-model ensemble distribution for each variable.

A sensitivity experiment was performed on the seasonal $ET_0$ timeseries to examine which of the four atmospheric drivers is responsible for the greatest influence on future $ET_0$ changes. For each PSA, daily $T_{\text{mean}}$, $q$, $u$, and $R_d$ climatology were computed using the base period. Next, $ET_0$ was computed four times, each time holding three of the four atmospheric drivers to the daily climatological values and letting the other driver vary (e.g., Cook et al., 2014; Scheff & Frierson, 2014; Williams et al., 2015; Zhao & Dai, 2015). This was done through the full LOCA time period (1950–2099), and seasonal $ET_0$ values were summed from daily values. Contributions to the total $ET_0$ anomaly relative to 1950–2019 were estimated for each year and then averaged over future periods (method detailed in Figure S3 and associated text).

### 2.4. Drought Indices

We examine both 2-week and 3-year drought indices in this work for wildland fire potential and long-term drought, respectively. The EDDI was computed following Hobbins et al. (2016) using a 2-week timescale. This short timescale can be used to examine rapid onset drought, or flash drought, and has been found to be effective for fire danger monitoring (McEvoy et al., 2019). Both meteorological phenomena
(e.g., frontal passage and downslope wind events) and persistent weather patterns lasting days-to-weeks (i.e., blocking high pressure) impact fuel moisture and flammability and are reflected in the 2-week EDDI. Further, we find over 25% of seasonal burned area in summer and autumn occurs coincident with extreme 2-week EDDI days across much of the region (Figure S4). For each year, daily counts of 2-week EDDI exceeding the historical 95th percentile during summer (June–August) and autumn (September–November) were found. Percentiles are relative to each day, not all days of the year. For gridMET, the entire 1979–2019 distribution was used to calculate EDDI. For LOCA data EDDI was computed using a fixed base period of 1950–2019 to constrain the distribution to the observed past. Data for 2020–2099 were ranked relative to the base period and capped on the upper or lower end of the distribution. The number of days for each year and season when EDDI exceeds the base period 95th percentile was calculated and then averaged for each future period. Any given day above the 95th percentile is likely not independent from neighboring days above this threshold given the serial correlation in the daily timeseries.

Multyear droughts were examined using the SPI (McKee et al., 1993) and SPEI (Vicente-Serrano et al., 2010). SPI is a multi-scalar drought index that considers only \( P_{rcp} \). SPEI incorporates the demand side of drought by using the climatic water balance (\( P_{rcp} – ET_{0} \)) as input. Precipitation is the driving factor in multyear hydrologic droughts with elevated \( ET_{0} \) acting to exacerbate drought severity. We therefore use SPEI instead of EDDI to examine the impact of \( ET_{0} \) on multyear droughts. SPI and SPEI were standardized using a non-parametric approach (Farahmand & AghaKouchak, 2015), which helps overcome the limitations of using different distributions to fit different variables. This standardization method was adopted by Hobbins et al. (2016) for EDDI and used for EDDI, SPI, and SPEI calculations in this study.

We computed 3-year water year (36-month ending September 30) SPEI (SPEI-36) and SPI (SPI-36) timeseries for each PSA using spatially averaged \( P_{rcp} \) and \( ET_{0} \). McEvoy et al. (2012) found SPEI timescales of 30–60 months strongly correlated to interannual variability in large reservoirs in California and Nevada with extreme low SPEI values tracking droughts and low reservoir levels. We therefore use a 36-month timescale to represent water supply droughts in the region. The U.S. Drought Monitor (Svoboda et al., 2002) classifies extreme drought as third to fifth percentile and exceptional drought as <third percentile. We use SPEI <fifth percentile to determine historical and future changes in extreme droughts. For historical SPI and SPEI using data from Williams et al. (2020), 1901–2018 was used for the distributions at each PSA. For LOCA SPI and SPEI we used 1950–2019 as the base period, and data for 2020–2099 were ranked relative to the base period and capped on the upper or lower end of the distribution (same as EDDI). A long duration aggregation window (36 months) is inherently serial correlated, and years below the fifth percentile are often overlapping and not independent from one another. In addition to counting the number of values, the overlaps were also counted to distinguish events (any overlaps) from single year values.

### 3. Results

#### 3.1. LOCA Seasonal Changes

The seven-model ensemble shows consistent increases in \( ET_{0} \) by the end of century (Figure 1 for RCP 8.5; Figure S5 RCP 4.5; Table 1). Winter and spring show increases of >20% over large swaths of the domain (Figures 1a and 1b, respectively), which is partially a function of the climatologically lower historical values in these seasons. Summer \( ET_{0} \) increases 10–15% over much of the domain with greater increases in the northern areas and a large area of lesser (5–10%) increases over southern areas (Figure 1c). Autumn changes of 10–20% (Figure 1d) are more uniformly distributed over the region.

Precipitation changes (Figure 2 for RCP 8.5; Figure S6 RCP 4.5; Table 1) are less consistent than \( ET_{0} \) both spatially and by season, similar to previous studies (e.g., Pierce et al., 2018). Winter (Figure 2a) shows the most spatial coherence with increases over nearly the entire domain, with a large extent of >30% and 45–60% + increases over Nevada. Spring (Figure 2b) and autumn (Figure 2d) show similar spatial patterns where decreasing \( P_{rcp} \) is found in California and southern Nevada and increases in central and northern Nevada. Summer changes are noisy over nearly all of California and northwest Nevada due to the Mediterranean climate and low (near zero for some locations) absolute values of \( P_{rcp} \) during this season. There is some evidence that future summer changes in precipitation in this region may be associated with monsoon processes that are better resolved by finer spatial resolution dynamical downscaling, as opposed to statistically downscaled coarse-resolution GCMs (Pierce et al., 2013).
Focusing on autumn since it is a key fire season and the start of the transition to the wet season, late century changes in \( P_{rcp} \), \( ET_0 \), and the drivers of \( ET_0 \) are shown in Figure 3 for the four PSAs. In addition to ensemble median, the spread is also shown to highlight uncertainty in projections, which arises from both natural climate variability and model uncertainty. All four PSAs show increased \( ET_0 \) with ensemble medians ranging from 13\% to 16\% across the PSAs and increases in all ensemble members, despite a modest spread in magnitude (Figure 3a). Changes in \( P_{rcp} \) (Figure 3b) are more variable than \( ET_0 \) changes. However, for all regions

| Season | \( ET_0 \) climatology (mm) | \( \Delta ET_0 \) (mm) | \( \Delta ET_0 \) (%) | \( P_{rcp} \) climatology (mm) | \( \Delta P_{rcp} \) (mm) | \( \Delta P_{rcp} \) (%) |
|--------|-----------------|----------------|----------------|----------------|----------------|----------------|
| Winter | 139             | 23             | 17             | 198             | 26             | 13             |
| Spring | 414             | 75             | 18             | 115             | -13            | -11            |
| Summer | 708             | 94             | 13             | 33              | -6             | -18            |
| Autumn | 343             | 50             | 15             | 92              | -8             | -9             |

Figure 2. Seasonal LOCA RCP 8.5 ensemble median percent change in \( P_{rcp} \) for the late century period (2070–2099) relative to the base period (1950–2019) in (a) winter, (b) spring, (c) summer, and (d) autumn.
except for Humboldt Basin most ensemble members show drying. For Humboldt Basin, note that natural
internal climate variability in regions where the mean change is projected to be near zero mandates that
some models will show increasing $P_{rcp}$ while others show decreasing. Ensemble medians at all four PSAs
show decreasing $u$ (Figure 3f) and increasing $q$ (Figure 3d) and $T_{mean}$ (Figure 3c). Increasing ensemble med-
ian $R_d$ was found at South Coast and Mid Coast, with decreases found at Northern Sierra and Humboldt
Basin (Figure 3e), although the results are distributed around zero in the individual ensemble members.
Other seasons show similar results for $ET_0$ and the drivers (not shown).

These tendencies are elucidated in the sensitivity experiments for autumn $ET_0$ using ACCESS1-0 (Figure 4),
which has $ET_0$ changes near the middle of the ensemble distribution. In all regions $T_{mean}$ contributes the
most to $ET_0$ changes. The tendency from warming $T_{mean}$ exceeds the actual $ET_0$ anomaly since there is an
opposite tendency from increasing $q$. Projected $q$ increases arise from increasing $T_{mean}$, but this sensitivity

Figure 3. Autumn late century LOCA RCP 8.5 changes in (a) $ET_0$, (b) $P_{rcp}$, (c) $T_{mean}$, (d) $q$, (e) $R_d$, and (f) $u$ at four PSAs. In each panel the first column of dots is South Coast (SC-CA), second column is Mid Coast (MCTM-CA), third column is Northern Sierra (NS-CA), and fourth column is Humboldt Basin (HUM-NV). Gray dots show LOCA ensemble members, blue dots show ensemble median, and red dots show the ACCESS1-0 model results. ACCESS1-0 results are shown in Figure 4 as the $ET_0$ change for this model is near the median for select PSAs.
analysis cannot account for the physical feedback between the two drivers. Contributions from $u$ and $R_d$ changes are much smaller than $T_{\text{mean}}$ and $q$. Results from the other LOCA ensemble members were similar to ACCESS1-0, always finding $T_{\text{mean}}$ to have the greatest contributions, with a smaller opposing tendency from $q$ (Figure S7) and minimal impact from $u$ and $R_d$. All other seasons have the greatest contributions from $T_{\text{mean}}$ to the total $ET_0$ anomaly with notably smaller relative $q$ contributions in summer compared to autumn (not shown).

3.2. Observed and Projected Changes in Extreme Fire Danger Based on the EDDI

The number of summer and autumn days with 2-week EDDI above the historical (1979–2019) 95th percentile value (EDDI$_{95}$) for each PSA are shown in Figure 5. Based on the 95th percentile statistic we should expect on average 4 days per year, per season above that threshold. Least-squares regressions indicate statistically significant ($p < 0.1$) increasing trends for Northern Sierra in summer and for South Coast, Mid Coast, and Northern Sierra in autumn. Notable for summer is the maximum counts (22 days) at Mid Coast occurred in 2018 when one of California’s largest recorded wildfire complexes occurred—the Mendocino Complex (Figure 5c). For Northern Sierra summer far more consecutive years with EDDI$_{95}$ counts above zero are found starting in 2000 (Figure 5e). During autumn, the highest day count (31 days) at Mid Coast occurred in 2019 (Figure 5d). Similarly, Northern Sierra also experienced its greatest autumn day count (25 days) in 2019, and 14 days were observed in 2018 when the Camp Fire occurred, the most destructive wildfire in California’s history. Fewer EDDI$_{95}$ days have occurred at Humboldt Basin in recent years with zero summer counts from 2017 to 2019 (Figure 5g) and zero autumn counts from 2015 to 2019 (Figure 5h).
LOCA projected change in the average number of summer and autumn EDDI₉⁵ days per year in each future period is shown in Figure 6 for RCP 8.5 (Figure S8 RCP 4.5). Using the 1950–2019 LOCA baseline one would expect on average 5 days per year, per season above the 95th percentile. Note this is slightly different than the expected value of 4 days per year for gridMET in Figure 5 since the base periods are different. Increases in EDDI₉⁵ days in summer and autumn are projected during the 21st century. Model medians project 30–48 summer EDDI₉⁵ days per year and 23–26 autumn EDDI₉⁵ days per year by late century, representing on average an eightfold and fivefold increase over baseline conditions, respectively. By late century the seasonal difference in day counts is particularly large at the South Coast and Northern Sierra regions. At the South Coast, the late century summer median day count is 47 compared to 26 days in autumn (Figure 6a), and at the Northern Sierra summer median day count is 52 compared to 23 days in autumn (Figure 6c). These results indicate a high likelihood of substantially more extreme 2-week EDDI days in summer and autumn relative to the base period which will contribute to more high fire danger days.

3.3. Observed and Projected Changes in Multiyear Droughts

Historical timeseries of SPI‐36 and SPEI‐36 for 1904–2018 at each PSA are shown in Figure 7. Similar prolonged drought periods are identified by SPEI and SPI but with differences in severity. In the 1950s SPI‐36 shows more extreme values than SPEI‐36, while in the mid-1990s onward the situation is reversed, with SPEI‐36 showing more extreme values. In each region SPI‐36 shows the lowest values not occurring during the 2012–2016 drought period, while SPEI‐36 shows the lowest values during the 2012–2016 drought period.

Figure 5. Historical (1979–2019) gridMET total counts of daily 2-week EDDI exceeding the 95th percentile value for (left column) summer and (right column) autumn at (a, b) South Coast, (c, d) Mid Coast, (e, f) Northern Sierra, and (g, h) Humboldt Basin. Red line in each panel shows the least square regression. Trends are reported in days per decade over the 41-year period.
everywhere except Mid Coast (Figure 7b), highlighting the exacerbated drought severity from recent warming and increased ET0.

Consecutive drought years are more harmful to ecosystems and water infrastructure than isolated years. At South Coast (Figure 7a) all SPEI-36 values <fifth percentile occurred between 2008 and 2018 with two consecutive years during 2008–2009 and three consecutive years for both SPEI and SPI—the only 3-year period during 2014–2016. Two consecutive years also occurred 2014–2015 in the Northern Sierra region (Figure 7c). Note that the aggregation window of 36 months makes consecutive years below the fifth percentile more likely.

The fraction of years for each future period with 36-month SPI and SPEI less than the historical fifth percentile value (SPI5 and SPEI5, respectively) at each PSA is shown in Figure 8 (Figure S9 RCP 4.5). SPEI5 was
found to generally increase through the 21st century with late century ensemble medians ranging from 17% to 73% with South Coast and Humboldt Basin having notably higher SPEI5 compared to Mid Coast and Northern Sierra. Far more limited changes were found in SPI5. Distinctly large gaps between ensemble median SPEI5 and SPI5 were found for late century at South Coast and Humboldt Basin. Much smaller differences between SPEI5 and SPI5 were found at Mid Coast to Mendocino and Northern Sierra even for late century, although SPEI5 almost always exceeded SPI5, and late century SPEI5 was still notable at 23% and 17% for Mid Coast to Mendocino and Northern Sierra ensemble medians, respectively. The more arid climate of South Coast and Humboldt Basin, where the $Prcp - ET_0$ balance is dominated by $ET_0$, and the large future changes in $ET_0$ relative to $Prcp$ at these locations result in far greater changes in SPEI5 compared to SPI5.

To further examine future changes in multiyear droughts the timeseries of SPEI5 and SPI5 for the South Coast is shown in Figure 9, and we summarize the late century counts (total numbers of values for a given period), events where an event is defined as two or more years in a row below the fifth percentile, and average duration of those events in Table 2 (early and mid century numbers shown in Tables S1 and S2, respectively). Minimal changes are found in early century SPEI5 counts (Table S1), but by mid century a sharp

![Figure 7. Historical 36-month SPI (green) and SPEI (orange) for the period 1904–2018 at (a) South Coast, (b) Mid Coast, (c) Northern Sierra, and (d) Humboldt Basin. Dashed gray line shows the 5th percentile. Precipitation and $ET_0$ data from Williams et al. (2020).](image-url)
increase can be seen in Figure 9a (Table S2) starting around 2040 for most of the LOCA ensemble members. For SPI5 (Figure 9b) far fewer long duration events were found. However, several ensemble members do indicate increases in both SPI5 counts and duration of events by late century.

4. Discussion
Consistent with recent studies investigating future changes in California Prcp variability and extremes (e.g., Gershunov et al., 2019; Pierce et al., 2013; Swain et al., 2018), we find projected increases in total Prcp during winter and decreases during the shoulder seasons of spring and autumn for much of California. For the less studied Nevada, similar patterns of Prcp change are found, but those for spring and autumn also show increases for the northern (particularly the northeast) part of the state. For ET0, our analysis contributes to new insight on the magnitude of change and spatial patterns at seasonal timescales based on high resolution projections.
Seasonal changes in $ET_0$ strongly reflect warming $T_{\text{mean}}$ with steady increases through the end of the 21st century. This is in contrast to steadily increasing $q$ which give a tendency towards decreasing $ET_0$. A sensitivity experiment revealed the strong increases in future $ET_0$ are driven predominantly by increasing $T_{\text{mean}}$. Influences from $q$ were also evident, though not as strong as $T_{\text{mean}}$ influences, and the main impact of $q$ was limiting further increasing $ET_0$, a compensating effect that could not be seen by simply looking at the future $ET_0$ trends. This further adds to the literature on the importance of using physically based $E_0$ over simple temperature-based approaches, which in this case would have misrepresented the partially compensating tendencies due to $T_{\text{mean}}$ and $q$. Another consideration is whether the sensitivity of $ET_0$ to the drivers might change in the future, which could be found by repeating the work of Hobbins (2016) but using future climatology periods instead of past.

**Figure 9.** LOCA historical and future RCP 8.5 timeseries of extreme (<fifth percentile relative to 1950–2019 base period) 36-month (a) SPEI and (b) SPI at the South Coast PSA. Individual years below the extreme threshold are represented by single red bars.

| Table 2 | LOCA South Coast Late Century 36-Month SPEI and SPI Statistics for Values Less Than the Fifth Percentile |
|----------------------------------|----------------------------------------------------------------------------------------------------------|
| **SPEI-36 late century <fifth percentile stats** |                                                                                                           |
| Counts ($n = 30$) | Fraction of years | Events | Average duration (years) |
| ACCESS1-0 | 28 | 0.93 | 1 | 28 |
| CNRM-CM5 | 5 | 0.17 | 4 | 1 |
| CanESM2 | 7 | 0.23 | 2 | 4 |
| GFDL-CM3 | 24 | 0.80 | 5 | 5 |
| HadGEM2-CC | 25 | 0.83 | 3 | 8 |
| HadGEM2-ES | 17 | 0.57 | 6 | 3 |
| MIROC5 | 20 | 0.67 | 5 | 4 |
| **SPI-36 late century <fifth percentile stats** |                                                                                                           |
| Counts ($n = 30$) | Fraction of years | Events | Average duration (years) |
| ACCESS1-0 | 7 | 0.23 | 3 | 2 |
| CNRM-CM5 | 0 | 0 | 0 | 0 |
| CanESM2 | 0 | 0 | 0 | 0 |
| GFDL-CM3 | 1 | 0.03 | 1 | 1 |
| HadGEM2-CC | 9 | 0.30 | 4 | 2 |
| HadGEM2-ES | 1 | 0.03 | 1 | 1 |
| MIROC5 | 6 | 0.20 | 5 | 1 |

*Note.* An event is defined as two or more years in a row below the fifth percentile.
Considering first 2-week EDDI, recent years with high counts of EDDI95 days at Mid Coast and Northern Sierra occurred during the same years with the largest and most destructive wildfires in California’s history prior to 2020 (Calfire, 2020a, 2020b), which agrees with the uptick in extreme fire danger found by Goss et al. (2020). In other cases and regions large fires did occur in years with low number of EDDI95 days (or zero), which indicates that fires can occur without short-term excess in ET₀ especially when factors other than short-term climate play a key role in the fire potential and spread. In general for California and Nevada, especially in summer and autumn, if extended periods of elevated ET₀ occur simultaneously with Prcp deficits the fire danger will increase.

By late century and relative to the historical baseline ensemble median EDDI95 days were found to increase 6–10 times in summer and 4–6 times in autumn, which is a much larger increase in extreme days compared to the doubling of autumn days with Fire Weather Index (FWI) values exceeding the 95th percentile by Goss et al. (2020). The FWI is part of the Canadian fire danger system and considers both fire weather and aridity of fuels (Goss et al., 2020). The FWI and EDDI represent different aspects of fire danger with EDDI95 day counts representing more of a sustained high fire potential over time compared to the shorter weather timescales incorporated into FWI. In autumn, the average number of days per year with EDDI95 by late century is similar to those during destructive 2017 and 2018 autumn fire seasons in northern California regions. However in summer, the median counts far exceed anything found in the observed period used in this study, with the greatest spread between summer and autumn found at South Coast and Northern Sierra. Greater EDDI95 counts in summer compared to autumn could be a result of ET₀ being less sensitive to q during summer and more sensitive to Tmeas, which allows for further increased ET₀. This analysis is not sensitive to EDDI timescale as similar results were found using both 1- and 3-month EDDI95 days (Figures S10 and S11).

Turning towards the longer timescales, regional differences in 36-month SPI versus SPEI projections in multiyear droughts can be mostly attributed to how water limited regional hydroclimates are (e.g., Vicente-Serrano et al., 2015). At Mid Coast and Northern Sierra there is a close balance between average water year total Prcp and ET₀ (less water limited) while at South Coast and Humboldt Basin water year total ET₀ far exceeds Prcp. With winter Prcp projected to increase (when most of the water year precipitation falls) and ET₀ also projected to increase, the wetting (Prcp) and drying (ET₀) tend to continue to balance in less water-limited regions. At more water-limited locations, increased drying is projected (far more extreme droughts in 36-month SPEI than 36-month SPI) as ET₀ already dominates the Prcp-ET₀ balance. For South Coast, a shift towards an even more water-limited regime is projected due to substantial decreases in spring and autumn Prcp (20–40%) combined with increased ET₀ that will further expand the imbalance between the two. Our results suggest that more multiyear droughts like the recent 2012–2016 drought will be found in the future, when even modest Prcp deficits are exacerbated through increased ET₀ and land surface drying (Shukla et al., 2015; Williams et al., 2015).

Increased frequency of extreme multiyear droughts (36-month SPEI) by the end of the century, even at Mid Coast and Northern Sierra, could further increase short-term, seasonal fire danger. Long-term droughts can degrade forests and other ecosystems; however, regional responses can vary substantially. Dong et al. (2019) found major declines in vegetation greenness for southern California in response to the 2012–2016 drought but increases in greenness in northern California and high elevations of the Sierra Nevada. In places where vegetation health decreases, fire danger will increase due to lower fuel moisture and higher flammability. These long-term drought impacts coupled with more extreme 2-week EDDI days and decreasing autumn Prcp will further increase fire danger during the autumn.

One uncertainty is the role of increasing carbon dioxide (CO2) on plant physiology and how that could change ET₀. Some argue that increasing CO2 will increase vegetation surface resistance and decrease plant water use, and using a fixed surface resistance for Ep (such as the ET₀ used in this study) might overestimate future ET₀ and related drought impacts (e.g., Milly & Dunne, 2016, 2017; Roderick et al., 2015; Swann et al., 2016; Yang et al., 2019). Simple adjustments can be applied to surface resistance in the ET₀ equation based on projected CO2 values (Yang et al., 2019). Vicente-Serrano et al. (2020) show that globally, when ET₀ is adjusted for rising CO2, annual values are reduced, but the trend is still increasing for both RCP 4.5 and 8.5. For California and Nevada, the same holds true with increasing ET₀ for both CO2-adjusted (based on Yang et al., 2019) and unadjusted estimates (Figure S12). Although we acknowledge this concern, experiments on actual vegetative responses to elevated CO2 find minimal or no drought reducing effects on
various types of vegetation and ecosystems (e.g., Bachofen et al., 2018; Birami et al., 2020; Diksaiytė et al., 2019; Duan et al., 2014; Jiang et al., 2020; Nackley et al., 2018). Furthermore, the 2012–2016 extreme hot drought in California and Nevada, intensified by CO2 driven warming (e.g., Shukla et al., 2015; Williams et al., 2015), resulted in major declines in vegetative health for parts of California (Dong et al., 2019) further calling into question whether future CO2 increases will mitigate drying, drought, and fire danger.

Based on a seven-member LOCA downscaled GCM ensemble we show that for California and Nevada, ET0 will steadily increase through the end of century for all seasons under both RCP 8.5 and 4.5 (Figure S5) scenarios. This will stress native ecosystems, increase fire danger, negatively impact agriculture where water demands cannot be met, and exacerbate impacts to society during periods of prolonged dryness. Projected Prcp changes vary with region and season, with notable increases during winter (whole region) and autumn (central and northern Nevada). During these seasons at these locations, a combination of increasing ET0 and increasing Prcp confounds fire danger signals; in that case, the timing of individual Prcp events and atmospheric drying events (e.g., heat waves and Santa Ana winds) might play the greatest role in determining fire potential. Conversely, in most of California a clear signal of increased fire potential is expected during autumn with projected increases in ET0 and decreases in Prcp.

The future projections of ET0 discussed here expand our understanding of possible drought and wildfire potential in California and Nevada, providing resource managers with a more holistic view of possible future scenarios. The regional differences revealed in this analysis demonstrate how future drying may vary across California and Nevada and the need for regionally focused climate change impact and adaptation assessment. Similar analysis could easily be applied to other areas around the globe, where drought and wildfire have significant impacts, to gain more insight into future changes in ET0 and climatic water balance components at regionally applicable timescales.

### Conflict of Interest

The authors declare that they have no conflicts of interest.

### Data Availability Statement

All data used in this analysis are publically available through the links as follows: gridMET (http://www.climatologylab.org/gridmet.html); LOCA (http://loca.ucsd.edu); Williams et al. (2020) precipitation and ET0 (https://www.ldeo.columbia.edu/~williams/megadrought/climate/0.25deg_monthly/multipродuct_1901_2018/observed/).

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