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Understanding the concurrent risk of mental health and dangerous wildfire events in the COVID-19 pandemic

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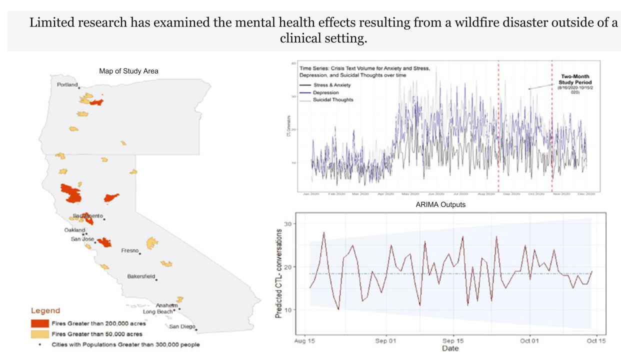
HIGHLIGHTS

- Little research has examined the mental health risks of concurrent disasters.
- We examined crisis response during the 2020 wildfire season and ongoing COVID-19 pandemic.
- We implemented two quasi-experimental analysis to evaluate adolescent mental health impacts.
- No statistically significant increases in CTL-crisis events during the 2020 wildfire season were observed.
- The 2020 COVID-19 pandemic was the main driver of crisis in adolescents and young adults.

GRAPHICAL ABSTRACT



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ABSTRACT

Little research has examined the mental health risks of concurrent disasters. For example, disasters like wildfires have been shown to have a strong association with psychological symptoms—the 2020 U.S. Western wildfire season was the worst on record and occurred while the country was still navigating the COVID-19 pandemic. We implemented two quasi-experimental analyses, an interrupted time series analysis, and a difference-in-difference analysis to evaluate the impacts of wildfires and COVID-19 on mental health crisis help-seeking patterns. Both methods showed no statistical association between exposure to wildfires and the seeking of mental health support during the COVID-19 pandemic. Results highlighted that 2020 wildfires were not associated with an acute increase in crisis texts for youth in the two months after the events, likely due to an already elevated text volume in response to the COVID-19 pandemic from March 2020 throughout the fall wildfire season (Aug to Oct 2020). Future research is needed outside of the context of the pandemic to understand the effects of extreme and concurrent climatic events on adolescent mental health, and targeted interventions are required to ensure youth and adolescents are receiving adequate support during these types of crisis events.

1. Introduction

As climate change intensifies weather extremes, natural hazards have the potential to concur and interact to amplify health risks. The ongoing COVID-19 pandemic is a health-induced disaster, with cases and

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deaths in the U.S. as high as 32.9 million and 584,000 deaths as of May 2021. The pandemic corresponded with several natural disasters, including Hurricane Laura (2020) and the Western U.S. Wildfires (2020). To date, little is known on the impacts of concurrent hazards of COVID-19 and natural disasters. Recent research demonstrated the potential compounding health risks, including amplification in COVID-19 infection rates and other adverse health effects, following the concurrent event of a natural disaster during the COVID-19 crisis (Quigley et al., 2020).

The 2020 wildfires were the worst fire season on record as over 25 million hectares burned across California and Oregon (Higuera and Abatzoglou, 2021). Previous studies have shown a strong association between mental health conditions like posttraumatic stress disorder (PTSD), major depressive disorder, and generalized anxiety disorder following wildfires in Canada (Moosavi et al., 2019) and psychological symptoms in Greece (Adamis et al., 2011), Australia (McFarlane et al. 1997; Reifels et al., 2015), and the United States (Marshall et al., 2007). Results have also suggested a stronger association in youth and adolescent populations with elevated rates of PTSD after wildfires in Australia (Yelland et al., 2010) and increases in depression and suicidal thinking among Canadian youth (Brown et al., 2019). In general, the varied mental health responses and sequence of progression in adolescents following a disaster can manifest as conditions from acute stress reactions, adjustment disorders, depression, panic disorder, anxiety, and PTSD (Kar, 2009). Despite ample international research, little research has been conducted on the mental health impacts of fire in the U.S., particularly among adolescent and youth populations. To date, no studies have examined the effects of climate disasters in the context of the ongoing COVID-19 pandemic.

This study will leverage a novel digital mental health data set, which has been validated with emergency department visits (Runkle et al., 2021a, 2021b), to examine the mental health impacts of the unprecedented 2020 wildfire events concurrently with the ongoing COVID-19 pandemic. As methods are still evolving to examine concurrent disasters, we employed two separate quasi-experimental methodologies to study the causal impact of the 2020 wildfires on crisis response in the backdrop of elevated crisis response brought on by the pandemic. Our results will provide new knowledge on the impact of the 2020 wildfire season and highlight the need for further research at the intersection of concurrent disasters and the effects of adolescent mental health,

2. Data

Near real-time scrubbed and anonymized data harnessed from a Crisis Line that serves users via text message, Crisis Text Line (CTL), has significant potential to capture population-level changes in mental health concerns, such as the ongoing COVID-19 pandemic and the impacts of natural disasters. CTL is a global not-for-profit organization that provides a free and confidential mental health texting service that is available 24 h a day, 7 days a week, and provides a large comprehensive dataset of mental health issues with over 6,000,000 conversations since August 2013 (Crisis Trends, 2021). CTL text-based conversations provide novel insight into help-seeking behavior concerning a wide assortment of commonly reported issues, including anxiety, bullying, depression, family and school-related problems, and suicidal thoughts. CTL's texting platform passively collects anonymous data that can provide valuable insight into the temporal and geographic variation of help-seeking behaviors and crisis mental health service support needs (Sugg et al., 2019a; Sugg et al., 2019b; Thompson et al., 2018). CTL users are matched with a trained crisis counselor who engages with the user via text message. At the end of each conversation, CTL users are invited to an optional survey that collects information on age, demographics, and other relevant identifiers (e.g., LGBTQ+ (Pisani et al., 2019). In addition, the service employs a complex algorithm to label text conversations with a crisis response tag (e.g., suicidal thoughts, self-harm, depression) and conversations are triaged based on whether or not a texter expressing suicidal thoughts or self-harm (characterized as imminent risk).

We included the following crisis response binary variables as mental health proxies in our analysis: suicidal thoughts, self-harm, anxiety and stress, depression, relationship issues, abuse (emotional, physical, and sexual), substance abuse, bereavement, and isolation. We also included an outcome measure for all crisis text events as an overall measure of crisis volume for a given geographic area. CTL-data is limited to the area-code spatial scale, however, nearly 3 out of 4 participants are adolescents and likely reside in the same location as their phone number. CTL data was restricted to participants who completed post-conversation surveys that included age, gender, sexual identity, and racial-ethnic information.

Wildfire locations were identified using the geospatial multiagency coordination (GeoMac)'s National Interagency Fire centers as geographic information system (GIS) shapefiles of fire perimeter extent. Fire impact areas were restricted to the three largest fires that impacted large population centers the 1.) LNU Lightning complex fire in Napa Valley, California (approximately 317,684 acres), 2.) the SCU Lightning Complex near San Jose, California (approximately 396,624 acres), and 3.) the Bobcat fire in Los Angeles County, California (approximately 115,998 acres) (Table 1, Fig. 1). Wildfire exposure was defined as an area code location directly impacted by wildfire (direct location of either the LNU Lightning Complex Fire, SCU Lightning Complex Fire, or the Bobcat fire). CTL conversations were assigned to wildfires using these area-code boundaries. Control locations were identified in the Western US as locations with an absence of wildfire (Supplemental Fig. 1) during the exposure period and were based on similar race, female to male ratio, age proportions, and when possible, employment rates (Table 1, Fig. 1).

This study was exempt from the Appalachian State University's IRB review board (protocol#: 23563).

3. Methods

Descriptive statistics were performed to examine the mean daily CTL volume and corresponding standard deviation. Paired tests were used to determine whether mean daily CTL volume for each outcome differed by intervention period (alpha = 0.05).

3.1. Interrupted time series analysis

Interrupted time series (ITS) allows for the comparison across time (pre/post design) within a single population (i.e., each individual serves as their own control) and is considered one of the stronger non-randomized experimental designs (Turner et al., 2020). By utilizing a single population, ITS avoids selection bias and unmeasured confounders (i.e., underlying trends that change slowly over time, secular changes), which are significant limitations among studies that utilize between-group differences (Bernal et al., 2018; Bernal et al., 2017). In our study, the pre-intervention period was defined as January 01, 2020, to August 16, 2020 (227 days) and the post-intervention period was defined as August 17 to October 15, 2020 (60-days) following each wildfire event: a) LNU Lightning Complex; b) SCU Lightning Complex; and c) Bobcat. The CTL-crisis response outcomes of each wildfire event were examined for the 1) impact group, the 2) control group, and 3) at the state level for California and Oregon for the 60-day post-intervention period.

An interrupted time-series design captured the immediate impact of crisis text patterns using autoregressive integrated moving average models (ARIMA) to analyze repeated measures of daily CTL volume and address time-series autocorrelation. The ARIMA (p,d,q) parameters were specified using autocorrelation and partial autocorrelation across lag periods. The final ARIMA model (0,1,1) was confirmed using plot residuals, lag plots, histograms of the residuals, the Ljung-Box statistic (p-value>0.05), and PACF/ACF values of lags and residuals. All diagnostics

Table 1
2020 Wildfires included in the analysis and respective impacted locations and control locations used in the DID methodology.

Fire name	Relative location	Date	Fire impact area codes	Control area codes (difference)[a]	Relative size (acres)
LNU lightning complex	California, Napa Valley	8/17-10/2	707 530	623 (AZ) 480 (AZ)	317,684
SCU lightning complex	California, San Jose, and many other cities	8/16-10/1	408 669 925 209	916 (CA) 505 (NM)	396,624
Bobcat	California, Los Angeles County	9/6-10/13	661 626	760 (CA) 323 (CA)	115,998

[a] Control locations were selected based on the absence of wildfire during the exposure period and similar racial, female to male ratio, age proportions, and when possible, employment rates.

confirmed no correlation and a relatively normal distribution among residuals. The final ARIMA models were constructed for all CTL conversations in wildfire impact areas and provided the forecasted expected text volume compared to the observed text volume (alpha $= 0.10$). Expected conversation rates for the impact period were forecasted using Hyndmans and Khankara's ARIMA algorithm R (Hyndman and Khandakar, 2008). A sensitivity analysis was computed for crisis response outcomes at the state level for California and Oregon for 60-days (August 17 to October 15) to ensure other spillover wildfire effects (e.g., smoke exposure) did not impact the larger geographical region.

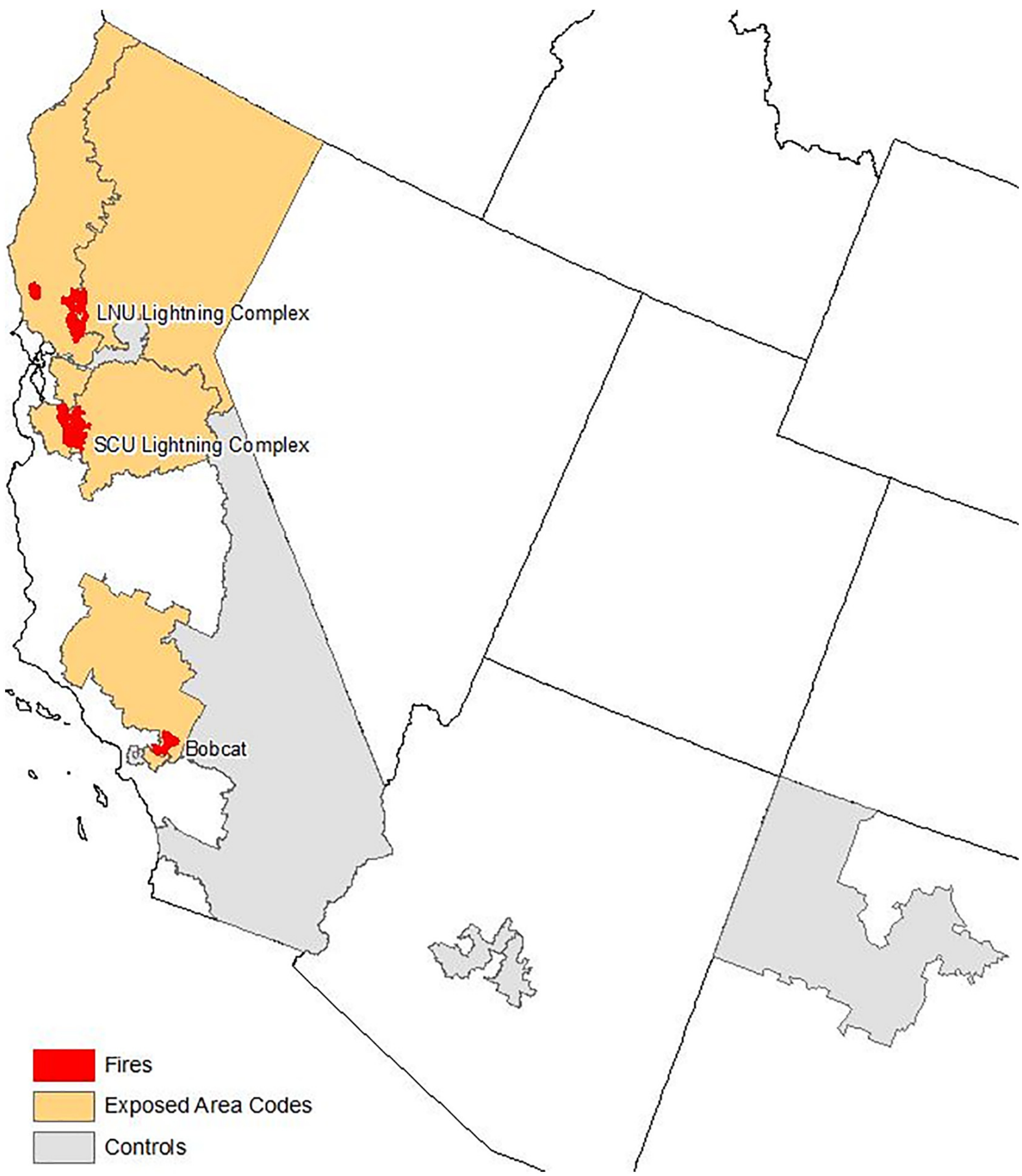

Fig. 1. Map of wildfire locations and corresponding area codes (spatial unit of analysis).

3.2. Comparative - ITS

One disadvantage of the use of interventional ARIMA in ITS is the inability to exclude some time-varying confounding events (e.g., wildfire and COVID-19) occurring at the same time (Bernal et al., 2018). Thus, in an effort to minimize the potential confounding of co-occurring events, we also included control (i.e., counterfactual) locations where wildfires did not occur. ARIMA (0,1,1,) were also computed on locations not impacted by wildfires. This comparative ITS design is typically not done in other ITS analysis, as few as one-fourth of ITS studies include some form of control (Turner et al., 2020). Comparative ARIMA models were constructed for the three control regions (Table 1, Fig. 1), and forecasted results were compared to observed values (alpha = 0.10).

3.3. The difference in difference (DID) analysis

Difference-in-difference (DID) is a separate quasi-experimental research study design for analyses of observational data using two-time points by differencing the change in the exposed group (locations impacted by wildfire) minus the change in the unexposed group (similar locations not affected by wildfire). One difference examines the impact of living in an area code impacted by wildfire (exposed) compared to an area code with no wildfire impacts (control). A second difference examined the geographical comparator during the timeframe of the wildfire event (control) compared to the time frame outside the wildfire event (exposed). For this analysis, the CTL data was restricted to area codes that were exposed and unexposed (control). Unlike our ARIMA analysis, the use of DID allows for the inclusion of the control group(s) (i.e., counterfactual) and the control of additional variables (e.g., age, repeated measures) (Li et al., 2021). In our study, generalized estimating equations were constructed for the following CTL outcomes 1.) Stress/Anxiety 2.) Isolation 3.) Depression 4.) Suicidal Thoughts 5.) Self-Harm 6.) Substance Abuse and 7.) Abuse for each fire. GEE models accounted for repeated measures of text conversations, using the actor I·D, using an autoregressive correlation structure (i.e., the unique identifier for each texter). After fitting the regression equation for each CTL outcome, we adjusted for the age of the CTL-texter in all final models, which showed no significant changes.

3.4. Sensitivity analysis

A final sensitivity analysis was computed for the Kincade fire (October 23, 2019) for area codes (707, 530) impacted by the wildfire to assess if wildfire had an impact on mental health prior to the pandemic period using the ARIMA (0,1,1) model. As control locations were not identified for these locations, no other analysis was conducted for this time period.

4. Results

The volume of texts received by CTL increased during the pandemic period (starting in March 2020) and remained elevated throughout the study period (October 2020, Fig. 2). The number of CTL texts for any reason during the exposure period were 14.76, 9.65, and 8.33 daily texts for the SNU lightning complex, the Bobcat, and the LNU lightning complex fire, respectively. Comparatively, the number of CTL texts for any reason during the non-exposure period (outside of the fire period) in the exact locations were 12.90, 8.01, 6.97 daily texts for the SNU lightning complex, the Bobcat, and the LNU lightning complex fire, respectively. Self-harm, stress/anxiety, isolation, relationship, and abuse were significantly higher in the wildfire time period (p-value <0.10) than the non-wildfire time period for area codes impacted by the three fires. In contrast, significant declines in suicidal thoughts and bullying texts occurred for impacted area codes during the post-wildfire exposure period compared to the pre-wildfire period (Table 2).

4.1. Interrupted time series analysis results

The ARIMA (0,1,1) was the best fit model to examine the pre-/post-change in daily CTL texts for wildfire impacted areas. The daily crisis texts were forecasted for the impacted area codes for August 16 to October 15, 2020, for all CTL texts (Fig. 3). Forecasted results were compared to observed values and were not significant across the pre-and post-intervention time period, except for select dates (Fig. 2). Using the ARIMA (0,1,1), forecast results were replicated for the state level (California and Oregon) and also found not to be significant (alpha = 0.10) (Supplementary Fig. 2). The 2020 wildfire control regions (Table 1) also showed pre- versus post trends that were not statistically significant for all CTL texts, similar to locations impacted by wildfires (Fig. 4). Exceptions included the dates of the control location for the SCU lightning fire that were significantly higher from 09/05–09/07 and 09/21.

4.2. DID results (during fires)

Fig. 5 shows the odds ratio and 95% confidence interval for the difference and difference estimator (location exposure*time exposure), the time of exposure, and location exposure. There were no significant differences in outcomes after adjusting for age, gender, or race in the final models.

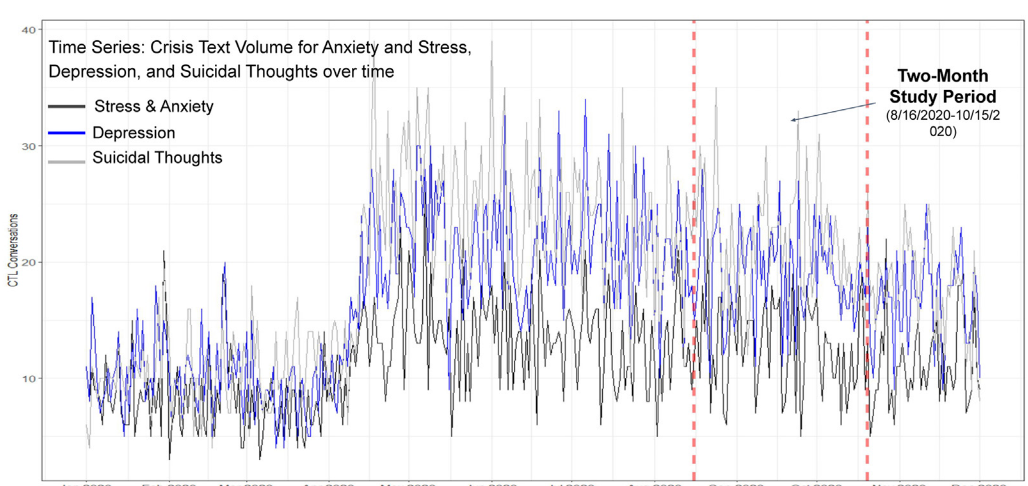

Fig. 2. Time-series of crisis texts for California and Oregon from January 2020 to December 2020.

Table 2
Comparison of CTL texts during the exposure time period (8/16/2020 to 10/15/2020) and outside the exposure time period (1/1/2020 to 8/15/2020 and 10/16/2020 to 12/1/2020) for fire impacted area codes. CTL texts are flagged with the following issues: depression, suicidal thoughts, self-harm, stress and anxiety, relationship issues, substance abuse, bereavement, bullying, eating issues, isolation, abuse, LGBTQ issues, racial issues.

	Strata	Non-wildfire time exposure	Wildfire time exposure	p
n		48,415	3430	
Depressed (%)	No	34,563 (71.4)	2415 (70.4)	0.227
	Yes	13,852 (28.6)	1015 (29.6)	
Suicidal thoughts (%)	No	37,921 (78.3)	2773 (80.8)	0.001
	Yes	10,494 (21.7)	657 (19.2)	
Self harm (%)	No	43,199 (89.2)	3035 (88.5)	0.185
	Yes	5216 (10.8)	395 (11.5)	
Stress and anxiety (%)	No	35,506 (73.3)	2276 (66.4)	<0.001
	Yes	12,909 (26.7)	1154 (33.6)	
Relationship (%)	No	36,525 (75.4)	2494 (72.7)	<0.001
	Yes	11,890 (24.6)	936 (27.3)	
Substance abuse (%)	No	47,705 (98.5)	3372 (98.3)	0.328
	Yes	710 (1.5)	58 (1.7)	
Bereavement (%)	No	47,087 (97.3)	3301 (96.2)	0.001
	Yes	1328 (2.7)	129 (3.8)	
Bully (%)	No	47,316 (97.7)	3386 (98.7)	<0.001
	Yes	1099 (2.3)	44 (1.3)	
Eating (%)	No	46,996 (97.1)	3317 (96.7)	0.245
	Yes	1419 (2.9)	113 (3.3)	
Isolated (%)	No	41,300 (85.3)	2848 (83.0)	<0.001
	Yes	7115 (14.7)	582 (17.0)	
Abuse (%)	No	45,907 (94.8)	3221 (93.9)	0.023
	Yes	2508 (5.2)	209 (6.1)	
LGBTQ (%)[c]	No	47,495 (98.1)	3365 (98.1)	0.999
	Yes	920 (1.9)	65 (1.9)	
Active rescue (%)[b]	No	48,215 (99.6)	3421 (99.7)	0.228
	Yes	200 (0.4)	9 (0.3)	
Imminent risk (%)[a]	No	47,597 (98.3)	3378 (98.5)	0.487
	Yes	818 (1.7)	52 (1.5)	
Race (%)	African American	2557 (5.3)	155 (4.5)	<0.001
	American Indian/Alaska Native	1455 (3.0)	77 (2.2)	
	Asian	4774 (9.9)	460 (13.4)	
	Hispanic	9098 (18.8)	708 (20.6)	
	Mixed race	1628 (3.4)	135 (3.9)	
	No response	7761 (16.0)	542 (15.8)	
	Other	450 (0.9)	36 (1.0)	
	Prefer not to answer	3064 (6.3)	210 (6.1)	
	White	17,628 (36.4)	1107 (32.3)	
Gender (%)	Female	30,615 (63.2)	2199 (64.1)	<0.001
	Male	5607 (11.6)	350 (10.2)	
	No response	7045 (14.6)	484 (14.1)	
	Non-binary	297 (0.6)	41 (1.2)	
	Other	3524 (7.3)	286 (8.3)	
	Transgender	1327 (2.7)	70 (2.0)	
Age (%)	0–13	5311 (11.0)	460 (13.4)	<0.001
	14–24	30,411 (62.8)	2019 (58.9)	
	25–44	7754 (16.0)	549 (16.0)	
	45–64	2194 (4.5)	133 (3.9)	
	65+	128 (0.3)	15 (0.4)	
	Not available	2617 (5.4)	254 (7.4)	

[a] Imminent risk: A CTL texter with suicidal thoughts and ideation with a plan to end life within 2-days.
[b] Active rescue: CTL is unable to de-escalate a texter with a plan for suicide resulting in the initiation of active rescue.
[c] LGBTQ = lesbian, gay, bisexual, transgender, and queer.

4.3. Sensitivity analysis

A final sensitivity analysis using ARIMA was computed for the Kincade fire (October 23, 2019) for area codes (707, 530) impacted by the wildfires to assess if this event was negatively associated with mental health prior to the pandemic. Results were not statistically significant, with the exception of two days (10/07/2019, 09/27/2019) across the 60-day time window (Supplemental Fig. 3).

5. Discussion

The objective of this study was to examine the mental health impacts of concurrent disasters, the 2020 wildfires, and the COVID-19 pandemic on adolescent and young adult mental health in the Western U.S. Overall, we found no association between wildfire exposure and excess crisis text for mental health support among youth and adolescents. Our results are surprising as the 2020 wildfire season was one of the worst on record (Higuera and Abatzoglou, 2021) and occurred amidst a global pandemic, which has upended the lives of many youth and adolescents. These results suggest that the mental health impacts from the unprecedented COVID-19 pandemic overshadowed the psychophysical implications of the 2020 wildfires, as the mental health impacts of COVID-19 have been substantial with significant increases in some crisis response outcomes (e.g., stress/anxiety, substance abuse, isolation, abuse, bereavement) among adolescents (Runkle et al., 2021a, 2021b).

Our null results contradict limited studies which have found a high prevalence of mental health conditions in young people after fire events (Brown et al., 2019; Dorn et al., 2008). Unlike previous work, which is

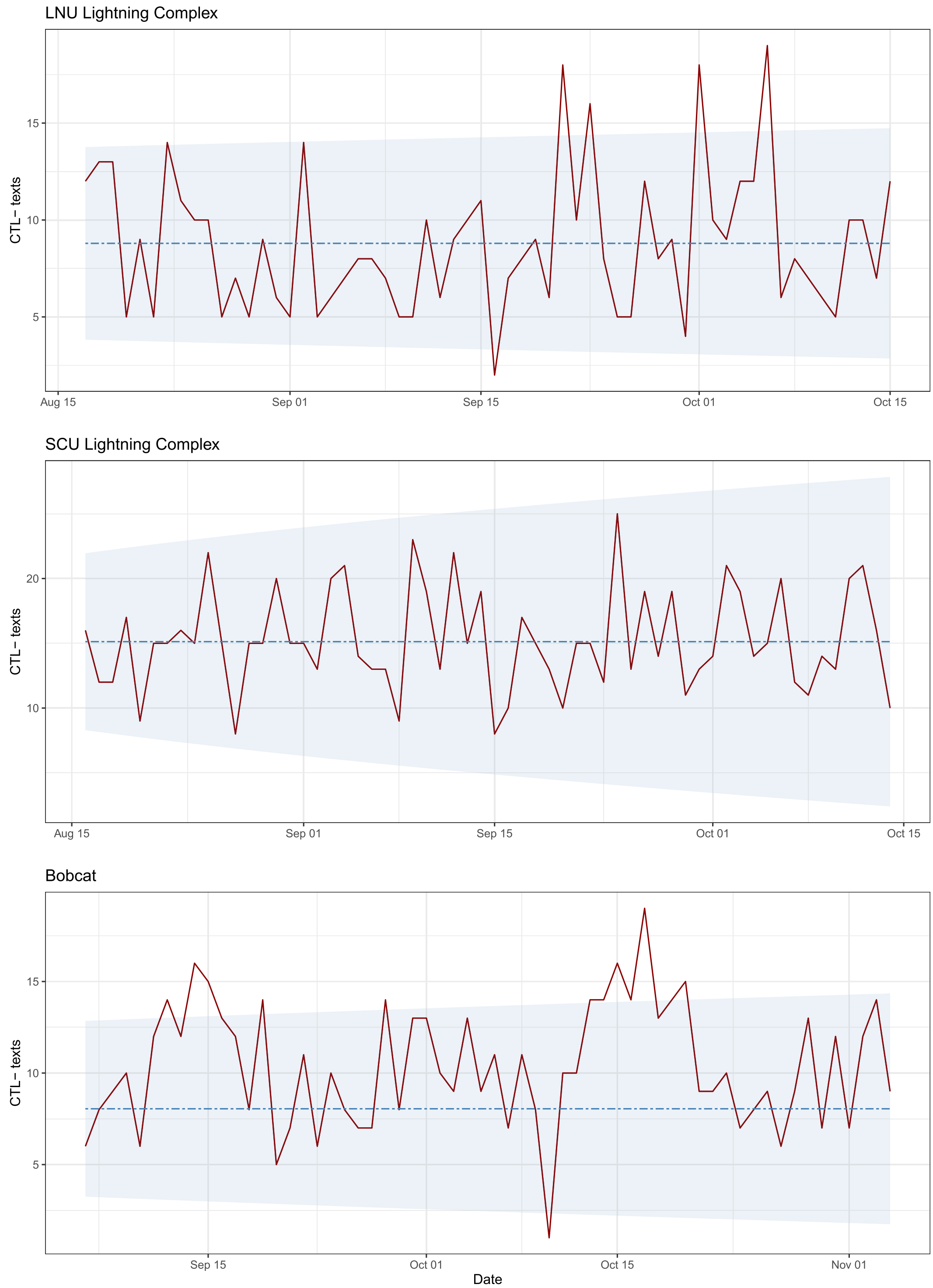

Fig. 3. Expected (dashed blue lines) versus observed (red lines) ITS results for LNU lightning complex figure (top), the SCU lightning complex fire (middle), and the Bobcat fire (bottom). Expected results are shown with 90% confidence intervals (blue shading).

limited to cross-sectional surveys (Brown et al., 2019) or electronic medical records (Dorn et al., 2008), our work utilized a real-time longitudinal data source of scrubbed and anonymized Crisis Text Line conversation data. The mixed findings among our analysis and others are potentially the result of incomparable study populations, the difference in study design, the analytic method to control for confounding or wildfire exposure classification, and the potential heterogeneity in wildfire exposure among different events. For instance, precise measures of wildfire exposure are difficult to obtain and can differ by the magnitude of the event or do not account for local adaptive response or the underlying resilience of the population (Goldmann and Galea, 2014). Regardless of how wildfire events are measured, greater or more intense exposure for directly impacted areas consistently and strongly predicts a higher risk of psychopathology, often showing a dose-response relationship (Maguen et al., 2012; Norris et al., 2002; Goldmann and Galea, 2014). These differences in research designs, exposure classifications, minimal consideration of resilience models, as well as the underlying COVID-19 pandemic may, in part, explain the differences in our results.

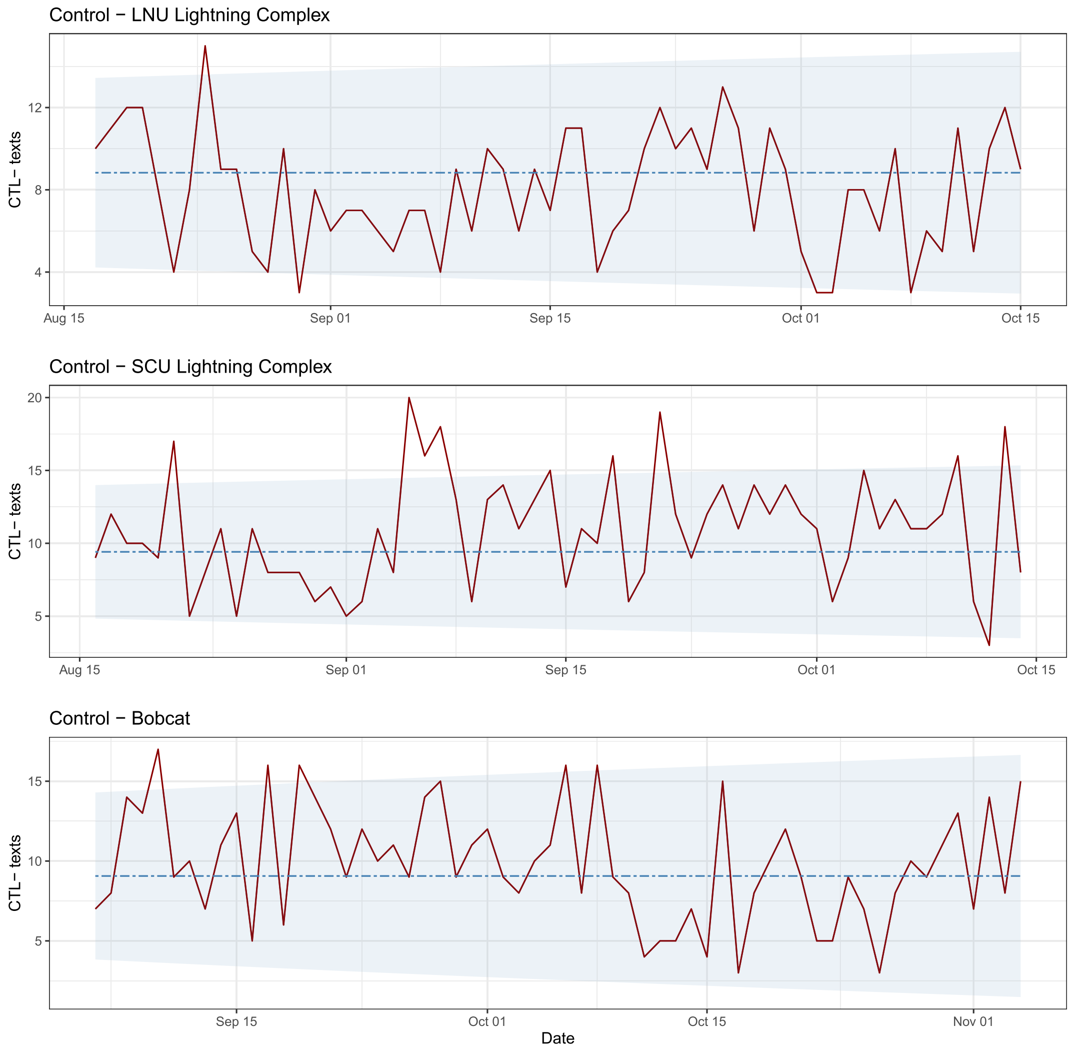

Fig. 4. Expected (dashed blue lines) versus observed (red lines) ITS results for **control regions** for the LNU lightning complex figure (top), the SCU lightning complex fire (middle), and the Bobcat fire (bottom). Expected results are shown with 90% confidence intervals (blue shading).

We did note a decrease in outcomes like depression and suicidal thoughts for exposed locations during the wildfire event. These decreases could be due to coming together during the community cohesion phase of disaster response (Townshend et al., 2015). The Federal Emergency Management Agency (FEMA) and Substance Abuse and Mental Health Services Administration (SAMHSA)'s widely used model highlights six phases of a single disaster, with high emotions in the impact (phase two), heroic (phase three), and honeymoon phases (phase four), which is characterized by the availability of disaster assistance, optimism, and altruism. Wildfire responses in our analysis may have been limited to these phases of emotion rather than the later phases that are characterized by disillusionment and abandonment (phase five) (DeWolfe, 2000). Our cohort of CTL users may follow similar patterns as the SAMSHA model. However, the SAMSHA model was constructed for a single disaster rather than multi-disaster events, and new frameworks are needed to understand the mental health patterns of concurrent and cascading disasters.

Most likely, the COVID-19 pandemic was the main driver of elevated crisis events during 2020, which resulted in the increased prevalence of texts for isolation, stress/anxiety, and depression after March 2020 (Runkle et al., 2021a, 2021b). The 2020 wildfires were not associated with an acute increase in crisis texts for youth in the two months after the events, likely due to an already elevated text volume in response to the COVID-19 pandemic. This result contrasts with other studies which have found elevated crisis text use six weeks after other natural hazards like the impact of Hurricane Florence on crisis text response in youth (2018), which occurred prior to the COVID-19 pandemic (Runkle et al., 2021a, 2021b). Adolescents and young adults were likely already experiencing psychosocial stressors before this wildfire event. Therefore, the concurrent disaster did not result in elevated rates beyond what they were currently reporting. For instance, typical CTL users may have already been engaged in CTL texts prior to the wildfire event and continued their use of the service during these wildfire events. Alternatively, adolescents and youth may have demonstrated resilience during the wildfire 2020 event using community cohesion and coping strategies from the COVID-19 pandemic and applying them to the 2020 wildfire event (Masten and Motti-Stefanidi, 2020). Despite our null findings, CTL and other adolescent mental health services should focus on outreach during these critical disaster periods, as other studies have noted increases in adverse mental health conditions 6-, 12-, and 18-months post-wildfire events.

6. Strengths and limitations

Our work had several notable strengths. First, quasi-experimental research designs have been underutilized in the wildfire and mental health literature. One advantage to these designs is the ability to address the potential for uncontrolled confounding by adding a control group

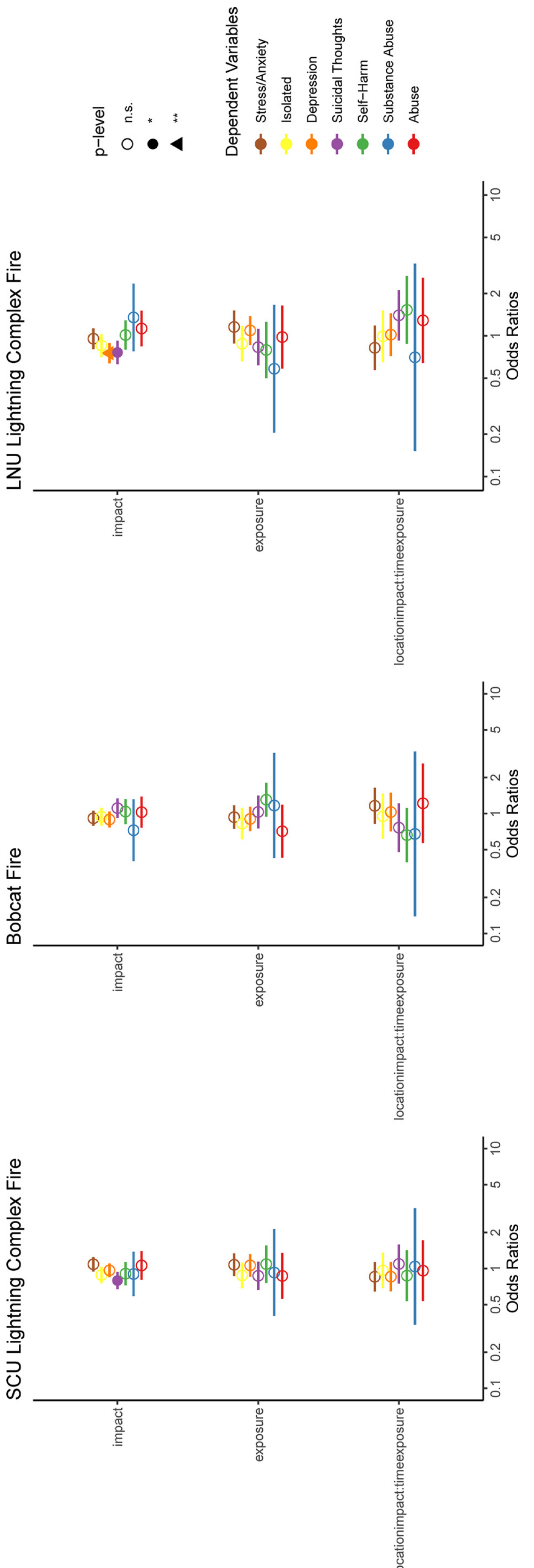

Fig. 5. The difference in difference analysis odds ratio results for the SCU lightning complex, Bobcat fire, and the LNU lightning complex fire. Odds ratios are shown at 95% confidence intervals for specific crisis outcomes. *refers to significance at p-value <0.05 **refers to significance at p-value <0.01 ***refers to significance at p-value <0.001, n.s., refers to not significant.

(DID analysis) or limiting between-group differences (ITS analysis). Designs that do not account for uncontrolled confounding and the use of more traditional methods (i.e., spatial regressions) have indicated significant associations between natural hazards events and health consequences, despite quasi-experimental methods applied to the same scenario showing little to no association (Grabich et al., 2015a, 2015b). Secondly, our study utilized a large, longitudinal data set of crisis texts which contrast with common cross-sectional surveys found in disaster-mental health literature that often fail to examine temporal trends and the delayed onset of psychosocial symptoms. Additionally, unlike other ITS studies that focus on the region impacted (e.g., Pridemore et al., 2008) and fail to show comparative or counterfactual results, we further replicated our ITS analysis for wildfire exposed area codes (impact group) and non-wildfire exposed area codes (control group). We included multiple directly impacted locations (e.g., state-level and area-code level) in our ITS analysis to account for difficult-to-measure factors, such as smoke (e.g., common across the state), and the inclusion of representative control groups to ensure no trends were observed in these locations. Lastly, our work utilized two robust causal analytic techniques common to quasi-experimental research designs, ITS and DID, to ensure our null results are robust.

A major limitation to our study was the inability to directly distinguish between COVID-19 impacts and 2020 wildfire impacts during our exposure time period. However, we employed a quasi-experimental research design that included a pre-intervention period and a post-intervention time period that also encompassed the start of the pandemic. At this time, methodologies are limited for assessing the risk of concurrent events like climate disasters and global pandemics. Our results would also benefit from the adjustment of confounding variables due to unmeasured population attributes, like underlying COVID-19 rates or mental health services use. However, due to the unique spatial scale of our data (area code), these data were not available. Moreover, we do not expect the distribution of these variables to change markedly within the two geographical areas. Hence our quasi-experimental approach, in which each texter serves as their own control, has likely accounted for any unmeasured confounding due to these temporal factors (Wing et al., 2018; Hetherington et al., 2021). Yet these approaches, like DID analyses, can be underpowered to detect small differences, and could also have contributed to our null findings (Wing et al., 2018).

Additionally, the aggregate level exposure to wildfire events estimated in our study at the area code level did not necessarily equate to 'actual' personal wildfire exposure, which is a strong predictor of mental health conditions (Goldmann and Galea, 2014). Lastly, in our analysis, the post-intervention period was defined over a short window of time as the wildfire dates corresponded to a 60-day post-intervention period. However, previous studies have found a high prevalence of mental health and addiction as long as 24-months after the wildfire (Reifels et al., 2015; Moosavi et al., 2019). We choose this smaller time window due to numerous large events during September–December 2020, including the U.S. presidential election, social justice issues (i.e., civil unrest from the murders of George Floyd and Breonna Taylor), and continued spikes in COVID-19 outbreaks. Future work should extend the analysis to a longer time interval to examine the delayed mental health effects in this vulnerable age group once the community cohesion or 'honeymoon' phase has subsided and disillusionment has set in. We also recommend that future research utilizes similar research frameworks on other mental health data sets to further explore the association between wildfires and mental health, especially in the context of compounding disasters.

7. Conclusion

This study was the first to examine the concurrent effects of mental health during the 2020 wildfire season and the ongoing COVID-19 pandemic. Our study leveraged a real-time anonymized data set of national crisis events in the U.S. from Crisis Text Line that allowed us to examine pre-and post-event crisis response to both the 2020 wildfires and COVID-19 pandemic. We implemented a quasi-experimental framework to investigate the trends in crisis events using both a difference in difference and interrupted time series analysis. Our results showed no statistically significant increases in CTL-crisis events during the 2020 wildfire season, suggesting that the 2020 COVID-19 pandemic was the main driver of crisis in adolescents and young adults during the study period. Future research and advanced methodologies are needed to disentangle the complex effects of concurrent and cascading disasters.

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CRediT authorship contribution statement

M.S. and J.R. formulated a research design and contributed to the writing of the paper. M.S. implemented the DID analysis and descriptive statistics. S.H. identified wildfire parameters and implemented the ITS analysis. K.M. and S.G. contribute to the writing and reviewing of the manuscript before publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Adamis, D., Papanikolaou, V., Mellon, R.C., Prodromitis, G., 2011. P03-19-The impact of wildfires on mental health of residents in a rural area of Greece. A case control population based study. Eur. Psychiatry 26, 1188.

Bernal, J.L., Cummins, S., Gasparrini, A., 2017. Interrupted time series regression for the evaluation of public health interventions: a tutorial. Int. J. Epidemiol. 46 (1), 348–355.

Bernal, J., Cummins, S., Gasparrini, A., 2018. The use of controls in interrupted time series studies of public health interventions. Int. J. Epidemiol. 47 (6), 2082–2093.

Brown, M.R.G., Agyapong, V., Greenshaw, A.J., et al., 2019. After the Fort McMurray wildfire there are significant increases in mental health symptoms in grade 7–12 students compared to controls. BMC Psychiatry 19, 18. https://doi.org/10.1186/s12888-018-2007-1.

"Crisis Trends." 2021 www.crisistrends.org. Crisis Text Line, March 2018. Web.

DeWolfe, D.J., 2000. Training Manual for Mental Health and Human Service Workers in Major Disasters. U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration, Center for Mental Health Services.

Dorn, T., Yzermans, J.C., Spreeuwenberg, P.M., Schilder, A., Zee, J.V.D., 2008. A cohort study of the long-term impact of a fire disaster on the physical and mental health of adolescents. J. Trauma. Stress. 21 (2), 239–242.

Goldmann, E., Galea, S., 2014. Mental health consequences of disasters. Annu. Rev. Public Health 35.

Grabich, S.C., Robinson, W.R., Engel, S.M., et al., 2015. County-level hurricane exposure and birth rates: application of difference-in-differences analysis for confounding control. Emerg. Themes Epidemiol. 12 (1), 19. https://doi.org/10.1186/s12982-015-0042-7.

Grabich, S.C., Robinson, W.R., Engel, S.M., Konrad, C.E., Richardson, D.B., Horney, J.A., 2015. County-level hurricane exposure and birth rates: application of difference-in-differences analysis for confounding control. Emerg. Themes Epidemiol. 12 (1), 1–8.

Hetherington, E., Adhikari, K., Tomfohr-Madsen, L., Patten, S., Metcalfe, A., 2021. Birth outcomes, pregnancy complications, and postpartum mental health after the 2013 Calgary flood: a difference in difference analysis. PLoS One 16 (2), e0246670.

Higuera, Philip E., Abatzoglou, John T., 2021. Record-setting climate enabled the extraordinary 2020 fire season in the western United States. Glob. Chang. Biol. 27 (1), 1–2.

Hyndman, R.J., Khandakar, Y., 2008. Automatic time series forecasting: the forecast package for R. J. Stat. Softw. 27 (3), 1–22.

Kar, N., 2009. Psychological impact of disasters on children: review of assessment and interventions. World J. Pediatr. 5 (1), 5–11.

Maguen, S., Neria, Y., Conoscenti, L.M., Litz, B.T., 2012. Depression and Prolonged Grief in the Wake of Disasters.

Marshall, G.N., Schell, T.L., Elliott, M.N., Rayburn, N.R., Jaycox, L.H., 2007. Psychiatric disorders among adults seeking emergency disaster assistance after a wildland-urban interface fire. Psychiatr. Serv. 58 (4), 509–514.

Masten, A.S., Motti-Stefanidi, F., 2020. Multisystem resilience for children and youth in disaster: reflections in the context of COVID-19. Adversity Resilience Sci. 1 (2), 95–106.

McFarlane, A.C., Clayer, J.R., Bookless, C.L., 1997 July 01. Psychiatric morbidity following a natural disaster: an australian bushfire. Soc. Psychiatry Psychiatr. Epidemiol. 32 (5), 261–268.

Moosavi, S., Nwaka, B., Akinjise, I., Corbett, S.E., Chue, P., Greenshaw, A.J., Agyapong, V.I., 2019. Mental health effects in primary care patients 18 months after a major wildfire in Fort McMurray: risk increased by social demographic issues, clinical antecedents, and degree of fire exposure. Front. Psych. 10, 683.

Norris, F.H., Friedman, M.J., Watson, P.J., Byrne, C.M., Diaz, E., Kaniasty, K., 2002. 60,000 disaster victims speak: Part I. An empirical review of the empirical literature, 1981–2001. Psychiatry 65 (3), 207–239.

Pisani, A.R., Kanuri, N., Filbin, B., Gallo, C., Gould, M., Lehmann, L.S., Ranney, M.L., 2019. Protecting user privacy and rights in academic data-sharing partnerships: principles from a pilot program at crisis text line. J. Med. Internet Res. 21 (1), e11507.

Pridemore, W.A., Chamlin, M.B., Trahan, A., 2008. A test of competing hypotheses about homicide following terrorist attacks: an interrupted time series analysis of september 11 and Oklahoma City. J. Quant. Criminol. 24 (4), 381–396.

Quigley, M.C., Attanayake, J., King, A., Prideaux, F., 2020. A multi-hazards earth science perspective on the COVID-19 pandemic: the potential for concurrent and cascading crises. Environ. Sys. Decis. 40, 199–215.

Reifels, Lennart, Bassilios, Bridget, Spittal, Matthew J., King, Kylie, Fletcher, Justine, Pirkis, Jane, 2015. Patterns and predictors of primary mental health service use following bushfire and flood disasters. Disaster Med. Public Health Prep. 9 (3), 275–282.

Runkle, J.D., Michael, K.D., Stevens, S.E., Sugg, M.M., 2021. Quasi-experimental evaluation of text-based crisis patterns in youth following hurricane Florence in the carolinas, 2018. Sci. Total Environ. 750, 141702.

Runkle, J.D., Sugg, M.M., Yadav, S., Harden, S., Weiser, J., Michael, K., 2021. Real-time.

Sugg, M.M., Dixon, P.G., Runkle, J.D., 2019. Crisis support-seeking behavior and temperature in the United States: is there an association in young adults and adolescents? Sci. Total Environ. 669, 400–411.

Sugg, M.M., Michael, K.D., Stevens, S.E., Filbin, R., Weiser, J., Runkle, J.D., 2019. Crisis text patterns in youth following the release of 13 reasons why season 2 and celebrity suicides: a case study of summer 2018. Prev. Med. Rep. 16, 100999.

Thompson, L.K., Sugg, M.M., Runkle, J.R., 2018. Adolescents in crisis: a geographic exploration of help-seeking behavior using data from crisis text line. Soc. Sci. Med. 215, 69–79.

Townshend, I., Awosoga, O., Kulig, J., Fan, H., 2015. Social cohesion and resilience across communities that have experienced a disaster. Nat. Hazards 76 (2), 913–938.

Turner, S.L., Karahalios, A., Forbes, A.B., Taljaard, M., Grimshaw, J.M., Cheng, A.C., McKenzie, J.E., 2020. Design characteristics and statistical methods used in interrupted time series studies evaluating public health interventions: a review. J. Clin. Epidemiol. 122, 1–11.

Wing, C., Simon, K., Bello-Gomez, R.A., 2018. Designing difference in difference studies: best practices for public health policy research. Annu. Rev. Public Health 39.

Yelland, C., Robinson, P., Lock, C., La Greca, A.M., Kokegei, B., Ridgway, V., Lai, B., 2010. Bushfire impact on youth. J. Trauma. Stress. 23 (2), 274–277.