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Downscaled CMIP5 projections of physical fire risk understate historical trends

Theo C Avila[1,*], **David C Lafferty**[2], **Madeline Stover**[1,3], **Spencer Guerrero**[3], **Charumeghana Samantula**[4], **Ian Sue Wing**[5] **and Ryan L Sriver**[3]

[1] Department of Physics, University of Illinois at Urbana-Champaign, Urbana, IL, United States of America
[2] Department of Biological and Environmental Engineering, Cornell University, Ithaca, NY, United States of America
[3] Department of Climate, Meteorology & Atmospheric Sciences, University of Illinois at Urbana-Champaign, Urbana, IL, United States of America
[4] Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, United States of America
[5] Department of Earth and Environment, Boston University, Boston, MA, United States of America
[*] Author to whom any correspondence should be addressed.

E-mail: ctavila2@illinois.edu

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Abstract

Reliable projections of wildfire risk are important for multi-sector impacts analysis. Statistically downscaled and bias-corrected Earth system model ensemble products are routinely used to analyze regional physical wildfire risk, but evaluations of historical observed trends and variability are lacking. Here, we evaluate physical fire risk over the western United States using the Canadian Forest Fire Weather Index (FWI) by comparing model outputs from the Coupled Model Intercomparison Project Phase 5 (CMIP5), statistically downscaled via the Multivariate Adaptive Constructed Analogs (MACA) approach, against the observational target dataset gridMET, a gridded high-resolution surface meteorological product. We analyze multidecadal trends and interannual variability in seasonal average FWI for the historical period and future projections under two emissions scenarios, and we compare MACA-CMIP5 ensemble results with a simple time series model that generates historical and future projections of seasonal FWI based on bootstrapping observed historical trends and variability. Our findings indicate that MACA-CMIP5 accurately captures the magnitude and spatial patterns of seasonally averaged FWI but tends to underestimate historical decadal trends. We show that future increases in fire risk may be underestimated relative to the simple time series model that projects historical variability into the future. We also highlight that model biases in relative humidity contribute significantly to model-data differences. Our results underscore the importance of historical hindcasting exercises for informing broader multi-sector applications.

1. Introduction

Wildfires pose significant risks to both natural and human systems. Extreme wildfire events have increased globally by 220% between 2003 and 2022 (Cunningham *et al* 2024). In Canada, large wildfires from May to September 2023 released 647 teragrams of carbon, more carbon emissions than all nations except India, China, and the United States (Byrne *et al* 2024). Regionally, wildfire patterns are also shifting; in the United States, the frequency of wildfires between 2005 and 2018 was three times greater than during 1984–1999, and the average fire size grew by a factor of four (Iglesias *et al* 2022).

Growing evidence indicates that increases in the area burned by large wildfires in the Western United States are driven by broader Earth system changes (Abatzoglou and Kolden 2013, Turco *et al* 2023). The number of large wildfires (greater than 1000 acres) increased significantly during 1984–2011, with the most significant trends in areas experiencing increased drought severity (Dennison *et al* 2014). Abatzoglou *et al* (2021) project that fuel limitations will not constrain forest fire area, with a predicted doubling in affected area from 2021 to 2050 compared to the previous thirty years (1991–2020). The frequency and severity of droughts associated with wildfires have also been increasing (Littell *et al* 2016). In the western US, increases in the frequency and extent of wildfires have led to a growing literature analyzing the changing dynamics of fire risk (Abatzoglou and Williams 2016, Williams *et al* 2019). For example, Abatzoglou and Williams (2016) found that global temperature and vapor pressure deficit changes have already contributed to an increase in the area burned by wildfires across this region and that this increase is likely to continue in the future. California, in particular, has been heavily impacted by devastating wildfires in recent years, exacerbated by intense drought and arid conditions (MacDonald *et al* 2016). The economic toll of these fires has been staggering: in 2018 alone, direct damages, such as destroyed buildings, and indirect costs like economic disruption, totaled $148.5 billion (Wang *et al* 2021).

Given the potential for severe human impacts of wildfires in the western US, fire risk projections are important for long-term, multi-sector vulnerability assessments, whether focused on specific fire weather metrics or the underlying meteorological drivers. One widely-used fire weather metric is the Fire Weather Index (FWI), or FWI (Van Wagner and Pickett 1985). FWI is calculated using daily weather readings and is a nonlinear, thresholded function of temperature, wind speed, precipitation, and humidity. FWI calculated from observational data products or gridded general circulation model (GCM) outputs can be used to assess changes in the frequency or severity of fire weather (Jones *et al* 2022). Analysis of observational data by Goss *et al* (2020) revealed that extreme fire weather days—those with FWI above the historical 95th percentile—have more than doubled since the 1980s. Their GCM ensemble projections further indicate that the frequency of such extreme fire weather days will increase by more than 25% by the end of the century compared to the historical period. Dong *et al* (2022) project that, by 2070–2099, under both RCP4.5 and RCP8.5 forcing scenarios, the annual number of large-fire days in California will increase by over 60% relative to the 1970–1999 baseline. In another study, Wotton *et al* (2010) used GCMs and the Canadian Forest FWI to project a 75% to 140% increase in fire activity across Canada by 2100.

Previous studies have not systematically evaluated the representation of both long-term trends and interannual variability in downscaled projections of fire weather indices. Understanding these effects is critical for assessing the reliability of future fire risk projections. Here, we analyze FWI variability in the western US using downscaled and bias-corrected GCM ensemble results from the Multivariate Adaptive Constructed Analogs (MACA) Coupled Model Intercomparison Project Phase 5 (CMIP5) (Abatzoglou and Brown 2012) product as well as the high-resolution observational data set, gridMET (Abatzoglou 2013), which was the basis for the MACA product. Downscaling and bias correction methods are useful tools to increase the spatial resolution of model outputs and minimize differences with observational products (Maraun and Widmann 2018). We analyze historical multi-decadal variability and implications for future projections, and we compare and contrast ensemble results with a simple time series model that generates future seasonal FWI projections based on historical trends and interannual variability. Our analysis finds that the MACA-CMIP5 ensemble generally underestimates FWI variability and trends in recent decades compared to gridMET over large portions of the western US, which may limit its effectiveness for estimating future changes.

2. Data and methods

We analyze outputs from the MACA version 2 ensemble, which includes projections from 18 CMIP5 models. MACA implements a multi-step approach that first bias-corrects GCM outputs using quantile mapping, removes epoch-based trends, identifies the best analog patterns from observed data, and then reintroduces trends with a final bias correction (Abatzoglou and Brown 2012). This method is particularly useful for fire weather applications as it jointly downscales temperature and humidity fields while incorporating wind variables—all important components for fire risk assessment. However, MACA has some limitations: like other statistical downscaling approaches, it assumes stationarity in the relationship between coarse-scale predictors and fine-scale outputs (Hewitson *et al* 2014). Additionally, the method's skill depends heavily on the underlying GCM's ability to accurately simulate synoptic-scale meteorological patterns, making GCM selection important for meaningful downscaling results (Abatzoglou and Brown 2012). Regardless of the GCM, statistical downscaling often faces challenges in reproducing historical extremes (Bürger *et al* 2012, Pierce *et al* 2015).

We select MACA-CMIP5 as our preferred downscaling method because of its high resolution (1/24°) and its previous use in studies analyzing western U.S. wildfire risk (e.g. Goss *et al* 2020, Gutierrez *et al* 2021) as well as in related fields, including hydrology (Chegwidden *et al* 2017), ecology (Yee *et al* 2021), and fire (Sheehan *et al* 2015). We also evaluated the statistically downscaled ensemble from the NASA

Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) (Thrasher *et al* 2022) and found that historical FWI trends and interannual variability were similar to those of the MACA-CMIP5 ensemble. Because NEX-GDDP-CMIP6 is less commonly used for physical fire-risk applications, has a coarser resolution, and does not downscale minimum relative humidity, we focus our analysis on the MACA ensemble based on CMIP5.

We calculate the FWI using the Python-based xclim climate indices library, which implements the standard methodology of the Canadian Forest Fire Danger Rating System (CFFDRS) (Wang *et al* 2015). Inputs include daily maximum surface temperature, minimum relative humidity, surface wind speed, and precipitation, consistent with previous studies (Abatzoglou *et al* 2019, Quilcaille *et al* 2023). We calculate seasonal FWI averages for the primary fire season (June to October) at each grid point to examine interannual variability and long-term trends. Our historical analysis spans 1979–2022, with the period 2006–2022 derived from the CMIP5 RCP8.5 scenario projections since CMIP5 historical forcings end in 2005. Future fire weather projections extend from 2023 to 2100 under both moderate (RCP4.5) and high-emission (RCP8.5) scenarios (van Vuuren *et al* 2011).

Our historical fire weather analysis uses gridMET, a high-resolution (1/24° or ∼4 km) gridded surface meteorological dataset that has been used for ecological, agricultural, and hydrological applications within the US. GridMET provides the daily weather variables required for FWI calculations by blending North American Regional Reanalysis (NARR)/NLDAS-2 reanalysis data with PRISM's terrain-sensitive temperature and precipitation fields (Abatzoglou 2013). Although gridMET is widely used for fire applications, some variables used in FWI, such as minimum relative humidity, show reduced accuracy in regions with complex terrain, including coastal zones and the Rocky Mountains. These differences are relatively minor, with the mean absolute errors of minimum relative humidity typically below 6% during the warm season (Abatzoglou 2013). We emphasize that, given the relatively short temporal span of the gridMET dataset, the resulting trends and projections should be interpreted with caution, as they may undersample long-term natural variability. Nonetheless, recent studies such as Queen *et al* (2025) have shown similar anthropogenic trends in FWI using longer datasets (e.g. ERA5 from 1951 to 2021), which support the robustness of these results. Further, we focus on gridMET for the observational analysis since it is the basis for the MACA-CMIP5 dataset., and our aim is to isolate and quantify the potential uncertainties that can arise with statistical downscaling approaches (Lafferty and Sriver 2023).

Our analysis employs bootstrap resampling to generate synthetic time series of historical and future seasonal FWI (Efron and Tibshirani 1994, Härdle *et al* 2003). The bootstrap approach preserves the observed characteristics of inter-annual variability while allowing us to quantify uncertainties in the decadal projections (Penalba and Rivera 2016, Sriver *et al* 2018). We isolate and focus on two forms of variability related to seasonal FWI: multi-decadal trends and interannual variability. We start by fitting a linear regression to the time series of annually averaged historical FWI at each grid location:

$$\mathrm{FWI}_t = \beta_0 + \beta_1 t + \epsilon_t$$

where t is time (year), β_0 and β_1 are intercept and slope and ϵ_t are residuals. Residuals are calculated by subtracting the predicted FWI values from the FWI values derived from gridMET, $\epsilon_t = \mathrm{FWI}_t - (\beta_0 + \beta_1 t)$. These residuals are then resampled with replacement (ϵ_t^*) and added to the original linear fit projected to the end of the century to generate synthetic realizations, which are used as the basis for estimating projected trends.

$$\mathrm{FWI}_t^* = \beta_0 + \beta_1 t + \epsilon_t^*.$$

Next, a new linear regression is fit to each synthetic time series to calculate a distribution of trends. By repeating this process and superimposing bootstrapped residuals onto the trends, an ensemble of entirely synthetic FWI time series is generated. This ensemble captures both high and low-frequency variability (from interannual to multi-decadal scales) and reflects the uncertainty across these time scales introduced through resampling. However, this approach is limited by gridMET's relatively short observational record (1979 onwards) as well as by assumptions about linear trends, potentially resulting in an undersampling of natural variability on longer time scales. These limitations are discussed below in more detail.

3. Results

We compare multiple metrics of FWI for the historical period (1979–2022) based on GridMET observations and the MACA ensemble (figure 1), including fire season average (June–October), multi-decadal trends, and the standard deviation of the residuals (defined as the difference between annual average and the linear trend). Time series statistics are calculated for each grid point and are considered independent of surrounding locations. For the MACA-CMIP5 ensemble, statistical estimates are calculated for each model before averaging across the ensemble. Note, that since the RCP scenarios began in 2006 for CMIP5, the historical period 2006–2022 corresponds to RCP8.5 projections for the MACA ensemble.

Figure 1 shows the historical seasonal average is nearly identical for the statistically-downscaled MACA models compared to gridMET observations (figure 1, left column). However, the multi-decadal

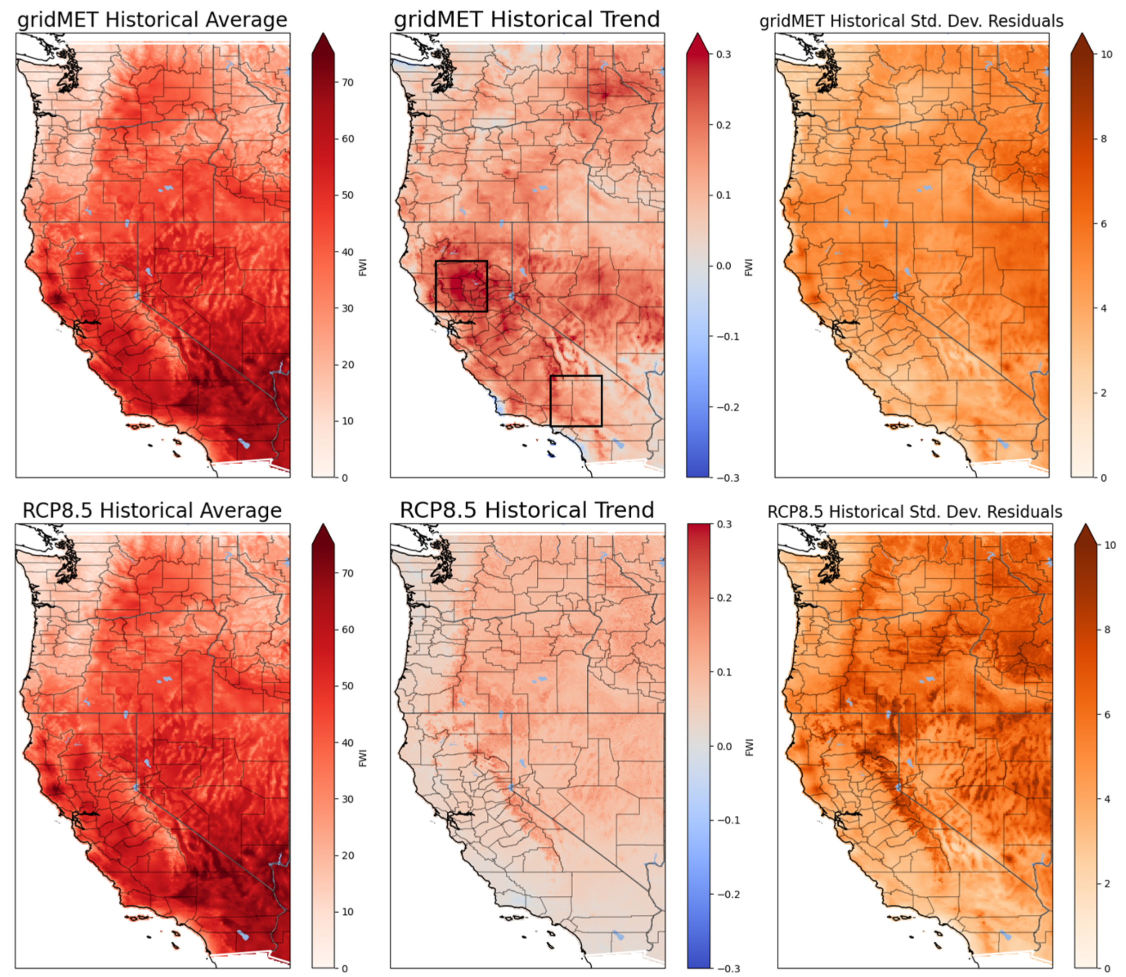

Figure 1. Historical variability in Fire Weather Index (FWI) for the summer fire season (JJASO) from 1979–2022. Plots show the fire season monthly average (left column), trend (center column), and standard deviation of residuals (right column), based on gridMET observations (top row) and MACA CMIP5 ensemble (bottom row). Black boxes (middle column) represent geographic regions, as shown in figure 3.

trends vary considerably (figure 1, center column). The observed trend is positive over much of the western US, including high fire risk areas in northern and southern California. In contrast, the MACA-CMIP5 trend is smaller in magnitude, and close to zero over some of the domain. The seasonal FWI residuals (figure 1, right column) provide an estimate of the magnitude of natural interannual variability by removing the long-term trend. The magnitude of interannual FWI variability generally agrees between GridMet and MACA over coastal regions, but MACA residuals tend to increase further eastward in the spatial domain. Note that because MACA models tend to underestimate long-term trends in seasonal FWI compared to gridMET, the observed overestimation in MACA residual FWI variability may be partly due to the under-detection of variance in the long-term trends. MACA's underestimation of historical FWI trends and over-estimation of interannual variability could pose challenges when assessing potential future changes in FWI based on these models.

Future projections of seasonal FWI from MACA for various time horizons (2060, 2090) and RCPs (4.5, 8.5) are shown in figure 2. For the observational gridMET data set, we utilize the bootstrap method (see Data and methods) to generate synthetic ensemble iterations based on resampling the residuals and projecting the trends out to 2060 and 2090. Random residuals are added onto the trends out into the future to create bootstrapped projections that include both long-term trends and interannual variability at each grid location. We use a synthetic ensemble sample size ($n = 18$) to be consistent with the number of MACA models, and plot the ensemble average in figure 2. For the MACA ensemble, we analyze the ensemble mean for the RCP4.5 and RCP8.5 projections for respective future years. Both ensembles show similar spatial patterns, but differences arise in the magnitude of these trends across the region. In general, our bootstrapped statistical ensemble projects greater fire risk, particularly over the southern half of our domain, relative to

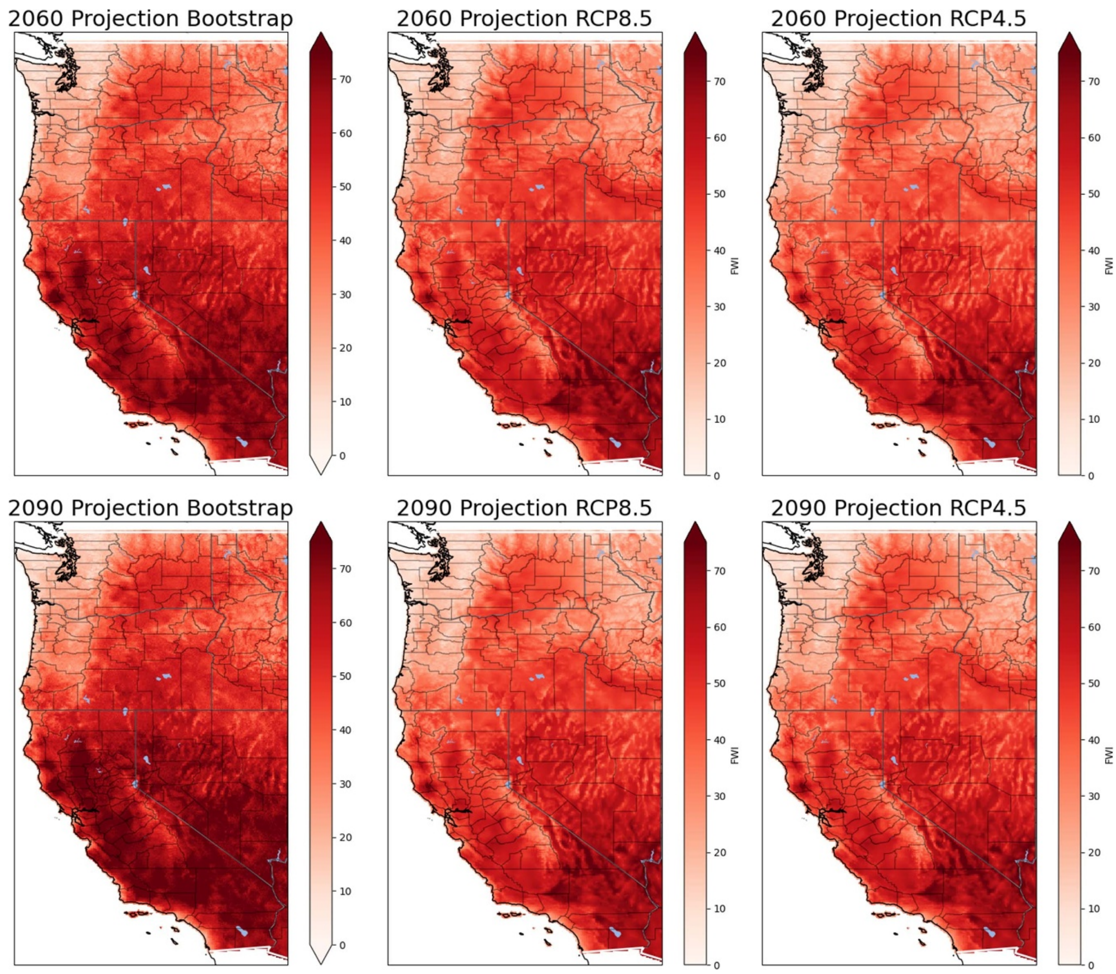

Figure 2. Future projections of the Canadian Forest Fire Weather Index (FWI) for the summer fire season (JJASO) for 2060 (top row) and 2090 (bottom row). Plots show bootstrap projections based on resampling historical trends (left column), as well as MACA CMIP5 models using the RCP8.5 (middle column) and RCP4.5 (right column) forcing scenarios.

MACA-CMIP5. The ensembles tend to agree over the northwestern US, but show considerable differences over parts of Nevada and California, where the statistical ensemble can exhibit FWI values 40% larger than MACA-CMIP5.

In order to isolate the differences between MACA and GridMET, we analyze time series of spatially averaged seasonal FWI metrics for two different high-fire risk areas in northern and southern California, denoted as 'Norcal' and 'Socal' (figure 3). The coordinate boundaries for Norcal are [−123, −121 deg lon], [38.5, 40.5 deg lat], and for Socal are [−118.5, −116.5 deg lon], [34, 36 deg lat] (see boxed areas in figure 1). For the gridMET time series model, we use a 200-model bootstrap ensemble to estimate the 95% confidence interval and subsample 18 trends to obtain a sample size consistent with the MACA-CMIP5 ensemble. The ensemble-data differences are relatively insensitive to ensemble size (supplementary figure 1). The CMIP5 ensemble linear regression is fit to the 1979–2090 data for each respective model, and the gridMET bootstrap trend is fit to the 1979–2022 bootstrapped data and then projected into the future.

As shown in figure 3, the MACA-CMIP5 models tend to under-estimate future trends in seasonal FWI for both northern and southern California compared to the bootstrapped projections based on historical variability. These findings are summarized in table 1, which displays northern and southern California FWI projections for the years 2030, 2060, and 2090. The bootstrapped projections exhibit higher FWI projections for all years compared to MACA. The differences increase over time and are more pronounced for the lower emissions scenario. These differences may be due in part to model errors in surface humidity and/or wind speed (supplementary figure 2), as discussed in the next section.

4. Discussion and conclusions

A key finding of this analysis is that the MACA-CMIP5 ensemble reliably reproduces the magnitudes and spatial variability of seasonal FWI for the western United States, but the models underestimate historical multi-decadal trends compared to gridMET observations which is the underlying observational

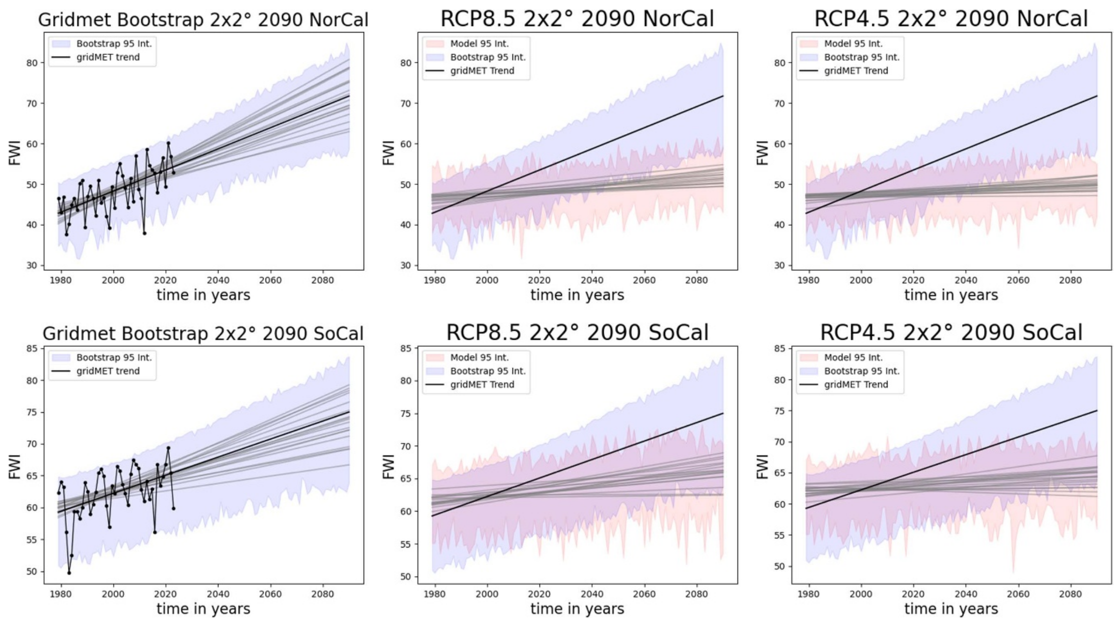

Figure 3. Time series of seasonal FWI averaged over the northern California region (top row) and southern California region (bottom row) highlighted in figure 1. The left column shows the historical observational FWI estimates (black circles) and trend (black line) projected into the future. Gray curves represent bootstrapped trends based on resampling of the residuals. Blue shading highlights the 95% range of the projected bootstrapped time series (trends + residuals). The center column shows results from the MACA CMIP5 projections for the RCP8.5 scenario. Gray lines represent model trends, and pink shading highlights the 95% model ensemble range. Observation-based trend (black line) and bootstrap range (blue shading) are shown for reference. The right column is the same as the center column but for a RCP4.5 scenario.

Table 1. Future projections for California, with standard deviations in parenthesis.

	Bootstrap	RCP8.5	RCP4.5
	Northern California		
2030 Projection	66.596 (4.09)	64.439 (3.23)	62.472 (3.49)
2060 Projection	71.284 (4.31)	63.999 (4.65)	62.635 (3.41)
2090 Projection	75.212 (5.04)	63.633 (5.12)	63.171 (4.26)
	Southern California		
2030 Projection	56.179 (4.70)	49.500 (3.57)	47.748 (2.94)
2060 Projection	64.141 (5.53)	48.910 (5.49)	45.975 (5.34)
2090 Projection	71.255 (6.17)	50.192 (4.61)	48.612 (3.95)

data set used in the downscaling. Spatially, the MACA-CMIP5 future projections show significant disparities in trends compared to the gridMET bootstrapped ensemble across the western United States, particularly between the northern and southern California locations illustrated in figure 3. In addition to trends, the year-to-year variability in seasonally averaged FWI can vary spatially, and we find that MACA-CMIP5 can overestimate interannual variability in many locations.

To investigate the cause of the model-data differences, we analyze historical time series and spatial trends and averages of the meteorological variables used in the FWI calculation (supplementary figures 2–4, 7–9), including surface temperature, precipitation, relative humidity, and surface wind speed. We find the MACA models do not typically capture historical downward trends in relative humidity, likely associated with humidity biases in CMIP5 models (Dunn *et al* 2017, Shaw *et al* 2024, Simpson *et al* 2024), which in turn contribute to the underestimation of FWI trends in the MACA-CMIP5 ensemble. Since this bias appears in the underlying CMIP5 models, and MACA explicitly preserves the GCM trends, we do not attribute it primarily to the downscaling process. While the MACA approach (Abatzoglou and Brown 2012) outperforms most other statistical downscaling methods in capturing daily and spatial variability of relative humidity, these evaluations do not assess long-term trends, which are controlled by the parent GCMs. It is possible that aspects of the MACA methodology, beyond the choice of training data, may amplify or modify these differences, but further investigation is needed. Additionally, if non-negligible biases exist in gridMET, they could propagate into the downscaled product. Many of these issues are not unique to statistical downscaling, and similar biases in temperature and near-surface water vapor have been documented using dynamically downscaled and bias-corrected data from the Community Earth System Model ensemble combined with the NARR data and the Weather Research and Forecasting Model at 4 km (Zhao *et al* 2020).

Using long-term station observations, the fire-season trends in gridMET for average maximum temperature and precipitation seem to be robust (supplementary figures 4 and 9). We also find the MACA-CMIP5 ensemble mean seasonal cycle of daily wind speed closely matches the gridMET climatology in both Northern and Southern California (supplementary figure 6). Quantifying the changes in interannual variability of Santa Ana wind events and their impacts on fire weather risk metrics would require a more targeted investigation (Guzman-Morales *et al* 2016). Note the meteorological contributions to FWI can vary over space and time, and compound metrics (such as wind speed combined with surface humidity) can also amplify physical fire risk (Yu *et al* 2023). A random forest approach was used to determine the relative importance of inputs to FWI for large areas of Northern and Southern California. This analysis indicated that the relative importance of FWI inputs varied spatially, with relative humidity being of high importance in both regions, consistent with Orgambides-García *et al* (2024).

Our results indicate that simple time series methods such as bootstrapping may offer a flexible and robust approach for estimating future projections of wildfire risk, particularly in comparison to downscaled GCMs. The model-data differences suggest that relying solely on GCMs for future projections, especially for extreme seasons, may result in large underestimations. The time series method in our analysis allows for a more straightforward interpretation of historical trends and projections for future years, relying only on historical variability. We assume multi-decadal FWI trends are linear with time, which neglects longer-term sources of natural variability and can potentially overlook complex earth system dynamics and feedbacks that may lead to nonlinear responses. Large ensembles can be a useful next step in exploring the effect of internal variability on multi-decadal trends and projections in FWI. The addition of longer-term natural variability in the time series model would increase the projected upper bound in future FWI projections and larger differences with projected upper-bounds from MACA-CMIP5 models. Additionally, analyzing trends and variability at each individual location presents a limitation, as it implicitly assumes that FWI is uncorrelated across time and space. However, this effect appears to be minimal as the statistical model generally captures the magnitudes and spatial patterns in historical FWI. Analysis of the partial autocorrelation (PAC) of the residuals shows they tend to be spatially heterogeneous: while many regions exhibit minimal lag-1 autocorrelation, some areas show PAC values approaching 0.4–0.5, with a general decline at higher lags. This persistence suggests our time series model may be under-sampling the interannual variance in areas with large autocorrelation (i.e. from multi-year drought or dynamical modes), which may be better represented using autoregressive models.

While FWI is widely used for physical fire risk assessment, other fire risk metrics, such as the McArthur Forest Fire Danger Index (Noble *et al* 1980) and the Hot Dry Windy Index (McDonald *et al* 2018, Srock *et al* 2018), are also useful. These metrics rely on different combinations of meteorological inputs and may respond differently to biases in the underlying variables. If the inputs of other fire-risk metrics are similar to FWI, using downscaled models with known long-term trend biases (e.g. relative humidity) may result in similar limitations as shown here for FWI.

These results suggest exercising caution when utilizing statistically downscaled GCMs for short- to long-term FWI projections as dynamical models often are unable to resolve fine-scale processes (Christensen *et al* 2008, Schneider *et al* 2017), and statistical downscaling methods generally may underestimate variance (Ekström *et al* 2015) or fail to reproduce extremes (Bürger *et al* 2012, Pierce *et al* 2015). The choice of the downscaling method can also contribute significantly to uncertainty, especially when dealing with complex topography or extremes (Wootten *et al* 2017). Other issues, such as interactions with land use change, population growth, energy systems, and economic development, as well as land-atmosphere couplings, can further complicate the reliability of projections by altering both exposure and vulnerability to wildfire risk.

Diagnosing differences between models and data is important for improving projections, as downscaled and bias-corrected models may exhibit signs of overconfidence based on historical comparisons. Addressing these discrepancies can help create more reliable short-term and long-term projections of FWI that are grounded in historical variability. Combining dynamical models with time series methodologies can help identify model biases and improve our ability to predict and understand changes in wildfire risk on regional scales.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://climate.northwestknowledge.net/MACA/data_portal.php.

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