IMPROVING WILDFIRE RISK ASSESSMENT IN THE CONTIGUOUS U.S. (1981-2020) USING A HIGH-RESOLUTION REGIONAL CLIMATE MODEL

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ABSTRACT

Wildfires have historically played an important ecological role, promoting biodiversity through natural landscape renewal. However, in recent decades, wildfire activity has become increasingly destructive, posing significant threats to ecosystems, infrastructure, and communities. This study investigates changes in fire weather conditions, as measured by the Fire Weather Index (FWI), across the contiguous United States from 1981–2020, focusing on regional and seasonal trends. Unlike traditional fire risk assessments that rely on coarse-resolution atmospheric reanalysis and global climate models, this study utilizes CONUS404, a convection-allowing regional climate model output. With its 4 km spatial resolution, COUNS404 is better at capturing localized fire weather conditions over complex terrains than these traditional datasets. Analysis across the four U.S. subregions (Pacific, Mountain, Central, Eastern) reveals the large-scale spatial variabilities of wildfire risk. In particular, the Pacific zone exhibits the highest and most rapidly increasing annual average FWI, indicating greater vulnerability to wildfire. Seasonal increases in average monthly FWI were observed during the early and late months of the year, particularly in January and November, suggesting a potential extension of the traditional fire season into winter and spring. Compared to the FWI derived from ERA5 (at 25 km resolution), CONUS404-based FWI captures more local-scale spatial heterogeneity of wildfire risks at finer scale, especially in topographically complex regions such as the western US. These findings highlight the need for high-resolution climate data in future wildfire research and risk management, particularly as fire seasons grow longer and more intense.

1. INTRODUCTION

Wildfire has shaped ecosystems for millennia, playing an essential role in maintaining biodiversity and ecological balance (Sugihara et al., 2006; Wallace Covington, 2000). However, the spatial and temporal patterns of wildfires have been increasingly disrupted by climatic changes, induced by both natural climate variabilities and anthropogenic environmental warming (The White House, 2023). For instance, from the 1970s to 2010s, the average fire season in the U.S. Pacific Northwest region increased fivefold, from 23 days to 116 days, alongside a fivefold increase in total area burned (Williams et al., 2019). In another study by Dennison et al. (2014), large wildfire events in this region also exhibited a notable increase from 1984 to 2011. These observations call for a better understanding and projection of wildfire activities and their environmental impacts on the regional scale.

In contrast to being influenced by natural climate variability over the past several centuries, like La Niña conditions or the Little Ice Age, wildfire patterns, in the modern era have been increasingly shaped by human influence (Abatzoglou et al., 2019; Marlon et al., 2012; Trouet et al., 2010). In the 20th century, fire suppression efforts and land-use changes contributed to reduced wildfire activity (Marlon et al., 2012; Trouet et al., 2010). However, recent decades have witnessed a renewed escalation in wildfire activity. A growing body of research links this trend to anthropogenic climate change, particularly increased global temperatures and prolonged droughts (Abatzoglou et al., 2019; Abatzoglou & Williams, 2016; Iglesias et al., 2022). This resurgence in wildfire activity has serious implications for human and ecological health. In California, for example, individuals over 65 years of age, those with disabilities, and residents with limited access to transportation are among the most vulnerable populations (Modaresi Rad

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et al., 2023). These social groups face greater challenges of evacuation during wildfire events compared to other communities, as tragically illustrated by the 2018 Camp Fire—one of the deadliest wildfires in California history, which claimed 85 lives, 80% of whom were over 65 years old (Modaresi Rad et al., 2023). Such statistics highlight the necessity of both short-term forecasting and long-term risk assessment in local, community-specific wildfire mitigation strategies.

Another concern related to recent wildfire behavior involves the economic costs associated with prevention, suppression, and remediation efforts. The National Interagency Coordination Center estimates suppression costs alone increased approximately ~10.5% from 1985 to 2020 (National Interagency Fire Center, 2025). Beyond just immediate response expenses, the lingering economic burden is also significant. A recent study estimates that wildfire-related $PM_{2.5}$ exposure from 2006 to 2020 resulted in approximately $160 billion in associated mortality costs (Law et al., 2025). These findings highlight not only the threats to human and ecological health, but also the escalating financial impacts from wildfires.

A common metric to quantify fire risk is the Fire Weather Index (FWI), which integrates meteorological information over time to estimate regional fire danger on a given day (Van Wagner & Pickett, 1985). While effective, the accuracy of FWI calculations depends heavily on the quality and accuracy of the input meteorological parameters (e.g., surface precipitation, temperature, wind, and humidity). Traditional datasets such as the ERA5 (a global weather reanalysis dataset produced by the European Centre Medium-Range Weather Forecasts (ECMWF); Hersbach et al., 2020) or global climate models (as those in CMIP6), have a spatial resolution of 25-100km. As a result, they are unable to capture fine-scale variability of weather conditions, limiting their ability to accurately represent environmental factors relevant to wildfire risk. This limitation is particularly significant in regions with complex terrain, such as mountainous western regions where wildfires frequently occur (Higuera et al., 2021).

To address this limitation, this study employs the CONUS404 dataset: a high-resolution regional climate dataset produced using the Weather Research and Forecasting (WRF) model (Skamarock et al. 2008). With a spatial resolution of 4 km, CONUS404 offers a detailed, consistent, and fine-scale decades-long depiction of climate variability across the contiguous United States. Its ability to resolve topographic effects in the mountainous west and land-atmospheric interactions, and mesoscale atmospheric processes in the Middle-to-Eastern US makes it especially well-suited for regional wildfire risk assessments.

The purpose of this study is to investigate how wildfire risk has changed in the contiguous U.S. since the 1980s under changing climate conditions. We quantify annual trends in wildfire risk within four regions and investigate the influence of weather conditions on observed changes in fire seasonality. Utilizing the high-resolution CONUS404 dataset, we assess the enhanced accuracy of FWI calculations relative to ERA5-based estimates. The next section will detail the data and methods used in this investigation. Section 3 will present the results of this research, followed by a discussion and conclusion in sections 4 and 5 respectively.

Feature	CONUS404	ERA5
Model Used	Weather Research and Forecasting (WRF)	Integrated Forecasting System (ECMWF IFS)
Resolution	~4km	~31km
Convection	Explicit (convection permitting)	Parameterized
Land Coverage	Contiguous United States; Parts of Mexico & Canada	Global
Time Span	Oct. 1979 – Sep. 30, 2021	Jan. 1940 – present
Best Usage	Fine-scale regional climate analysis (e.g., hydrology, storms, wildfires)	Large-scale global climate analysis (e.g., climate change)

Figure 1. *Comparison of key features of the CONUS404 and ERA5 models.*

2. DATA & METHODS

The Fire Weather Index (FWI) system, developed by the Canadian Forestry Service, is a widely used tool for estimating daily wildfire risk based on the previous day's meteorological conditions (Lawson and Armitage, 2008; Van Wagner and Pickett, 1985). In this study, we apply the FWI system to examine how fire weather conditions have changed across the contiguous United States from 1981 to 2020. By analyzing long-term trends in FWI, we aim to better understand how a warming climate may contribute to changing wildfire risk, informing historical trends and future projections.

FWI calculations rely on four meteorological inputs taken daily at local noon: 2m air temperature

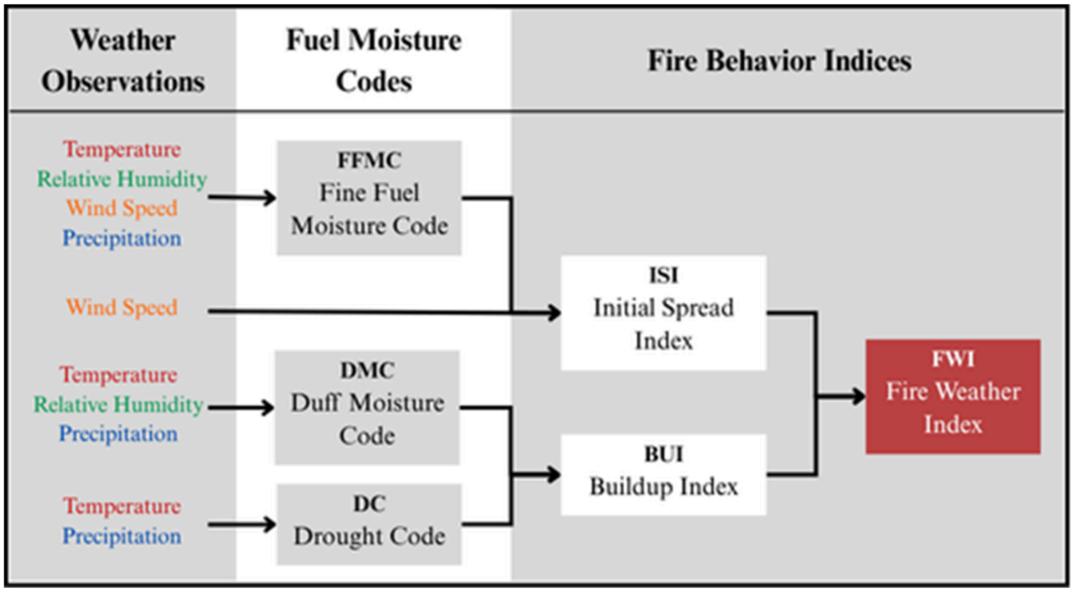


Figure 2. *Workflow illustrating the sequential computation process of the Fire Weather Index (FWI), including the four meteorological inputs and derived sub-indices.*

(°C), 2m relative humidity (%), 10m wind speed (km/h), and 24-hour precipitation accumulation (mm). In this study, we obtained these variables from the CONUS404 climate model.

Traditionally, fire weather research has relied on global reanalysis datasets such as the ERA5 to provide meteorological inputs. However, their coarse spatial resolution (10-100km) limits their ability to capture the fine-scale topographic and convective processes that significantly affect fire behavior (Prein et al., 2015; Rasmussen et al., 2023).

To address the limitations of coarse-resolution global datasets, we use the CONUS404 dataset. Developed by the U.S. Geological Survey (USGS) and National Center for Atmospheric Research (NCAR), CONUS404 is a high-resolution, convection permitting climate model for the contiguous United States. It was generated using the Weather Research and Forecasting (WRF) model (Rasmussen et al., 2023), configured with a 4 km horizontal grid spacing. The simulation spans from October 1979 to September 2021 and includes hourly and daily atmospheric and land surface variables (Rasmussen et al., 2023). For this study, we take the 1981-2020 (inclusive) data for FWI estimation.

A key advantage of CONUS404 is its ability to explicitly resolve convection weather systems, including mesoscale convective systems (MCSs), which are often poorly represented in coarser global models that rely on parameterizations. These improvements make it particularly well-suited for fire weather analysis, where spatial variability in temperature, humidity, wind, and precipitation can substantially alter wildfire potential. By using CONUS404, this study aims to produce high-resolution, spatially representative fire weather trends across the contiguous United States over a 40-year period

The FWI is calculated through a sequential process based on daily meteorological inputs. These inputs are used to estimate three soil moisture codes, each representing a different layer of forest fuel. These moisture codes are then used to calculate two fire behavior indices, which together determine the FWI value. This methodology follows the structure outlined by Van Wagner and Pickett (1985).

Fuel Moisture Codes

- The Fine Fuel Moisture Code (FFMC) represents the moisture content of the uppermost layer of surface litter (≤1.2cm depth) and responds the quickest to changing weather conditions (±16hr time-lag). It incorporates all four weather variables and is measured on a scale from 1 to 101, with higher values indicating drier fuel. This variable plays a significant role in ignition probability and extent of spread.
- The Duff Moisture Code (DMC) represents the moisture content in moderately deep (1.2-7cm depth) and loosely compacted organic matter. This layer has a slower response time (±12-day time-lag) and does not include wind speed in its calculation.

This variable contributes to fire intensity, with higher values signifying increased dryness.

- The Drought Code (DC) reflects deep (7-18cm depth) and compacted organic layers and is used to estimate long-term drought conditions, with a moisture response time-lag of about 53 days. This variable informs fire-prone conditions and contributes to fire intensity including the depth of the burn and fire suppression potential.

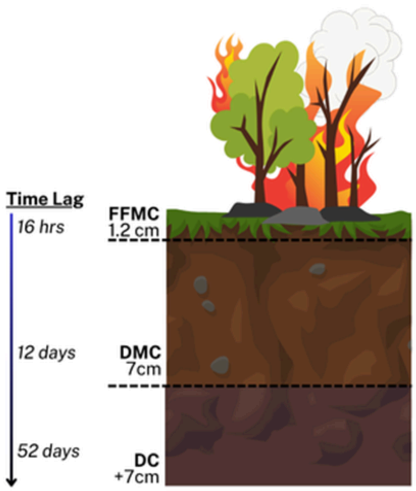


Figure 3. *Illustration of the fuel moisture codes and their corresponding depth and time-lag.*

Fire Behavior Indices

- The three moisture codes above are used to calculate two fire behavior indices: the Initial Spread Index (ISI) and Buildup Index (BUI). The ISI combines FFMC with wind speed to estimate the potential rate of fire spread. It is important to note that this index does not take fuel type into account, meaning that actual spread rates can differ between fuels with the same ISI. The BUI uses DMC and DC to gauge the total amount of fuel available for combustion.
- The FWI is derived from the ISI and BUI, producing an index that represents potential fire risk under given weather conditions. The standard thresholds that determine risk severity are indicated in figure 4.

Severity Level	FWI Value
Very low	< 5.2
Low	5.2 – 11.2
Moderate	11.2 – 21.3
High	21.3 – 38.0
Very High	38.0 – 50.0
Extreme	≥ 50.0

Figure 4. *Standardized threshold FWI values and their corresponding severity rating.*

To assess both national and regional variability, we analyze FWI data within four subregions: Pacific (Z19), Mountain (Z18), Central (Z17), and Eastern (Z16). Figure 5 illustrates these regional divisions and their corresponding codes.

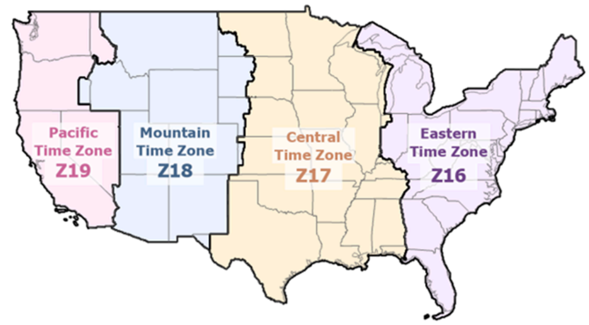


Figure 5. *Spatial division of U.S. time zones with corresponding zone codes (Z19-Z16).*

3. RESULTS

To understand how wildfire risk has changed over time across the U.S., we analyzed annual trends in the FWI from 1981 to 2020. Figure 6 presents the average annual FWI across the four U.S. zones. As indicated by the trendlines and slope values, the Pacific zone (Z19) has experienced the greatest increase in FWI during this period, followed by the Mountain (Z18), Central (Z17), and Eastern (Z16) zones, respectively. This figure also highlights the average FWI in each zone, with the Pacific zone consistently exhibiting higher FWI levels than other regions. Fluctuations in FWI are relatively consistent across the four zones, with peaks and dips occurring at similar intervals nationwide, reflecting the control by large-to-planetary-scale environmental conditions. While the Pacific zone exhibited the steepest increase, only the Eastern zone showed a statistically significant trend ($p = 0.0482$), with weaker significant trends in the central and western zones.

Figure 7 illustrates the average monthly FWI across the four zones for two 20-year periods. The blue line (with circles) depicts the mean FWI values from 1981 to 2000, while the orange line (with squares) shows the mean FWI values from 2001 to 2020. The figure highlights a noticeable increase in FWI during the early and late months of the year, with the most substantial increase occurring in November (10.07%) and January (13.58%).

To investigate the drivers behind this observed shift, figure 8 demonstrates the relationship between

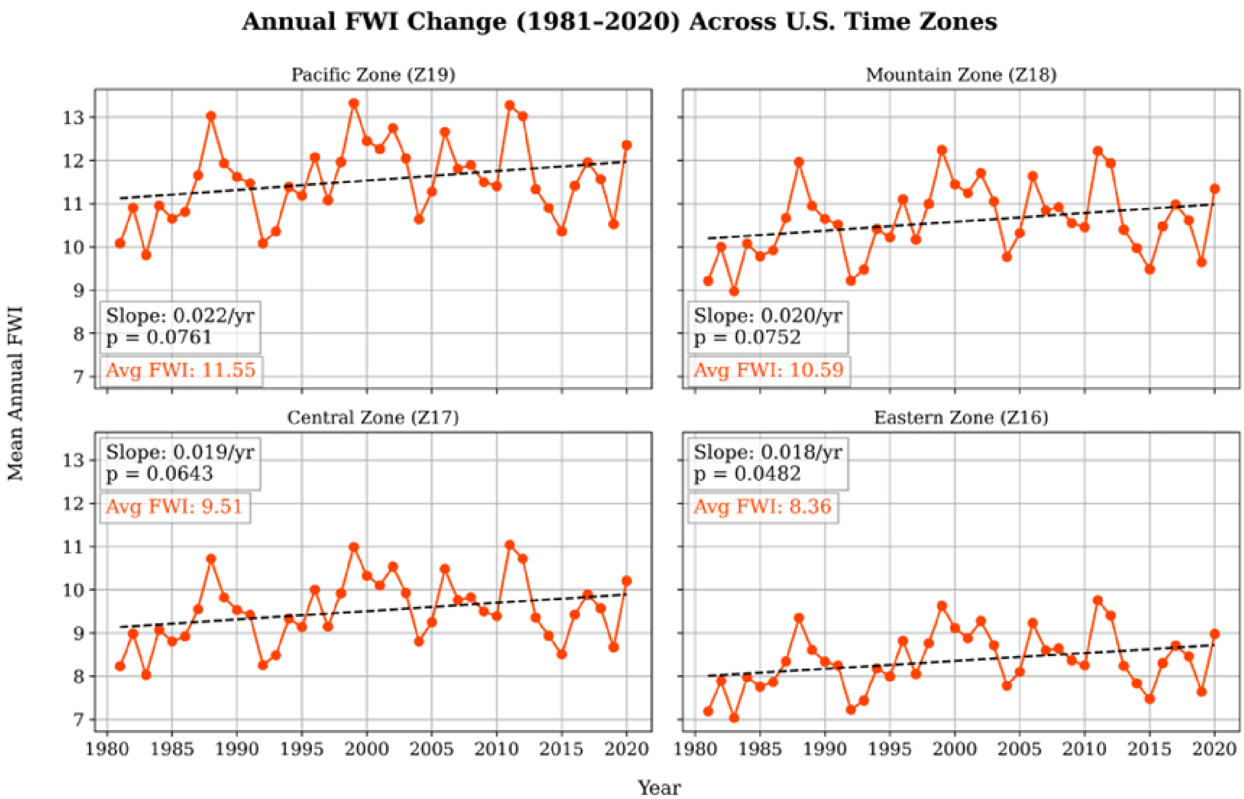


Figure 6. *Average annual FWI values plotted from 1981 to 2020 across the four U.S. time zones. Mean FWI and linear regression slopes are included for each region.*

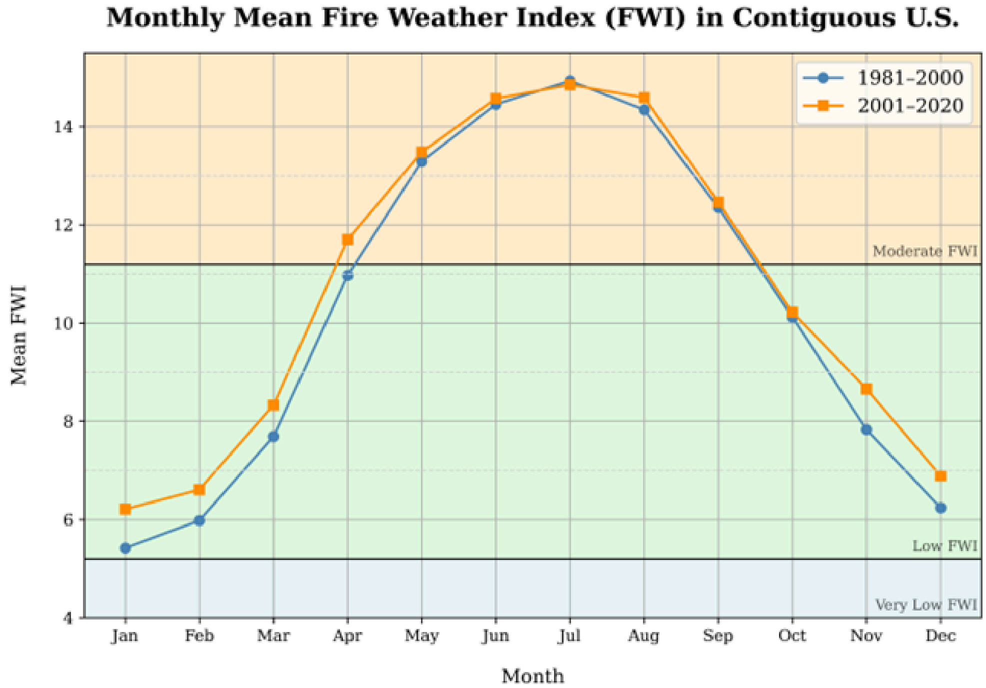
monthly FWI change (shown in figure 7) with the four weather variables used in its calculation: temperature, relative humidity, wind, and precipitation. Among these, changes in FWI had the strongest correlation with the change in precipitation, showing a strong negative relationship with an R^2 value of 0.836. A similarly negative correlation was also found with relative humidity, with an R^2 value of 0.752. In contrast, wind and temperature showed no obvious relationship with R^2 values of 0.065 and 0.008 respectively.

To examine the long-term evolution of fire weather severity, we analyzed the frequency of annual FWI severity levels at a five-year return period from 1985 to 2020. Figure 9 focuses on three major California cities: Los Angeles (Fig. 9a), San Francisco (Fig. 9b), and San Diego (Fig. 9c). These urban areas were selected for their large populations and historically high regional wildfire risk.

Figure 9a shows the evolution of FWI severity levels in Los Angeles. From 1985 to 2000, days classified as high, very high, or extreme made up a large portion of each year's FWI distribution. After 2000, the number of very high and extreme FWI days declined, while high FWI days initially increased before sharply decreasing between 2015 and 2020. In recent years, the number of days with very low, low, and moderate FWI has risen, with moderate FWI days showing the most pronounced increase.

Figure 9b presents the frequency of FWI severity levels in San Diego. The number of high FWI days remained relatively steady from 1985 to 2020, with a brief decline around 2000 and a spike in 2005. Extreme FWI days were consistently low throughout the period, peaking in 2000. However, both extreme and very high FWI days have been increasing since 2010.

Figure 9c illustrates FWI severity in San Francisco. Since 2015, there has been a considerable rise in the number of days classified with a high, very high, and extreme FWI, with the greatest increase occurring in the high category. Despite these variations extreme FWI days remain the least frequent. An increase in more severe FWI was accompanied by a decline in the number of days with a very low, low, and moderate FWI, with very low FWI days showing the greatest decrease.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
FWI 1981-2000	5.42	5.98	7.69	10.97	13.29	14.45	14.93	14.34	12.35	10.12	7.83	6.24
FWI 2001-2020	6.21	6.61	8.33	11.70	13.48	14.57	14.85	14.59	12.46	10.22	8.66	6.89
Difference	0.79	0.63	0.64	0.73	0.19	0.12	-0.08	0.25	0.11	0.10	0.83	0.65

***Figure** 7. Average monthly Fire Weather Index (FWI) values across the contiguous United States for 1981–2000 and 2001–2020. Tabulated values represent the mean monthly FWI anomalies (2001–2020 relative to 1981–2000). Shaded background regions correspond to FWI intensity categories: light blue denotes very low FWI (≤ 5.2), green represents low FWI (5.2—11.2), and yellow indicates moderate FWI (11.2—21.3).*

Across all three cities, Figure 9 highlights that Los Angeles has experienced the highest number of extreme FWI days. However, each location shows evidence of increasing frequency in more severe FWI levels between 1985 and 2020.

Figure 10 illustrates the influence of weather data spatial resolutions on FWI estimates, comparing the 4 km CONUS404 and 25 km ERA5 datasets on October 8th, 2012–one day before the Fern Lake Fire in the Rocky Mountains. This location was selected to showcase the advantages of the CONUS404 dataset in regions with complex terrain. Zoomed-in views of the fire site further emphasize how resolution differences affect FWI evaluation: ERA5 assigns a relatively low FWI at the fire location, whereas CONUS404 captures a significantly elevated FWI.

Figure 11 presents a similar comparison for the Chimney Tops 2 Fire, which ignited on November 23rd, 2016. Displaying the FWI one day prior to ignition, this figure emphasizes the contrast in spatial resolution between the two datasets. In this case, ERA5 presents a higher FWI at the fire location compared to CONUS404. Given the complex topography of the Smoky Mountains, this region serves as an ideal case study for evaluating model performance in wildfire risk assessment.

4. DISCUSSION

The findings from figure 6 show that average yearly FWI has increased in all four zones from 1981 to 2020, with the Pacific zone (Z19) exhibiting the largest increase. This zone also recorded the highest overall mean FWI, suggesting a persistently elevated fire potential relative to the Mountain (Z18), Central (Z17), and Eastern (Z16) zones, respectively. Although the Eastern zone is the only region with a statistically significant trend ($p = 0.0482$), the absence of statistical significance in the remaining zones (p-values between 0.06 and 0.08) does not necessarily imply the absence of trends. Rather, it may reflect greater interannual

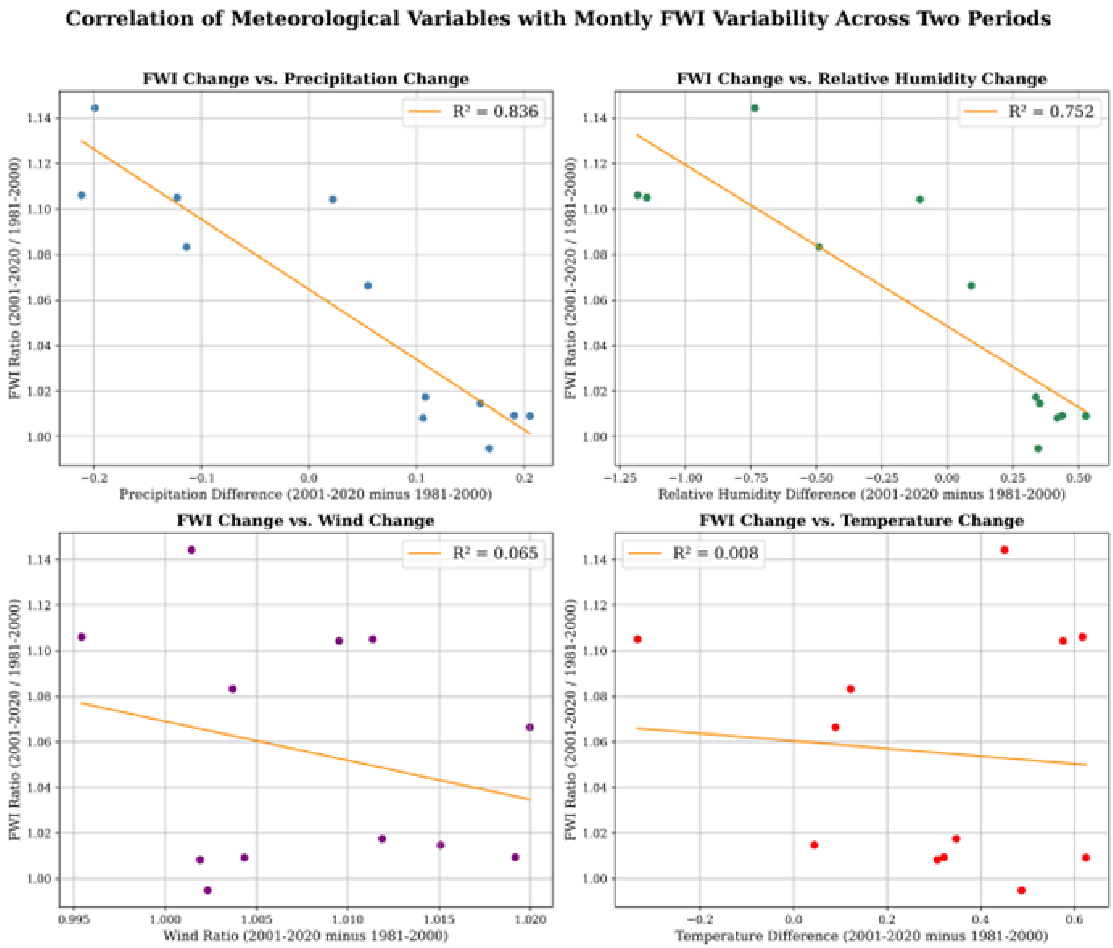


Figure 8. *Relationships between monthly FWI changes and the four meteorological variables (temperature, relative humidity, wind, and temperature).*

variability or weaker trends within those regions over the study period.

The observed increase in long-term average monthly FWI, particularly in January and November, as shown in figure 7, suggests that the fire season may be extending into the early and late months of the year. In contrast, the average FWI during the traditional peak fire season (May to September) remains relatively stable. However, this does not necessarily indicate a lack of intensification in fire weather conditions, as monthly means may obscure trends in daily or sub-daily extremes. Notably, April exhibits an increase in monthly mean FWI severity from low to moderate levels, signaling a rise in fire risk during the transition period into the peak fire season.

To evaluate the contribution of each meteorological factor and FWI component to the change of FWI seasonality, we calculated the correlation between these monthly mean FWI change and month mean-meteorological factors, as shown in figure 8. Variations in precipitation showed to have the strongest negative correlation against FWI seasonality changes (R^2 = 0.836) highlighting the close relationship between drought conditions and fire risk. Relative humidity variations had the second highest correlation (R^2 = 0.752), suggesting its important role in FWI seasonality trends.

The trends observed in figure 9 highlight a shift in fire weather severity across three major California cities, with increasing frequencies of high, very high, and extreme FWI days. The simultaneous decline in days characterized by very low, low, and moderate FWI suggests the intensification of fire weather conditions over time, with a growing proportion of the year characterized by more hazardous fire potential in these urban areas.

Both figures 10 and 11 highlight the enhanced spatial detail provided by the high-resolution

CONUS404 dataset in topographically complex regions. In figure 10, CONUS404 depicts higher FWI values in the Rocky Mountains prior to the Fern Lake Fire, whereas ERA5 shows a broader area of lower fire risk. In figure 11, ERA5 indicates elevated fire danger across much of the Smoky Mountains ahead of the Chimney Tops 2 Fire, while CONUS404 provides a more spatially varied and localized assessment. Although we cannot determine which estimate is more accurate without observational validation, these examples emphasize the added value of CONUS404's finer spatial resolution for characterizing local fire weather conditions.

Together, these findings underscore the importance of using a high-resolution climate model output, such as CONUS404, for wildfire risk assessment. Its fine scale allows for more localized and reliable estimates of FWI, particularly in topographically complex regions. Additionally, the broader trends observed in figures 6 and 7 highlight spatial and seasonal patterns in fire weather conditions. The consistently higher FWI in the Pacific zone (Z19), as well as the considerable FWI increase in January and November, suggest not only regional disparities in wildfire risk but also a possible extension of the fire season. Figure 8 demonstrates the weather conditions responsible for this shift in the fire season, with variations in precipitation showing the strongest relationship. When combined with the results from the FWI severity analysis (Fig. 9), which shows increasing frequencies of high and extreme FWI days in major California cities, these findings point to a growing and more geographically variable fire threat. Together, these findings emphasize the need for accurate, fine-scale data to support community preparedness, targeted resource allocation, and informed policy development in the face of evolving wildfire risk.

5. CONCLUSIONS

Using the high-resolution regional climate dataset, CONUS404, this study examines historical changes in wildfire risk across the contiguous United States from 1981 to 2020. The analysis was divided across four U.S. subregions – Pacific, Mountain, Central, and Eastern – to assess regional trends in annual fire risks. Monthly analyses were also conducted to investigate decadal shifts in fire seasonality. Lastly, fire weather assessments based on the traditional ERA5 reanalysis were compared with those derived from CONUS404, allowing us to illustrate the benefits of high-resolution modeling for capturing localized fire risk.

The key findings of this study are as follows:

- Annual average FWI has increased across the four U.S. zones, with the Pacific zone showing the highest average and most pronounced rise in FWI from 1981 to 2020, followed by the Mountain, Central, and Eastern zones, respectively. These trends indicate a nationwide intensification of fire weather conditions, most notably in the Pacific zone.
- The cold season (November through March) has exhibited a greater increase in fire potential compared to the warm season. This suggests that fire weather conditions are emerging earlier and persisting later in the year, signaling an extension of the fire season.
- Variations in precipitation are shown to have the strongest influence on monthly changes in FWI, closely followed by relative humidity. Wind and temperature variations have a much weaker influence on monthly FWI change.
- Three major cities in California – Los Angeles, San Diego, and San Francisco – have seen an increase in FWI severity from 1985 to 2020. This reflects the larger regional pattern of increasing wildfire risk across the Pacific zone.
- The coarse spatial resolution of the ERA5 limits its ability to capture local topographic and convective processes that strongly influence fire weather, resulting in regionally biased/unreliable assessments – either overestimating or underestimating risk. In contrast, the higher-resolution CONUS404 dataset is more effective for local fire risk assessment due to its ability to resolve terrain and convective systems.

Future studies should explore peak wildfire years in greater detail, examining the specific weather conditions that contributed to elevated fire risk. It is also necessary to investigate the role of ignition sources, distinguishing between human-caused and naturally occurring fires in relation to fire weather conditions. This may provide improved insight into how different ignition drivers interact with meteorological factors, potentially informing target prevention and mitigation strategies.

6. ACKNOWLEDGEMENTS

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The statements, findings, conclusions, and recommendations presented here are those of the author(s) and do not necessarily reflect the views of the National Science Foundation, NOAA, or the U.S. Department of Commerce.

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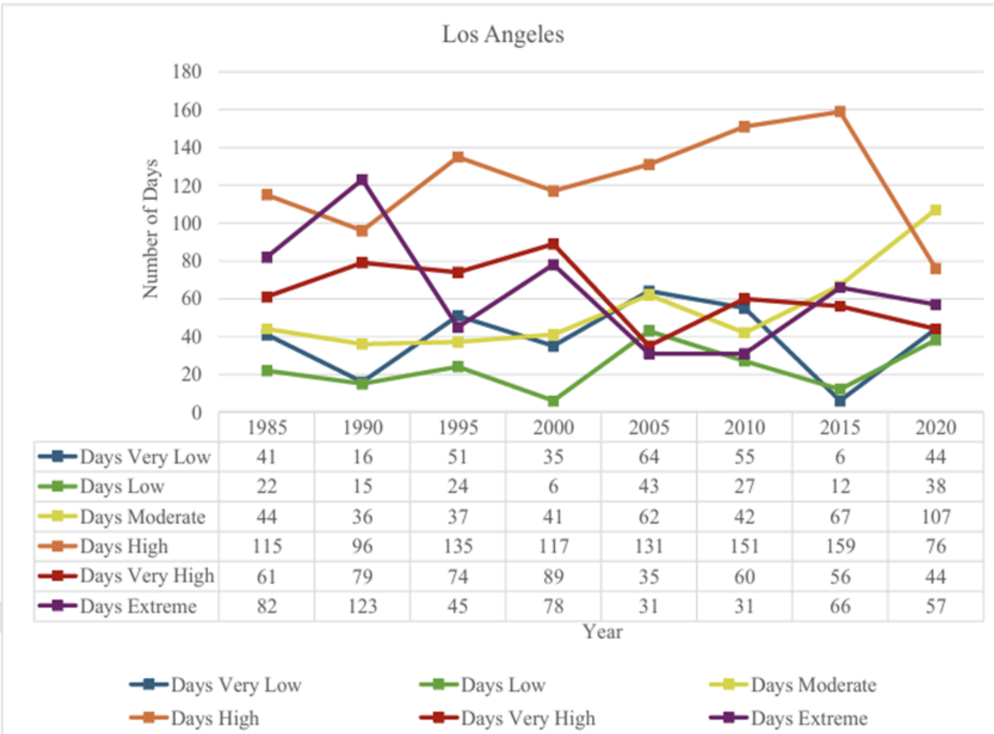
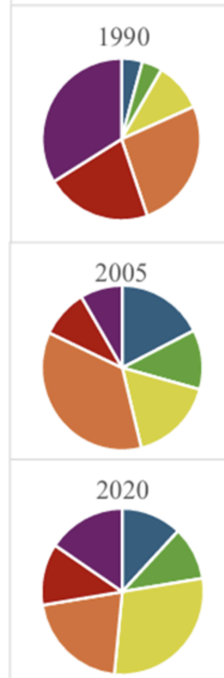
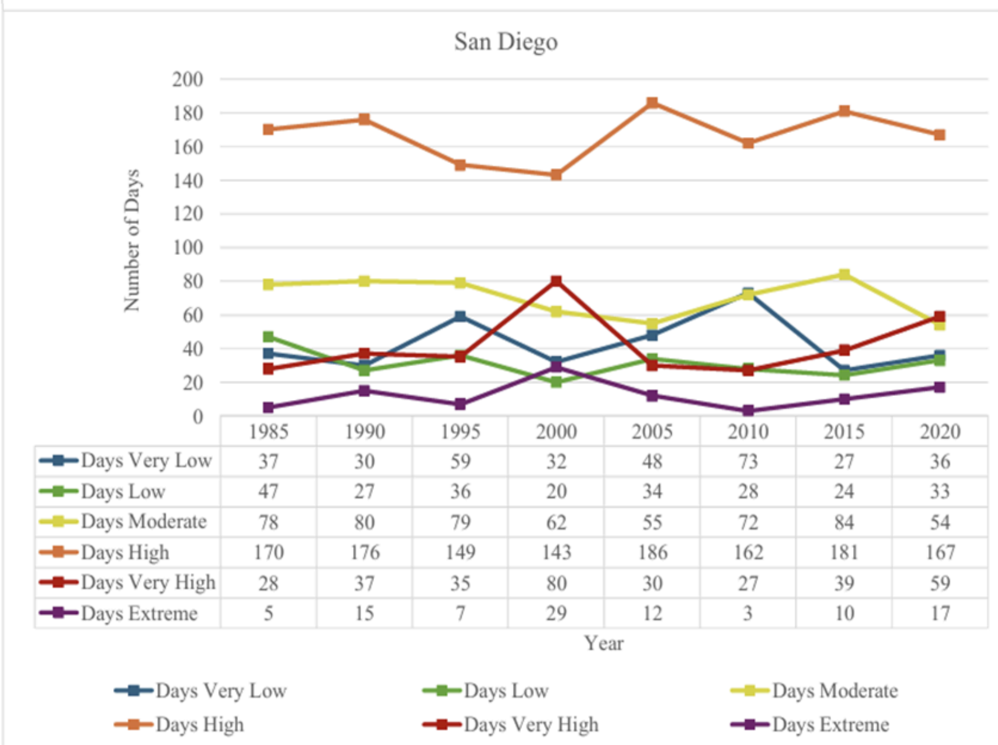
Annual Frequency of FWI Severity Levels (1985-2020)

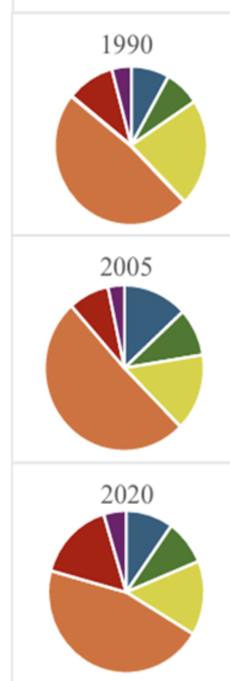


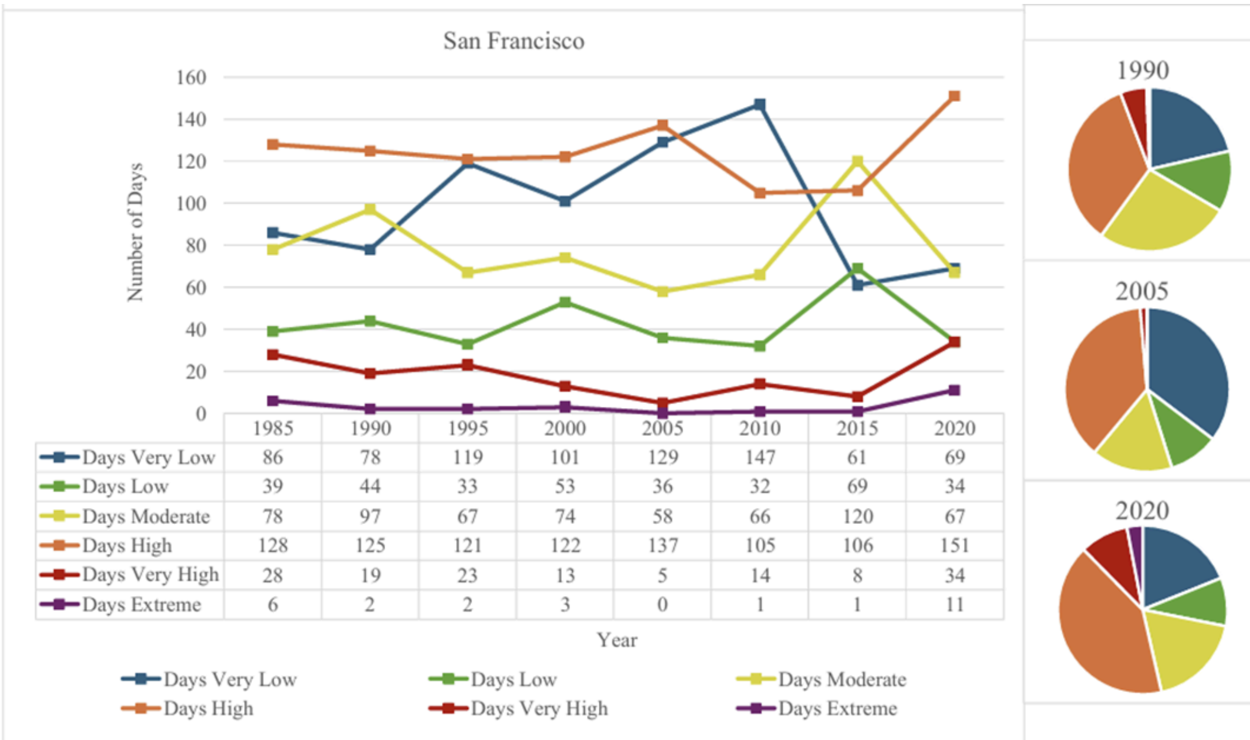
	1985	1990	1995	2000	2005	2010	2015	2020
Days Very Low	41	16	51	35	64	55	6	44
Days Low	22	15	24	6	43	27	12	38
Days Moderate	44	36	37	41	62	42	67	107
Days High	115	96	135	117	131	151	159	76
Days Very High	61	79	74	89	35	60	56	44
Days Extreme	82	123	45	78	31	31	66	57





	1985	1990	1995	2000	2005	2010	2015	2020
Days Very Low	37	30	59	32	48	73	27	36
Days Low	47	27	36	20	34	28	24	33
Days Moderate	78	80	79	62	55	72	84	54
Days High	170	176	149	143	186	162	181	167
Days Very High	28	37	35	80	30	27	39	59
Days Extreme	5	15	7	29	12	3	10	17





	1985	1990	1995	2000	2005	2010	2015	2020
Days Very Low	86	78	119	101	129	147	61	69
Days Low	39	44	33	53	36	32	69	34
Days Moderate	78	97	67	74	58	66	120	67
Days High	128	125	121	122	137	105	106	151
Days Very High	28	19	23	13	5	14	8	34
Days Extreme	6	2	2	3	0	1	1	11

Figure 9. *Annual frequency of Fire Weather Index (FWI) severity levels based on a five-year return period (1985–2020) for three California cities: (A) Los Angeles, (B) San Diego, and (C) San Francisco. Pie charts summarize severity proportions using a fifteen-year return period.*

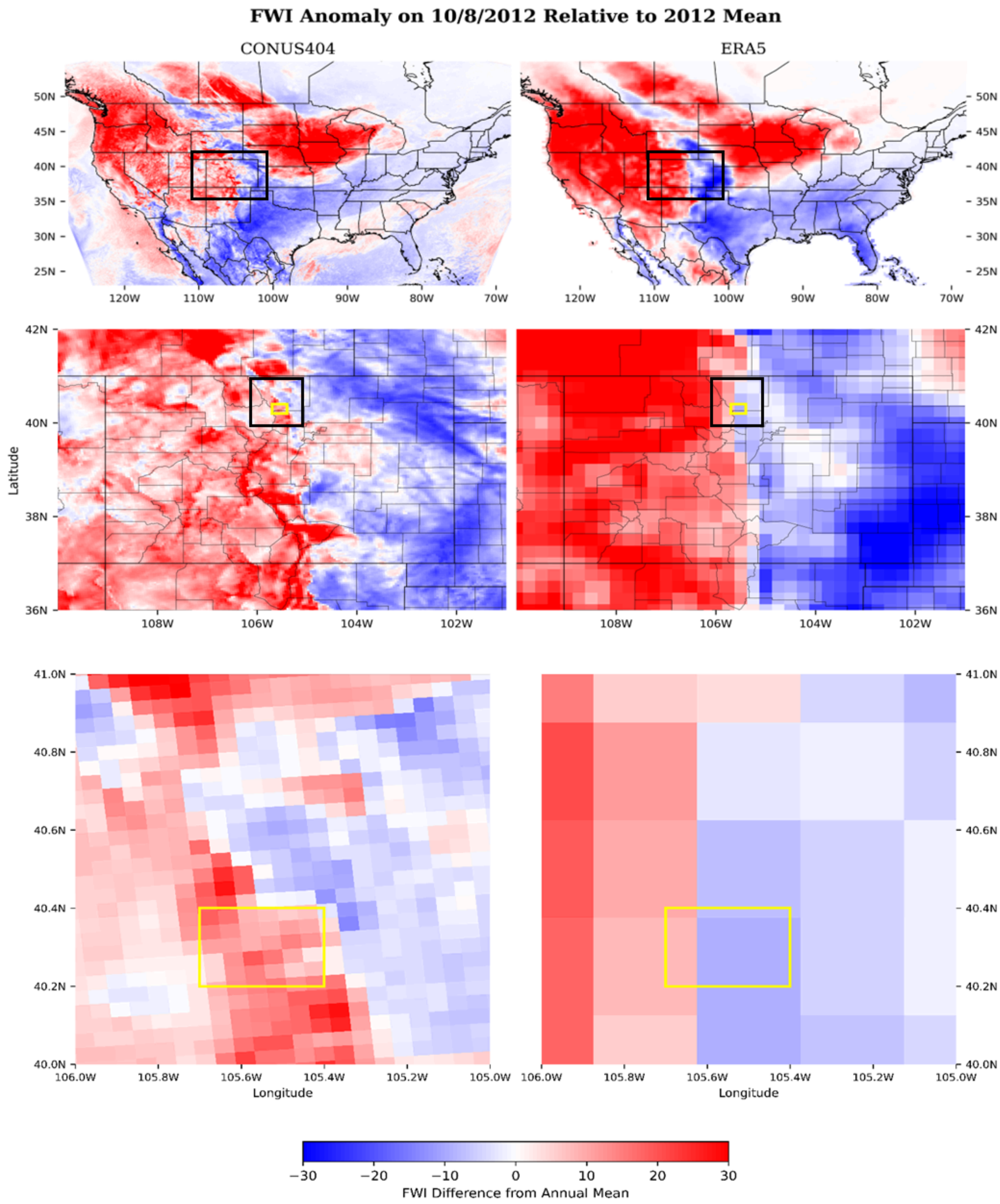


Figure 10. *Spatial comparison of FWI anomalies on October 8, 2012, from the ERA5 and CONUS404 reanalysis. The yellow box indicates the location of the Fern Lake Fire. Black boxes act as extent indicators.*

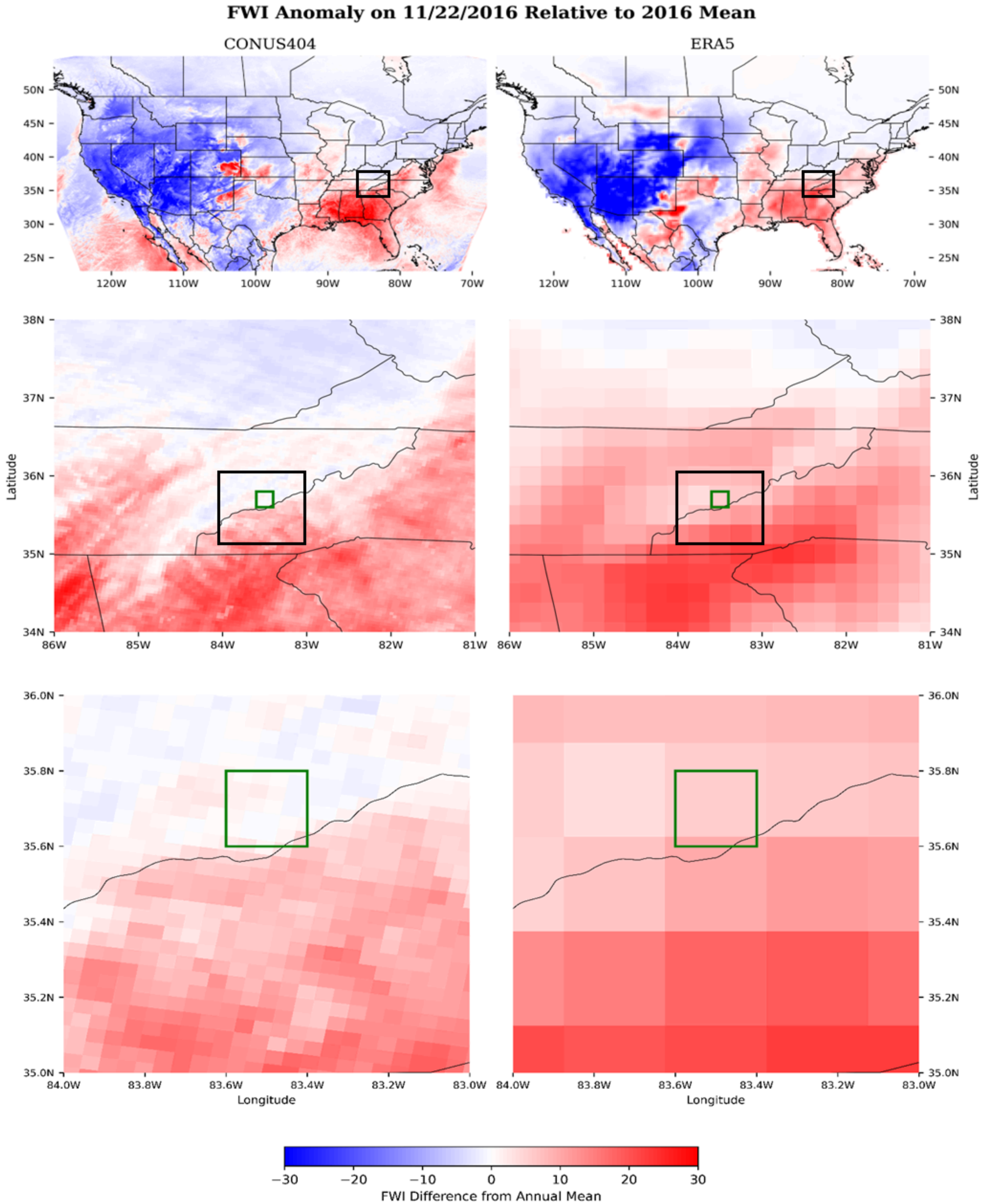


Figure 11. *Spatial comparison of FWI anomalies on November 22, 2016, from the ERA5 and CONUS404 reanalysis. The green box indicates the location of the Chimney Tops 2 Fire. Black boxes act as extent indicators.*