Just How Vulnerable are American States to Wildfires? A Livelihood Vulnerability Assessment

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Abstract

Wildland fires are becoming more destructive and costly in the United States, posing increased environmental, social, and economic threats to fire-prone regions. Quantifying current wildfire risk by considering a wide range of multi-scale, and multi-disciplinary variables such as socio-economic and biophysical indicators for resiliency and mitigation measures, deems inherently challenging. To systematically examine wildfire threats amongst humans and their physical and social environment on multiple scales, a livelihood vulnerability index (LVI) analysis can be employed. Therefore, we produce a framework needed to compute the LVI for the top 14 American States that are most exposed to wildfires, based on the 2019 Wildfire Risk report of the acreage size burnt in 2018 and 2019: Arizona, California, Florida, Idaho, Montana, Nevada, New Mexico, Oklahoma, Oregon, Utah, Washington, and Wyoming. The LVI is computed for each State by first considering the State's exposure, sensitivity, and adaptive capacity to wildfire events (known as the three contributing factors). These contributing factors are determined by a set of indicator variables (vulnerability metrics) that are categorized into corresponding major component groups. The framework structure is then justified by performing a principal component analysis (PCA) to ensure that each selected indicator variable corresponds to the correct contributing factor. The LVI for each State is then calculated based on a set of algorithms relating to our framework. LVI values rank between 0 (low LVI) to 1 (high LVI). Our results indicate that Arizona and New Mexico experience the greatest livelihood vulnerability, with an LVI of 0.57 and 0.55, respectively. In contrast, California, Florida, and Texas experience the least livelihood vulnerability to wildfires (0.44, 0.35, 0.33 respectively). LVI is strongly weighted on its contributing factors and is exemplified by the fact that even though California has one of the highest exposures and sensitivity to wildfires, it has very high adaptive capacity measures in place to withstand its livelihood vulnerability. Thus, States with relatively high wildfire exposure can exhibit relatively lower livelihood vulnerability because of adaptive capacity measures in place. On the other hand, States can exhibit a high LVI (such as Arizona) despite having a low exposure, due to lower adaptive capacities in place. The results from this study are critical to wildfire managers, government, policymakers, and research scientists for identifying and providing better resiliency and adaptation measures to support the American States that are most vulnerable to wildfires.

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Abstract

Wildland fires are becoming more destructive and costly in the United States, posing increased environmental, social, and economic threats to fire-prone regions. Quantifying current wildfire risk by considering a wide range of multi-scale, and multi-disciplinary variables such as socio-economic and biophysical indicators for resiliency and mitigation measures, deems inherently challenging. To systematically examine wildfire threats amongst humans and their physical and social environment on multiple scales, a livelihood vulnerability index (LVI) analysis can be employed. Therefore, we produce a framework needed to compute the LVI for the top 14 American States that are most exposed to wildfires, based on the 2019 Wildfire Risk report of the acreage size burnt in 2018 and 2019: Arizona, California, Florida, Idaho, Montana, Nevada, New Mexico, Oklahoma, Oregon, Utah, Washington, and Wyoming. The LVI is computed for each State by first considering the State's exposure, sensitivity, and adaptive capacity to wildfire events (known as the three contributing factors). These contributing factors are determined by a set of indicator variables (vulnerability metrics) that are categorized into corresponding major component groups. The framework structure is then justified by performing a principal component analysis (PCA) to ensure that each selected indicator variable corresponds to the correct contributing factor. The LVI for each State is then calculated based on a set of algorithms relating to our framework. LVI values rank between 0 (low LVI) to 1 (high LVI). Our results indicate that Arizona and New Mexico experience the greatest livelihood vulnerability, with an LVI of 0.57 and 0.55, respectively. In contrast, California, Florida, and Texas experience the least livelihood vulnerability to wildfires (0.44, 0.35, 0.33 respectively). LVI is strongly weighted on its contributing factors and is exemplified by the fact that even though California has one of the highest exposures and sensitivity to wildfires, it has very high adaptive capacity measures in place to withstand its livelihood vulnerability. Thus, States with relatively high wildfire exposure can exhibit relatively lower livelihood vulnerability because of adaptive capacity measures in place. On the other hand, States can exhibit a high LVI (such as Arizona) despite having a low exposure, due to lower adaptive capacities in place. The results from this study are critical to wildfire managers, government, policymakers, and research scientists for identifying and providing better resiliency and adaptation measures to support the American States that are most vulnerable to wildfires.

1. Introduction

Wildfires play a crucial component in ecosystem dynamics by balancing fuel types and creating appropriate vegetation for maintaining healthy forested regimes. For instance, some plant species and communities have evolved thick bark or fleshy leaves that shield them from heat, while others require flames to melt their waxy coating for seed propagation (Pyne, 2019). Despite the integral ecological role of wildfires, uncontrolled burns can cause widespread environmental, economic, social and sustainable development impacts (Roman et al., 2012; WHO, 2014; Ghorbanzadeh et al., 2019). Such wildfire impacts include losses to human lives; incurring financial losses from buildings and homes; widespread social, health and economic costs through evacuations, smoke exposure, and loss of tourism revenue (Richardson et al., 2012; Moritz et al., 2014; Kramer et al., 2018). The Insurance Information Institute, gives an example of financial loss due to wildfires include the 2019 wildfires in California and Alaska that created a loss of 4.5 billion dollars in damages, largely resulting from the California Kincade and Saddle Ridge wildfires. In order to minimize ignition and spread during this time, California's electrical utility provider issued rolling blackouts to homes and businesses during high wind and extreme dry conditions, however, this inevitably cost the State billions of dollars in losses (NCEI, 2020). It is therefore evident that wildfires have a direct impact on the livelihood of many residents in fire-prone communities within the United States, making them vulnerable to wildland fire exposure within a changing climate and landcover regime (Westerling et al., 2006).

Likewise, changes in social and climate conditions can also significantly affect fire regimes, producing greater potential damage than those previously thought (Roman et al., 2012). Social factors, such as the expansion of the wildland-urban interface (WUI) (where human settlements, buildings, and wildland vegetation meet) have influenced the dramatic increase in wildfire suppression costs, as well as the number of homes lost to wildfires in the United States (US) over the past 30 years (Association for Fire Ecology, 2015; Abatzoglou and Williams, 2016; Kramer et al., 2018). The 2019 wildfire risk report shows that the US experienced the sixth-highest acres burned in 2018 since the mid-1900s. According to the National Interagency Fire Center (NIFC) report, California has topped the list in the US with over 1.8 million acres burned in 2018. Climate factors, such as extreme weather conditions can also influence the escape of wildfire during suppression practices, leading to unplanned destructive fire behavior (Calkin et al., 2005; Kramer et al., 2018), thereby, worsening environmental and socio-economic impacts.

There have been many wildfire risk-assessment studies that use a wide range of fire risk indices (Baijnath-Rodino et al. (*in review*). However, many wildland fire risk indices focus on specific components of wildfires (behavior, danger, threat) and use different metrics and frameworks in their derivations. For example, a fire risk index may only consider biophysical components such as weather conditions, topography, fuel, fire size, rate of spread, suppression difficulty, fire occurrence, or burn severity. Studies such as that by Alexandre et al. (2016), have evaluated fire risk on structures, taking into account variables pertaining to topography, spatial arrangement, and vegetation, but they did not account for meteorological factors (atmosphere and weather patterns), building materials, and fire suppression efforts within different fire regions. However, it is acknowledged that combining multi-scale socio-economic and biophysical variables into a risk and vulnerability assessment framework can be challenging. While various studies have attempted to bridge the gaps among the social, natural, and physical sciences and contributed to new methodologies that confront this challenge (Polsky et al., 2007; Hahn et al., 2008), not much of this approach has been applied to specifically assess wildfire vulnerability in wildland fire prone regions of the US. Therefore, there is a need to systematically integrate multi-scale, multidisciplinary variables into a framework to evaluate wildfire vulnerability in highly exposed wildland fire regimes, a method often lacking in other risk assessment studies. Thus, the integration across scales and disciplines to produce a wildfire vulnerability assessment can be conducted by creating a framework to assess the livelihood vulnerability of highly exposed regions to wildfires. A livelihood vulnerability framework incorporates not only wildfire exposure in a particular region (such as biophysical factors) but also quantifies the sensitivity of a region to wildfire exposure, and its ability to withstand these biophysical exposures (known as adaptive capacity). Thus, producing a livelihood vulnerability framework is an appropriate method for assessing the vulnerability of communities to wildfire exposure by not only taking into account biophysical factors, but by also quantifying socio-economic influences.

A common thread in the literature is the attempt to quantify multidimensional parameters (biophysical, social, and economic) using diverse indicator variables as proxies that can be integrated and combined to produce a vulnerability assessment such as Chambers and Conway, (1992) , who investigated a sustainability livelihood approach (Hahn et al., 2008). The field of climate vulnerability assessment, as a whole, has evolved to address the need to quantify the ability of communities to adapt to changing environmental conditions (Hahn et al., 2008) (such as changes in wildfire exposure). Thus, a vulnerability assessment is appropriate for describing a diverse set of methods that are used to systematically integrate and examine interactions between humans and their physical and social environment (Hahn et al., 2008).

The definition of the term *vulnerability* varies among disciplines (Adu et al., 2017). However, there is similar consensus in the definition of vulnerability to climate change by the IPCC and Food and Agriculture Organization (FAO). These studies define vulnerability as the extent or degree to which a system (geophysical, biological, or societal) is at risk and incapable of thriving under negative effects of an exposure (such as climate change) (FAO, 2006; IPCC, 2007; Adu et al., 2017). Assessing the *livelihood vulnerability* of a system, thus, specifically addresses how a system's basic necessities of living, such as shelter, work conditions, health and environment are vulnerable or affected by an exposure, such as wildfires. Studies, such as that by Hahn et al. (2008) combined previous climate vulnerability methods to construct a livelihood vulnerability index (LVI) to estimate the differential impacts of climate change on several African communities. Their method follows heavily on the working definition of vulnerability as a function of three contributing factors (exposure, sensitivity and adaptive capacity) as defined by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2001). **Exposure represents the magnitude and duration of the climate-related exposure** (in our case wildfires); **sensitivity describes the degree to which a system is affected by the exposure**; and **adaptive capacity describes the system's ability to withstand or recover from the exposure** (Ebi et al., 2006; Hahn et al., 2008).

The LVI uses multiple indicators that are aggregated into the IPCC's three contributing factors to produce a vulnerability framework. Studies have applied the LVI method, such as Albizua et al. (2019) to assess farmers' livelihood vulnerability to global changes in irrigation agricultural practices in Spain. They show that an increase in the adoption of irrigation practices have increased the short-term adaptive capacity while displacing small-scale farming. Suryanto et al. (2019) have also used the LVI approach to assess the livelihood vulnerability of flood risks to farmers for different regions in Indonesia. Results indicate that regions with similar physical characteristics and agricultural dependencies show similar vulnerability levels. It is acknowledged that there are numerous interpretations on how best to apply exposure, sensitivity, and adaptive capacity concepts to quantify vulnerability (Sullivan, 2002; O'Brien et al., 2004; Vincent, 2004; Ebi et al., 2006; Thornton et al., 2006; Polsky et al., 2007), with key differences among studies that include methods used for scaling, gathering, grouping, and aggregating indicator variables (Hahn et al., 2008).

We adopt an LVI approach, similar to Hahn et al. (2008), to evaluate recent wildfire impacts in the US. This is conducted by developing a framework that combines a set of indicator variables (at multiple spatiotemporal scales) into their respective contributing factors to determine the critical biophysical and anthropogenic components influencing livelihood vulnerability of selected wildfire prone States. The information gained from this assessment will provide a clearer understanding as to which States are most vulnerable to wildfires despite their level of wildland fire exposure. This information will be critical to researchers, government organizations, and policymakers in identifying, allotting, and providing better resiliency and adaptation measures, such as aiding in financial, environmental, and social support to the States that are most vulnerable to wildfires.

2. Data and Methodology

Assessing the LVI to wildfires across selected American States are conducted in two folds. First, we develop a framework comprising a set of biophysical, social, and economic factors that is used to assess each region's livelihood vulnerability. A Principal Component (PCA) analysis is applied to the set of indicator variables under each contributing factor to determine the validity of our framework. Second, once confident with our framework, we calculate the LVI and its contributing factors for each State.

The terminologies and definitions corresponding to our framework are summarized in Table 1, which describes the overarching contributing factors comprising of exposure, sensitivity, and adaptive capacity (color coded red, blue and green, respectively). These contributing factors are divided into major components (first level of divisions within each contributing factor). These major components are further divided into sub-components (second level of divisions within each major component) and subsequent indicator variables (measurable units of data for each sub-component) (figure 1). In our study, the exposure factor pertains to wildfire. Thus, the major components are wildfire occurrence, topography, weather, and extreme weather events. Sensitivity describes the degree to which each State is affected by wildfires. Its major components include demographic, ignition causes, and selected environmental indices that describe specific factors pertaining to wildfires, such as drought and air quality. Finally, adaptive capacity describes the ability of each State to withstand or recover from wildfires. The major components of adaptive capacity include natural capital, physical capital, human capital, social network, and financial capital. Our framework (Table 2) includes the justification for selecting each indicator variable as it pertains to wildfires.

The LVI analysis is conducted for 14 fire prone American States. The States selected are Arizona, California, Florida, Idaho, Montana, Nevada, New Mexico, Oklahoma, Oregon, Utah, Washington, and Wyoming because they experienced the highest risk of wildfires in 2018, as determined from by the maximum acres burnt in 2018 and 2019 and as documented in the NIFC 2019 Wildfire Risk Report (Table A1 in the appendix). In 2018, over 8.7 million acres of US land burned because of wildfire, marking the sixth-highest total since historical records began in the mid-1900s. The 14 States analyzed in this study had the largest acreage burnt in 2018 across the United States (Figure 2). Though Alaska was included as a top State listed in the 2019 Wildfire Risk Report, it was excluded from our study due to the lack of missing comprehensive data and, if included, would have impeded our comparison analysis among the other States.

Our analysis is conducted to determine the current LVI and not future LVI projections. Therefore, most of the data gathered for our assessment was acquired within the past decade (2010-2019. The exception is given to certain indicator variables that represent a long-term climatological average (1950 to 2019). In addition, the elevation data for each State was acquired from 1980, with the understanding that the elevation of each State is not time sensitive and would not have changed drastically if the measurements were acquired in 2019. The year in which the data was acquired for each indicator variable in our framework is indicated in Table 2.

Furthermore, most of the data acquired are entered directly into the framework as raw values, meaning that they did not require additional computations before the LVI was calculated. However, some indicator variables under exposure, sensitivity, and adaptive capacity required further processing to be amenable and included in the analysis. Indicator variables under the exposure that required initial computations included annual average wind speed, humidity, annual precipitation, number of days with greater than 0.1 inches or more of precipitation, and annual temperature. The National Center for Environmental Information (NCEI) provides annual averages of each indicator for various weather observation stations located in each State. The values for every weather observation station within each State were spatially averaged over the State and temporally averaged over a 30-year period (annual 1950-2019) before being used in our LVI calculations.

The indicator variables requiring initial computation under sensitivity included the Palmer Modified Drought Index (PMDI) and the number of smokers. The National Oceanic and Atmospheric Administration (NOAA) collects monthly PMDI values from weather observing stations throughout the US every year. The 2019 annual average was calculated for each station and then averaged amongst all the stations within a State. We calculate the number of smokers using data from the United Health Foundation, which provided the percentages of smokers for every State. To accurately convey the proportions between the States, the State's population for that year was multiplied by its respective percentage of smokers. Finally, for adaptive capacity, only the indicator variable pertaining to the total area of lakes had to be computed. The original data only provided the area for each individual lake, thus, we had to aggregate the area for all lakes to produce the cumulative lake area in each State.

The motivation for including the selected indicator variables in our framework was based on current risk assessment information suggested by the open literature, such as potential health risks due to wildfires (Gannon et al., 2020). Other examples include indicator variables pertaining to fuel, weather, and topography (included in our framework) that are important drivers of wildfire danger and behaviour, as referenced heavily in the literature (Keeley and Syphard, 2019; Banerjee, 2020). Environmental indices such as the PMDI and air quality were also included. While we acknowledge that there are many fire indices that could be integrated (Baijnath-Rodino et al. (*in review*), we selected PMDI because of its available spatial and temporal data for our study and because PMDI is a useful indicator in describing an essential environmental factor (drought) required for the potential onset, ignition, and behaviour of a wildfire (Wotton, 2006). Adding more fire indices and sub-indices would add redundancy to our framework. We further acknowledge the nuances that arise from subjectively allocating each indicator variable to a specific contributing factor in our framework and for that reason we subsequently applied a PCA to our indicator variables in order to gain confidence of our indicator categorizations within our framework.

PCA is a variable-reduction technique that takes a large set of variables and organizes them into a smaller set of principal components. For the purposes of this study, PCA was used to verify our framework by ensuring the indicator variables were loading into the respective major components that they were assigned. When conducting a PCA, four assumptions are made about the dataset: (1) the variables are measured at the continuous level; (2) there is a linear relationship between the variables; (3) there is adequate sample size; and (4) the dataset contains no outliers (Lund and Lund, 2018). In addition, two tests are conducted to determine whether the results of the PCA will be beneficial when validating our framework: the Kaiser-Meyer-Olkin (KMO) Sampling Adequacy Test (Williams et al., 2010) and Bartlett's Test of Sphericity (Tobias and Carlson, 1969). The KMO test measures the proportion of variance among the indicator variables that may be caused by underlying factors. KMO is an average of the measure of sample adequacy (MSA) for each indicator variable within their respective major component. MSA values range from 0 to 1 and represent the extent of a given indicator belonging to a group (Kaiser, 1970). Smaller KMO values indicate fewer correlations between a given variable and the other indicators. Therefore, if the KMO value is less than 0.5, the results from a PCA will not be useful because the indicators do not share high correlations with each other. Bartlett's test of sphericity is conducted to determine whether the correlation matrix of the indicators is an identity matrix. The null hypothesis is that the indicators are orthogonal or not correlated. The values for this test range from 0 to 1, with 0 representing a rejection of the null hypothesis. If the indicator variables are not correlated, they are thereby unsuitable for factor analysis. In addition, a significance value that is less than 0.05 indicates that PCA will provide helpful information. Table A2 in the appendix provides the KMO test scores for each major component by using the indicator data gathered from the 14 States.

Once the indicator variables we selected had passed these tests, a PCA was conducted. The normalized data input for PCA were the standardized index values for each indicator (standardized index calculation methods to follow). The normalized data encompasses all the indicator values for each State and for a given year (Table 2). The PCA gives insightful data such as a correlation matrix, communalities, and total variance explained. However, the output that helped reorganize and strengthen our framework was the component matrix. The component matrix displays the Pearson correlations between the indicator variables and principal components. The component matrix was used to verify whether the indicator variables loaded into their respective major components. This indicates that they are measuring the same underlying construct and are, therefore, correctly grouped accordingly in our framework.

Subsequently, we calculate the LVI and the corresponding contributing factor values for each of the analyzed States. Our methods for computing the LVI follows a similar approach to Hahn et al. (2018) and Suryanto et al. (2019). Before the computation, we need to interpret whether the magnitude of each indicator value, under each contributing factor, is influencing the contributing factor positively or negatively. If affecting the contributing value negatively, then the inverse value is taken. For example, most indicator variables under exposure suggest that a higher value corresponds to a higher wildland fire exposure. However, States with higher values of humidity and precipitation suggests that these indicator variables will yield a lower wildland fire exposure. Table 2 shows the reason for including each indicator variable in our framework, with the inverse values highlighted.

To compute LVI, we first compute the Standardized Index (SI) for each indicator variable, where I, is the original indicator variable for each individual State, $Imax$ and $Imin$ represent the State with the maximum and minimum value , respectively, corresponding to that particular indicator, equation 1.

$$SI = \frac{I - Imax}{Imax - Imin} \qquad (1)$$

Second, the Major Component (MC) value for each State is computed by averaging the standard indices, over the number (n) of all indicators used in each major component, equation 2.

$$MC = \frac{\sum_{i=1}^{n} SI}{n} \qquad (2)$$

Third, each Contributing Factor(CF) is computed by taking a weighted average of each computed major component. This is done by multiplying each major component by its number of indicators (Wi), equation 3.

$$CF = \frac{\sum[MC \cdot Wi]}{\sum Wi} \qquad (3)$$

Finally, the LVI for each State is computed by combining the contributing factors of exposure(E), adaptive capacity(AC), and sensitivity(S), equation 4.

$$LVI = (E - AC) \cdot S \qquad (4)$$

The LVI and the values for each contributing factor are computed, based on our framework (Table 2). Once the LVI is computed for each State, a constant value of 0.5 is added to each LVI to simply aid in visualizing and interpreting the rank of LVI (Albizua et al.2019). The results are presented and discussed in the results section.

3. Results

Principal Component Analysis (PCA)

A PCA was conducted for each major component to test the indicators categorized within them. Table A2 in the appendix shows the results after running the KMO and Bartlett test. All of the values from the KMO test are at least 0.5, which is the minimum required value to conduct a PCA as described in Williams et al. (2012). The only major component that is not at least 0.5 is that of weather, which has a value of 0.488. Previous research such as Wuensch (2012) suggests a KMO value of at least 0.6 in order to proceed with PCA. However, due to the small sample size and indicators tested per PCA (adaptive capacity, 13; exposure, 11; sensitivity, 9) it is difficult to achieve a KMO value of at least 0.6. Also, in this study, PCA was not utilized for its typical purpose of reducing variables, but rather, performed to verify whether the indicators within each major component loaded onto one principal component.

Table A2 in the appendix also contains the results for the Bartlett test. Some of the major components achieved a desirable value of less than 0.05. However, some had values greater than 0.05. This is not an issue for two reasons. First, the major components that had a value greater than 0.05 had only two indicators to test. Only having two variables to create a correlation matrix would make it very difficult to achieve a value below 0.05. Second, the purpose of conducting a Bartlett test is to assess whether the correlation matrix diverges significantly from an identity matrix for data reduction (Zach, 2019). Since the goal of the PCA is not variable reduction, the correlation matrix only needed to be proven as not an identity matrix, that is, a value closer to 0 than 1.

After computing the PCA, we analyzed the generated component matrices. To validate the framework, the indicators had to have a strong loading into their respective major components. A strong loading is considered to be any value above 0.5 and suggests that the indicators are measuring the same underlying construct. Despite the fact that a PCA was conducted for each major component, the results are compiled into three tables (Tables A3-A5 in the appendix), one for each contributing factor. Overall, most of the indicators demonstrated a strong loading into their respective major components. However, there were some indicators that had weak loadings, under a value of 0.5, for example, annual average wind speed and annual average temperature in exposure. These indicators had a factor loading of 0.166 and 0.39, respectively for the major component of weather. These low values indicate an inverse relationship between the other indicators under weather (Yong and Pearce, 2013). When a State is characterized by higher wind speed and temperature, they are more likely to be exposed to wildfires. The other indicators under weather involve humidity and precipitation. If a State is characterized by higher humidity and precipitation, then they are less likely to be exposed to wildfires. The same logic can be applied to the following indicators: acres of forests, number of timber/woodworkers, and annual PMDI. These indicators all have negative loadings for their respective major components. These inverse relationships were reflected in the calculation of the LVI. With PCA verifying the construction of the framework, the validity of the LVI results is strengthened.

LVI

We compute the LVI for each of the 14 American States analyzed (figure 3). Most of the States we analyzed exhibit similar LVI values. However, Arizona and New Mexico experience the greatest livelihood vulnerability, with an LVI of 0.57 and 0.55, respectively. In contrast, California, Florida, and Texas experience the least livelihood vulnerability to wildfires (0.44, 0.35, 0.33, respectively) (figure 4). To understand these LVI results, we delve into analyzing each contributing factor.

Exposure

First, we examine each State's susceptibility to wildfire by examining the exposure contributing factor. The exposure results indicate that California, Nevada, and Arizona exhibit the highest exposure to wildfires (0.63, 0.52, and 0.49, respectively) while Oklahoma, Florida, and Montana have the least exposure (0.25, 0.21, and 0.19, respectively) (left panel in figure 5). To understand the exposure results, we assess the four major components of exposure (*wildfire, topography, weather,* and *weather extreme events*) for each State (right panel in figure 5). *Wildfire* (blue) is predominant for the State of California, Texas, and Arizona. This is because these States experience the greatest number of wildfires and the greatest acres burnt due to wildfires in 2019. Nevada and Arizona also experience relatively greater values of *weather* (yellow), which indicates favorable weather conditions for the development of wildfires, such as relatively higher winds speeds and lower humidity. In addition, *weather extreme events* (green) represent extreme wildfire and extreme heat events and are most prevalent in California and Nevada.

The major component, *topography,* represents mean height and highest elevation for each State. This variable is important because higher elevations in complex terrain can be conducive to the propagation of wildfire behavior, add uncertainties to the prediction of the wildfire rate of spread (Storey et al., 2020), and make fire suppression efforts more challenging. Thus, States with higher topographic values could potentially be more at risk, or dangerously affected by wildfires. Nevada also ranks high in *topography*. While *topography* is also relatively high for other States, such as Wyoming and Utah, other major components, such as *wildfires, weather,* and *weather extremes* are negligible, thereby, reducing the overall exposure of wildfires in these States. Furthermore, Florida, Oklahoma, and Montana have the lowest exposures because all of their major components under exposure are ranked very low in comparison to the other States.

Sensitivity

Second, we assess the degree to which each State is affected by wildfires by investigating the sensitivity contributing factor. The results for sensitivity (left panel in figure 6) show California as the most sensitive State to wildfires (0.84). This is followed by Texas, with a sensitivity of 0.66. Montana and Wyoming are the least sensitive. California, Texas, and Florida are the most sensitive to wildfires because they yield the highest values of each major component under sensitivity (*demographic*, *ignition causes,* and *environmental index*) (right panel in figure 6). *Demographic* comprises sub-components, such as the wildland-urban interface (WUI) and population. States with greater areas of WUI or populations within WUI would be more sensitive to wildfires because they are within a region more exposed to wildfire events. *Ignition causes* attributed to outdoor activities such as campfires and smoking would also increase the potential inception of human-caused fires. In addition, States that experience poorer air quality and more drought will be more sensitive during and after wildfire events and seasons. The *environmental index* remains relatively constant among all States (yellow). However, California and Texas are the most sensitive States because they are driven primarily by the major components of *ignition causes* (red) and *demographic* (blue). The least sensitive State is Montana (0.08) because, in comparison to the other States, all its major components are ranked relatively low.

Adaptive Capacity

Third, we assess the ability of each State to withstand or recover from wildfires by analyzing the contributing factor of adaptive capacity. Our results indicate that California, Texas, and Florida exhibit the greatest adaptive capacity to wildfires (0.69, 0.67, and 0.48, respectively) while Oregon, Idaho and Montana are the least adaptive (0.15, 0.12, 0.12, respectively) (left panel in figure 7). The reasons for the adaptive capacity disparities among the States have to do with the major components (or capitals) each State has (*natural, physical, human, social network*, and *financial*) Table 1.

What drives the adaptive capacity to be relatively high for California, and to a slightly lesser extent Texas, are their *social network* (green) *physical capital* (red) and *financial capital* (orange) (right panel in figure 7). These two States have social structures in place to facilitate safety measures in times of wildfires such as allocating firefighters and first responders to wildland fire emergencies. These States are also more equipped with transportation accessibilities, such as closer airports and access to public roads, in case of major wildfires. California and Texas also have greater access to communication within their households, including internet signals for receiving warning alerts, both of which can be beneficial to one's livelihood during the State of an emergency wildfire evacuation. These States also rank highly in financial capital, such as having relatively higher household incomes and fire management assisted grants, which can lend financial support during wildland fire emergency hazards. Additionally, Florida also has a high adaptive capacity that is primarily driven by its *natural capital*. It has the greatest water area of all the States analyzed, thereby providing the State with water resources for fire suppression.

In contrast to the States with the highest adaptive capacity, Montana, Idaho, and Oregon rank very low in all capitals. Also, while some States rank high in one major component, it suffers in others, thereby driving down the rank of its overall adaptive capacity value. For example, New Mexico has a relatively high human capital in comparison to other States, which corresponds to residential density and occupation; however, all its other capitals are negligible, resulting in an overall low adaptive capacity to wildfires. This emphasizes the need to evaluate all the contributing factors in adaptive capacity to get a holistic view of the allotted resources available to aid in wildfire's resiliency measures. Adaptive capacity is one of the most important determining factors in risk assessment, as highlighted by Davies et al. (2018) who show that wildfire hazard potential can be reduced once the adaptive capacity of the State is taken into consideration.

4. Discussion

Assessing each contributing factor and its respective major components and subcomponents have provided an in-depth analysis of why the livelihood vulnerability of some States to wildfires are higher than others. Many media and scientific reports constantly show California as the State with the most dangerous and destructive wildfires, especially in recent years. The NIFC report showed that California had the highest acres burned and maximum damages in 2018 among all the American States. According to the 2019-2020 California Budget Summary, approximately ten of the most destructive wildfires in California have occurred since the year 2015. Thus, one might think that California, with the highest exposure, would have the highest LVI. Our study indicates that while California is the most exposed, and sensitive to wildfires (figure 8), it has a very high adaptive capacity to help offset its livelihood vulnerability. The California Administration has implemented solutions and recommendations to reduce wildfire risk to improve the State's emergency preparedness, response, and recovery capacity; and to further protect vulnerable communities. The 2019-2020 State budget includes 918 million dollars in additional funding to comply with these efforts. For these reasons, it is evident why California is one of the States that exhibits a lower livelihood vulnerability to wildfires.

Similarly, Texas has the lowest LVI of all the States analyzed. Despite its high sensitivity, its exposure to wildfire is relatively lower than more than 25% of the other States and has the second-highest adaptive capacity. Texas is highly sensitive to wildfires. According to Texas A&M Forest Service (2020), there have been over 150,000 wildfires consuming more than 9 million acres since 2005 with 71,499 wildfires in 2017 alone. Ninety percent of wildfires in Texas are human caused as a result of debris burning, sparks from welding and grinding equipment, poorly discarded smoking materials, vehicles' exhaust systems, and arson. Moreover, according to Headwater Economics (2018) parts of Texas that are experiencing the fastest population growth are spatially correlated with regions of highest wildfire threat and greater proportions of vulnerable people. These factors explain why Texas is highly sensitive to wildfires. However, we suggest that similar to California, Texas has a very high adaptive capacity, which drastically influences its livelihood vulnerability to wildfires. This high adaptive capacity is driven primarily by social network, physical capital, and financial capital. According to the Texas A&M Forest Service (2020), Texas has resources to deploy wildfire risk information and create awareness about wildfire concerns across the State through using a Texas Wildfire Risk Assessment Portal (TxWRAP). Furthermore, data produced from this portal is part of the Texas Wildfire Risk Assessment Project (WRA) that has further positioned the Texas Forest Service as a national leader in wildfire protection planning. These resources have positioned Texas to help withstand natural hazards pertaining to wildfires.

Additional considerations should also be taken into account for States like Arizona that exhibit a high LVI, as well as for States like California that exhibits a high exposure, but low LVI. Arizona has high biophysical exposures of wildfires and high sensitivity to environmental indices such as drought and poor air quality. According to the U.S. Census Bureau, Arizona is among the top three States with highest rates of population growth in the nation. There have been more than 120,000 new residents (doubled California's 50,635 new residents) in the 2018-2019 time period alone, with a projected population of over 10 million people by 2050, according to the Arizona Commerce Authority. It can be assumed that with such growth, urbanization, transportation, and communication services will increase, thereby, making Arizona more sensitive to wildfire risk, as

9 out of 10 wildland fires are started by humans according to the Arizona Department of Forestry and Fire Management.

There is also future concerns for the State of California, despite having a low LVI. Its resultant exposure to wildfire is the highest amongst all States, thereby requiring continuous observations and monitoring. According to Miller et. al. (2020), the increased number of fires in California is due to a combination of climate change that has heightened hot and dry conditions and fire suppression policies that have allowed the accumulation of fuels in the landscape. As stated by numerous dependencies in the California Forest Carbon Plan in 2018, wildfire emissions are projected to increase by 19%-101% using the 1961-1990 years as the baseline period. If current forest management techniques and global greenhouse gas emissions continue, wildfire smoke will increase, only exacerbating these emissions and worsening the current health impacts. Therefore, looking to the future, mitigation and resilience strategies need to be developed and adopted for the high LVI States, such as Arizona; and continued efforts are required for, relatively, low LVI but high exposure States such as California in order to facilitate and provide resources to help adapt to biophysical wildfire hazards in the future.

Actions are being taken to address wildfire impact across California and the United States by the Environmental Protection Agency (EPA), the US Forest Service, and other agencies. EPA recently published a Wildland Fire Research Framework coordinating its wildland-fire-related research across multiple national research programs that will be implemented in the 2019-2022 Strategic Research Action Plans (EPA, 2019). This framework has different roles for multiple federal agencies to collaborate with the EPA Office of Research and development. The US Forest Service has a network of fire labs and research stations that focus on understanding and modeling fire processes. Other agencies, such as The National Weather Service focuses their efforts on smoke plume modeling and hazard mapping. The National Aeronautics and Space Administration (NASA), promotes the use of Earth observations and models focused on addressing issues pertaining to wildland fire in support of management strategies, business practices, and policy analysis and decision support. According to EPA (2019), other agencies across the United States that are involved in wildfire assessment include, but not limited to: the Fire Research Division by the National Institute of Standards and Technology (NIST); Centers for Disease Control and Prevention (CDC); National Institute of Environmental Health Sciences (NIEHS), the U.S. Fire Administration by the Federal Emergency Management Agency (FEMA); the Division of Atmospheric and Geospace Sciences by the National Science Foundation (NSF); the Atmospheric System Research (ASR) Program by the U.S. Department of Energy (DOE); the Office of Wildland Fire (OWF) by the U.S. Department of Interior; The Fire Ecology and Research and Wildland Fire Program by the National Park Service (NPS); the Fire and Aviation Program by the Bureau of Land Management (BLM), and the Wildland Fire Science and Wildfire Hazards program by the U.S. Geological Service (USGS). However, despite these efforts, fire management practices and policies need to continue to evolve. This is because policies used in the past are not necessarily the ones required moving forward.

The need to adopt contemporary practices are beneficial for resiliency and mitigation methods. For example, following a massive fire that burned 3 million acres in Montana, Idaho, and Washington, Silcox, (1910), policies focusing on fire suppression and prevention became dominant in the early 1900s and was the foundation of California’s economic theory of wildfire management (Headley et al., 1916; Rideout et al. 2008). However, according to the recent California Policy Center (2017), fire suppression techniques only worked as short term solutions, resulting in over one-hundred million dead or dying trees, overgrown forests, and fuel accumulation, increasing the risk for dangerous wildland fires. Thus, the continued need for evolving and enhancing fire management techniques and practices is essential for accurately monitoring and improving wildfire risk assessments.

One fire management practice is the implementation of prescribed burns. Prescribed fires are a technique used to manage fuels in forests in a coordinated and planned manner (McCaw, 2012), and policymakers recognize the critical importance prescribed burns have on reducing the impact of large and damaging wildfires (York et al., 2020). However, more implementation of prescribed burns is currently needed. While 1 billion dollars in California state-wide funding is aimed at reducing the century-long buildup of forest fuels in the next five years, only a small fraction of prescribed burns are being conducted. For instance, although the California Carbon plan has a goal of treating 500 000 acres of private land each year, in 2017-2018 only 33 000 acres of private land were managed (Newsom, 2019; York et al., 2020). Private landowners own approximately half of the mixed-conifer forests in California, and prescribed burns can help protect their property and contribute to reducing the impact of large wildfires to the broad public. Another caveat, however, is the need for burn permits, which are significantly challenging to obtain by landowners (York et al., 2020). Thus, while progress is being made to adopt mitigation and resilience strategies to addressing wildfire risk, issuing and obtaining burn permits are still problematic. Therefore, we emphasize the need for constant re-evaluations to policies and management practices in wildfire assessment risk, especially during the rapidly changing climate and land-use/land-cover conditions that will inevitably impact communities' livelihood vulnerability to wildfire events.

5. Conclusions

Across the United States, wildfires can produce great environmental and socio-economic risks. To quantify these risks across multi-scale, socio-economic, and biophysical variables, we produce a framework to compute a livelihood vulnerability index for the top 14 American States that are most at risk for wildfires. Our framework comprises contributing factors (exposure, sensitivity, and adaptive capacity), major components, sub-components, and indicator variables. Our framework was further justified by performing a principal component analysis to provide additional confidence in our approach.

Our results indicate that the States of Arizona and New Mexico experience the greatest livelihood vulnerability, with an LVI of 0.57 and 0.55, respectively and California, Florida, and Texas experience the least livelihood vulnerability to wildfires (0.44, 0.35, 0.33, respectively). LVI is weighted strongly on the contributing factors. For example, while California has a high exposure and sensitivity to wildfires, it has high adaptive capacity capitals that offset these concerns. Additionally, livelihood vulnerability depends largely on sensitivity indicator variables, such as population density. We acknowledge that with Arizona's high LVI, and steady population growth, that continued wildfire risk management and urban planning strategies are essential for reducing the biophysical and socio-economic impact of wildfires in the future and to further avoid an increase in its LVI.

The results from this study are critical to researchers, government and policymakers, in identifying, allotting, and providing better resiliency and adaptation measures to support the American States that are most vulnerable to wildfires. Further research can be conducted, following the same framework for each of the State's geo-political subdivisions in order to better understand the risk and vulnerability of growing wildland-urban interface zones and to determine what urban-boundary limitations should be considered for risk assessment studies. Moreover, additional research can be conducted to assess future LVI scenarios by employing high-resolution forecast models to help guide future wildland fire exposure projections in vulnerable communities within the United States.

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Table 1. LVI terminology definitions, colour coordinated by major components in each contributing factor: adaptive capacity (green), exposure (red) and sensitivity (blue). Gray highlights denote terms that are frequently used in livelihood vulnerability literature

Terminology	Definition
Contributing factor	Overarching biophysical and socio-economic factors used to calculate LVI (exposure, adaptive capacity, and sensitivity)
Adaptive capacity	The system's (State's) ability to withstand or recover from the exposure (wildfire)
Exposure	The magnitude and duration of the climate-related exposure such as a drought or change in precipitation
Sensitivity	The degree to which the system/community is affected by the exposure (wildfire)
Major component	The first level of divisions within each contributing factor
Financial capital	Considers financial resources a system (State) has to help adapt to an exposure (wildfire) e.g. grants, income
Human capital	Considers human resources a system (State) has to help adapt to an exposure (wildfire) e.g. Occupation type
Natural capital	Considers natural resources in a system (State) that helps a system adapt to an exposure (wildfire) e.g. Lakes, forests
Physical capital	Considers materials and resources that a system (State) has to help adapt to an exposure (wildfire) e.g. Transportations and communication types
Social network	Considers social constructs that are in place by a system (State) to help adapt to an exposure (wildfire) e.g. Safety practices

Wildfire Occurrence	Considers metrics used to quantify the number of wildfires in a State, e.g. wildfire occurrence, loss of wildland
Topography	Considers metrics used to quantify topography of landscape, e.g. elevation height
Weather	Considers the meteorological metrics that influences wildfire behavior, e.g. air temperature
Weather Extreme Events	Considers metrics that quantifies extreme environmental conditions conducive for wildfires e.g. extreme heat
Demographic	Considers metrics that describe population structure of a State, e.g. population density
Ignition causes	Considers metrics pertaining to potential ignition sources for the onset of a wildfire, e.g. smoking
Environment Indices	Indices that compute a potential risk related to wildfires, e.g. an air quality index
Subcomponent	The second level of divisions within each major component
Indicator variables	Measurable units of data for each sub-component
Livelihood vulnerability index (LVI)	A vulnerability assessment tool to address issues of sensitivity, exposure and adaptive capacity to climate change (wildfire) in fire-prone communities

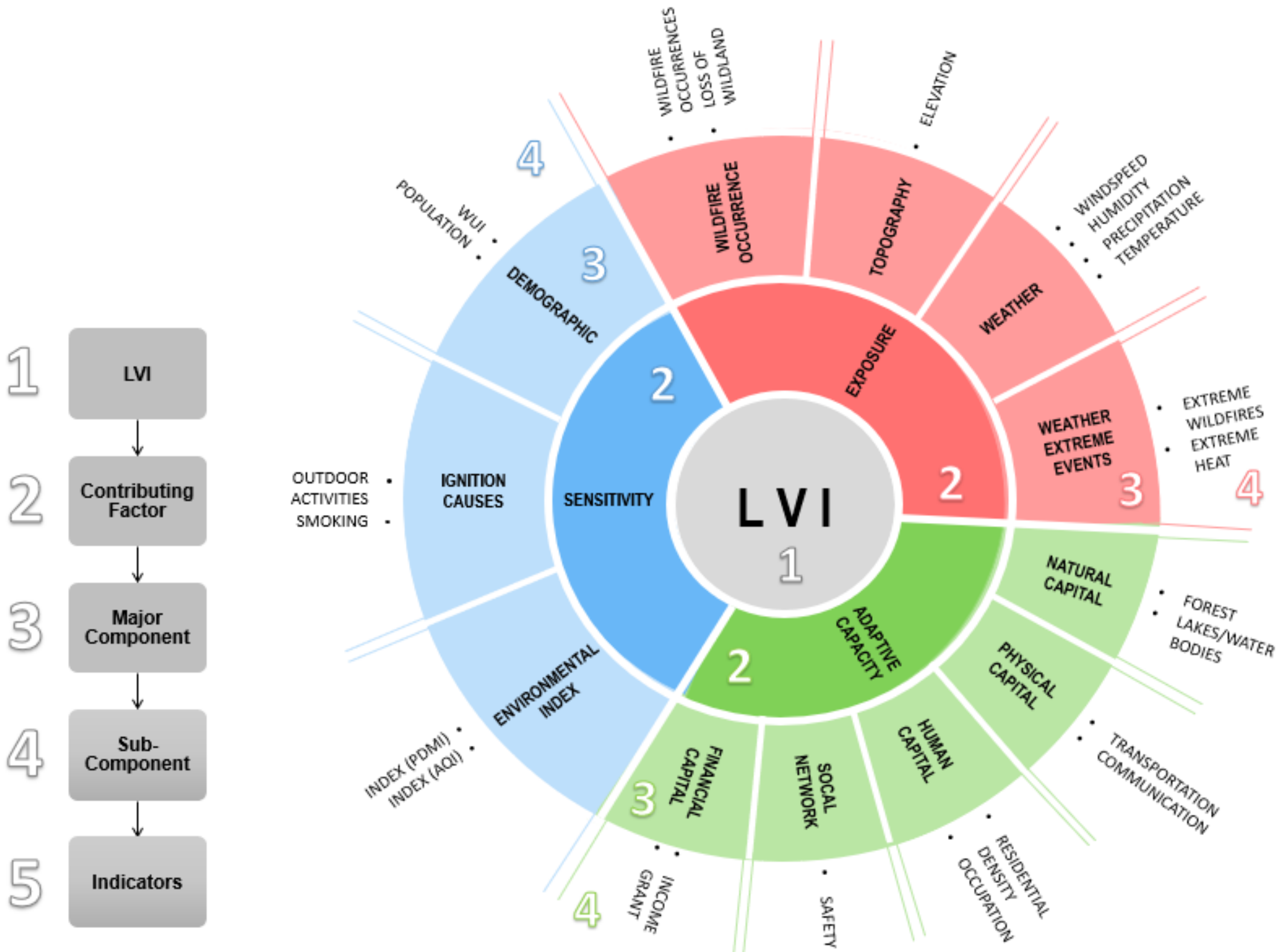

Figure. 1 Description of the framework developed for the LVI (box 1 and the central gray circle). LVI is represented by contributing factor (box 2). The contributing factors are sensitivity (blue), exposure (red), and adaptive capacity (green). The contributing factors are further divided into major components (box 3). The major components are color-coordinated with the contributing factors. The major components for sensitivity (blue) are demographic, ignition causes, and environmental index (light blue); for exposure (red) are wildfire occurrence, topography, weather, weather extreme events (light red); for adaptive capacity (green) are social network, natural, physical, human, and financial capital (light green). Major components are divided into sub-components (box 4) and represented by the sub-components in the outermost part of the circle. The sub-components are further divided into indicators (box 5) and not shown in this figure. Refer to Table 2 for each indicator variable.

Table 2. LVI framework with a description of the contributing factors, major components, sub-components, indicator variables and their corresponding justifications for being included in the framework. The headings of red, green, and blue represent the contributing factors of exposure, adaptive capacity, and sensitivity, respectively. Highlighted indicators represent values that contribute negatively to the contributing factor, and the inverse value is computed for input into the LVI calculation

EXPOSURE						
Major Components	**Sub-Components**	**Indicator Variables**	**Justification**	**Units**	**Year**	**Data Source**
Wildfires	Wildfire occurrence	Number of wildfires (2019)	States that have experienced more wildfires will have vulnerable residents	number in 2019	2019	https://www.iii.org/fact-statistic/facts-statistics-wildfires#Wildfires%20By%20State,%202019
	Loss of wildland	Number of acres burnt to wildfires in 2019	Changes in land cover can have negative environmental knock-on effects such as flash flooding; loss of wildland means more investments required to restore forests and structures lost in these regions	Acres	2019	https://www.predictiveservices.nifc.gov/intelligence/2019_statssumm/fires_acres19.pdf
Topography	Elevation	Mean height above sea level	Higher elevations may lead to additional complexity in wildfire prediction behaviour uncertainties	meters	1980	https://pubs.usgs.gov/gip/Elevations-Distances/elvadist.html
		Highest elevation	Higher elevations may lead to additional complexity in wildfire prediction behaviour uncertainties	meters	1980	
Weather	Wind speed	Annual average wind speed	Higher wind speeds can cause wildfires to spread faster; cause spot fires, and reduce suppression efforts	mph	1950-2018	https://www.ncdc.noaa.gov/ghcn/comparative-climatic-data
	Humidity	Annual average humidity	Higher the humidity the less likelihood of wildfires developing	%	1950-2018	
	Precipitation	Average annual precipitation	Higher the precipitation the less likelihood of wildfires developing	inches	1950-2018	
		Average number of days with 0.1 inch or more precipitation a year	Higher the number days with 0.1 inches or more of rain, the less likelihood of wildfires developing	days	1950-2018	
	Temperature	Annual average temperature	Higher the temperature the greater the likelihood of wildfires	°F	1950-2018	

Weather Extreme Events	Extreme wildfires	Percent of wildfires occurring between 1980 to 2010	Regions that are susceptible to more extreme wildfires will have more vulnerable communities	%	1980-2010	http://www.usa.com/
	Extreme heat	Percent of extreme heat events between 1980 to 2010	Regions with more extreme heat event will be more vulnerable to wildfires	%	1980-2010	

ADAPTIVE CAPACITY						
Major Components	**Sub-Components**	**Indicator Variables**	**Justification**	**Units**	**Year**	**Data Source**
Natural Capital	Forest	Acres of forests	Greater the number of forests the greater the potential fuel source	acres	2016	https://www.fs.usda.gov/sites/default/files/fs_media/fs_document/publication-15817-usda-forest-service-fia-annual-report-508.pdf
	Lakes/water bodies	Water area	Greater the number of water bodies the more water resources are available to help with fire suppression	square miles	2016	https://www.usgs.gov/special-topic/water-science-school/science/how-wet-your-state-water-area-each-state?qt-science_center_objects=0#qt-science_center_objects
		Area of lakes	Greater the number of water bodies the more water resources are available to help with fire suppression	acres	2010	https://www.uslakes.info/
Physical Capital	Transportation	Miles of public road	Greater the miles of public roads available, the better equipped states are to assist with evacuation routes	miles	2020	https://www.bts.gov/content/state-transportation-numbers
		Major airports	Greater the number of airports, the better suited states are to assist with evacuation routes	number	2020	https://www.bts.gov/content/state-transportation-numbers
	Communication	Households with a computer	Greater the number of computers will there by help with accessing warning information	number	2014-2018	https://www.census.gov/quickfacts/fact/map/CA,US/HSG445218
		Households with broadband internet connection	Greater the number of households with internet will thereby help with accessing warning information	number	2014-2018	https://www.census.gov/quickfacts/fact/map/CA,US/HSG445218
Human Capital	Residential density	Persons per households	Damages due to wildfire, how many people in household are affected	Number	2019	https://www.census.gov/quickfacts/fact/table/US#

	Occupation	Timber/wood labour	The number of people actively involved in the forestry industry, with lower numbers suggesting less people impacted by potential wildfires	number	2019	https://data.bls.gov/oes/#/geoOcc/Multiple%20occupations%20for%20one%20geographical%20area
Social Network	Safety	Firefighters	Greater the number of firefighters, greater the resources to help with fire suppression	number	2019	https://data.bls.gov/oes/#/geoOcc/Multiple%20occupations%20for%20one%20geographical%20area
		First responders (EMTs)	Greater the number of firefighters, greater the resources to help with fire suppression	number	2019	https://data.bls.gov/oes/#/geoOcc/Multiple%20occupations%20for%20one%20geographical%20area
Financial Capital	Income	Median household income	Greater the income, the more resources, and capacity they have to adapt and respond to exposure	dollars	2018	https://www.census.gov/library/visualizations/interactive/2018-median-household-income.html
	Grant	Fire management assistance grants	Greater the number, the better assistance for fire suppression efforts	number	2017	https://fas.org/sgp/crs/misc/R44966.pdf

SENSITIVITY						
Major Components	**Sub-Components**	**Indicator Variables**	**Justification**	**Units**	**Year**	**Data Source**
Demographic	WUI	WUI area	Area most at risk for wildfires	km2	2010	https://www.fs.fed.us/nrs/pubs/rmap/rmap_nrs8.pdf
		Number of houses within WUI zones	Houses at high and extreme risk from wildfire in the most wildfire-prone states	Number	2010	
		Population at risk in WUI Zones	Densely populated areas are more exposed and require more resources during wildfire natural disaster	Number	2010	
	Population	Population density (2019)	May require more assistance and at-risk during wildfire event	Number	2019	https://www.census.gov/quickfacts/fact/map/CA,US/HSG445218

		Housing units	The greater urbanization sprawl, the more it can infringe on forested regions	Number	2019	https://www.census.gov/quickfacts/fact/table/US#
Ignition Causes	Outdoor Activities	Number of camping sites	Campsites may have campfires and might be ignition sources	Number	2019	https://camping-usa.com/campgrounds/
	Smoking	Number of smokers	Smokers are considered individuals likely to start a fire by accident	Million People	2019	https://www.americashealthrankings.org/explore/annual/measure/Smoking/state/CA
Environmental Index	Index (PDMI)	2019 Annual PDMI	Uses temperature and precipitation to estimate relative dryness. (Palmer Modified Drought Index)	Number	2019	https://www.ncdc.noaa.gov/temp-and-precip/drought/nadm/indices/palmer/div#select-form
	Index (AQI)	Annual AQI	Population that is likely to experience increasingly severe adverse health effects.	Number	1999-2009	http://www.usa.com/rank/us--air-quality-index--state-rank.htm?hl=CA&hlst=CA

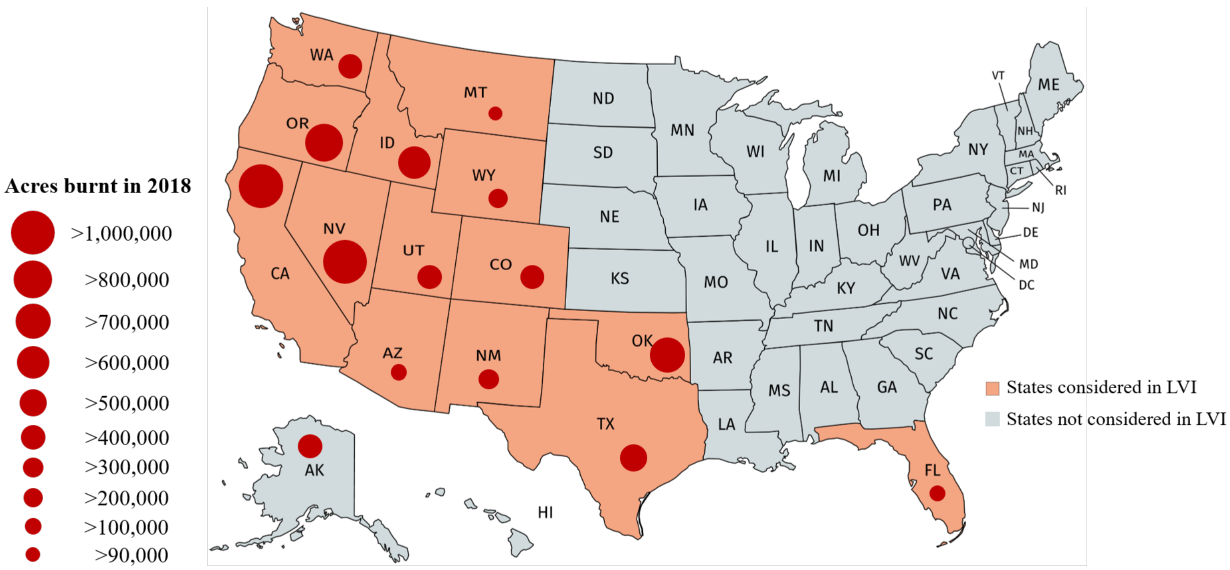

Figure. 2 Map of the United States with the States analyzed shaded in orange and states not considered shaded in gray. The states considered were selected based on the 2019 Wildfire Risk report on the acreage size burnt in 2018 and 2019, indicated by the red circles, ranging from the smallest circle (burn area less than 90 000 acres) to the largest circle (burn area exceeding 1 million acres). Note, while Alaska was a top State for burnt area, it was removed from the LVI analysis due to lack of available data.

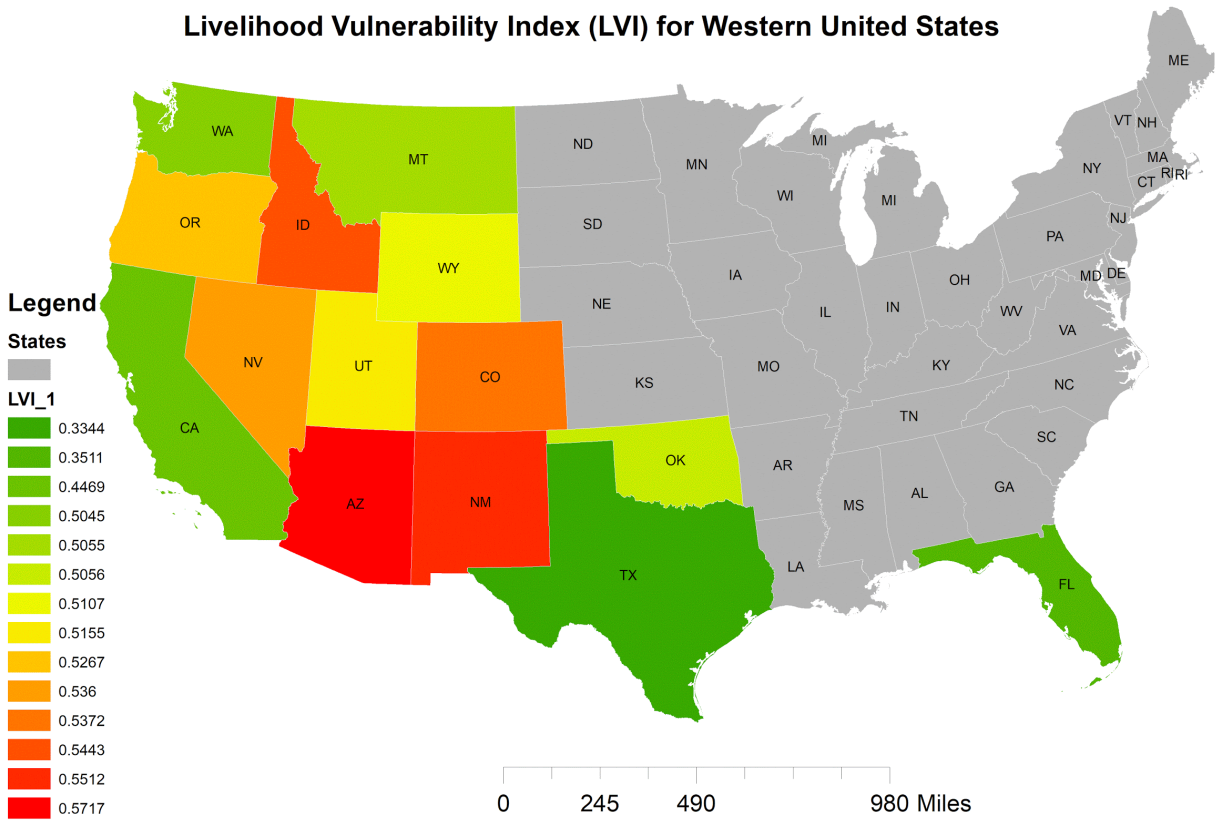

Figure. 3 Spatial plot of each States' LVI value, with its magnitude corresponding to the color bar where darker red and darker green indicate the highest and lowest LVI, respectively. States shaded gray have not been analyzed in this study.

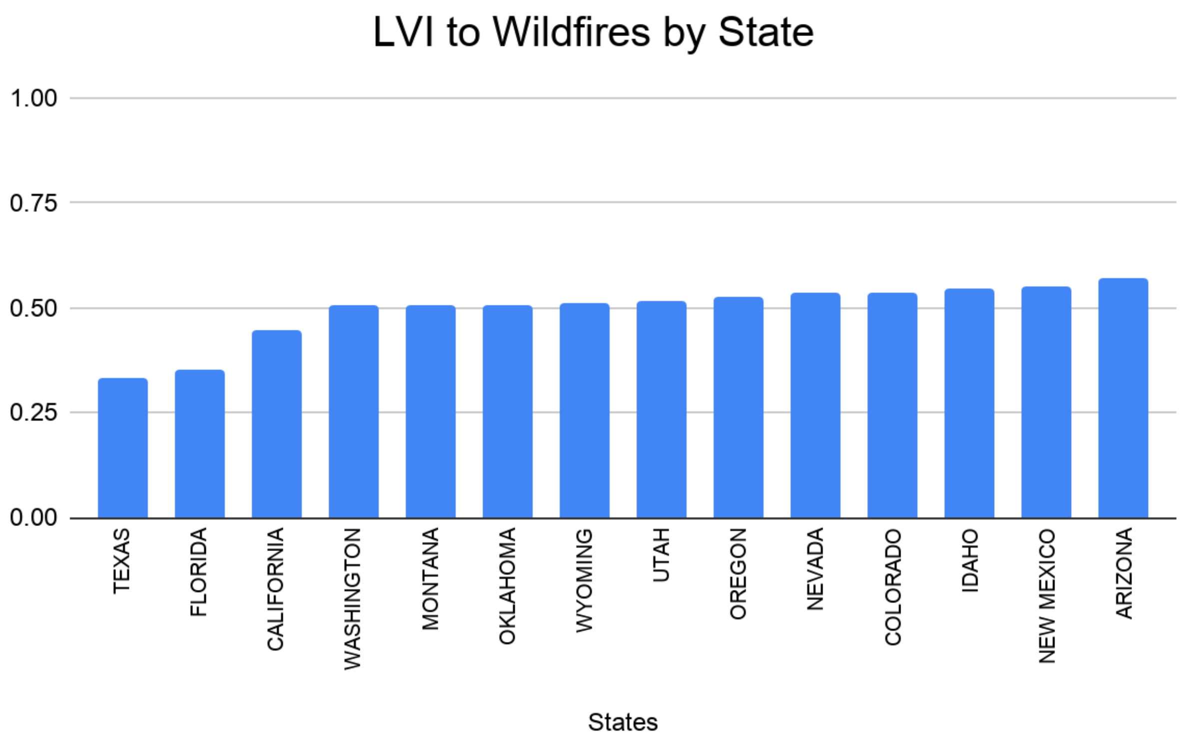

Figure. 4 Histogram showing the LVI of the 14 selected states in the US with Arizona having the highest LVI and Texas having the lowest LVI.

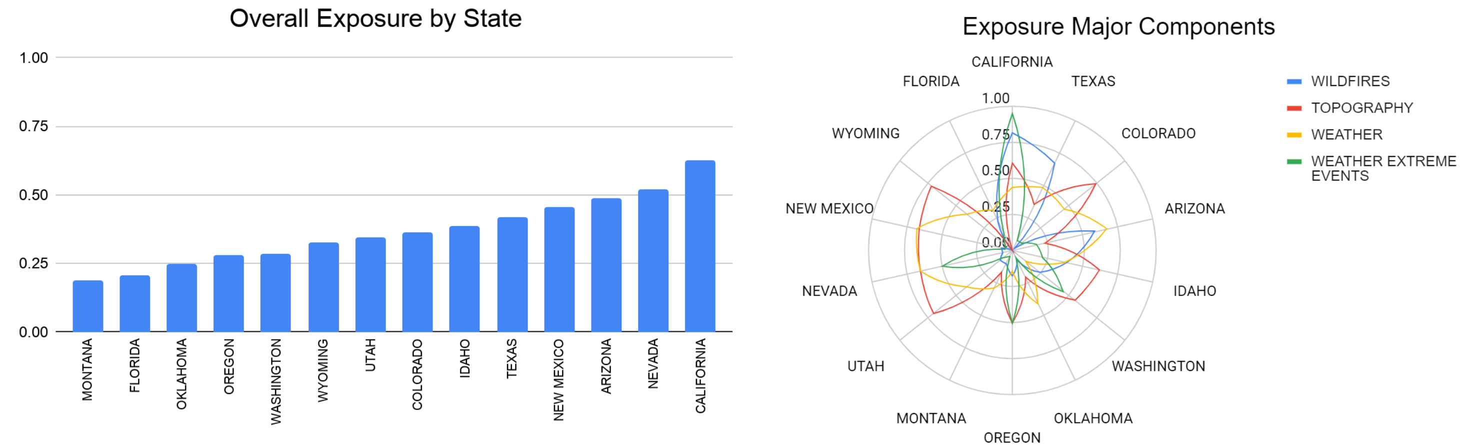

Figure. 5 Figure on the left panel shows histogram with the overall exposure of the 14 selected states in the US with California having the highest exposure (with respect to wildland fire) and Texas having the lowest overall exposure. The figure on the right panel shows a radar plot showing the different major components of the exposure contributing factor, namely, wildfires (blue), topography (red), weather (yellow), and weather extreme events (green) for the selected 14 states of the US.

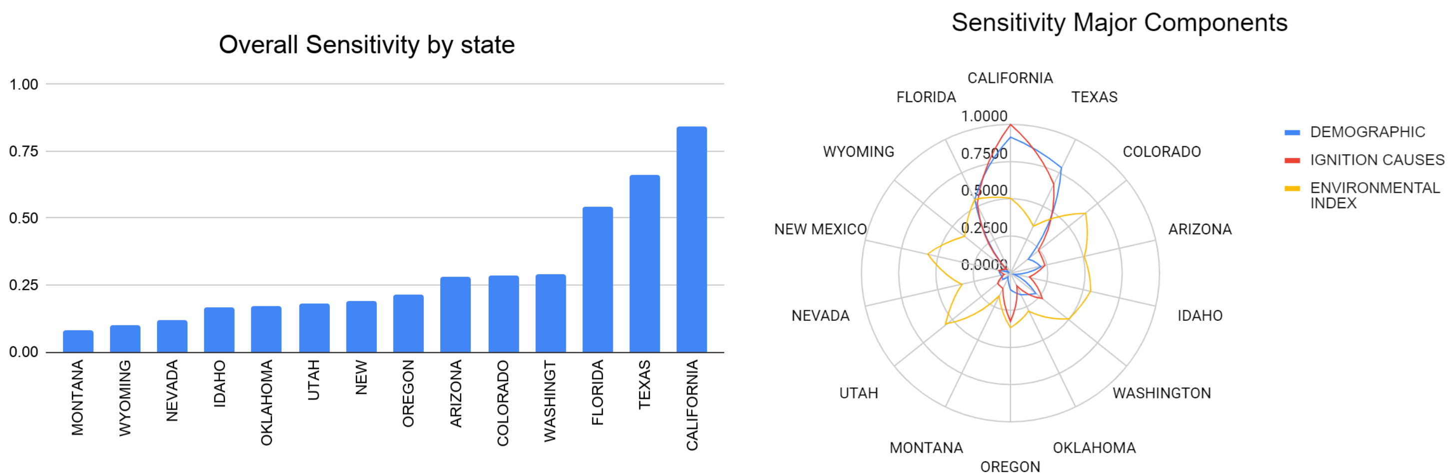

Figure. 6 Figure on the left panel shows histogram with the overall sensitivity of the 14 selected states in the US with California having the highest sensitivity (with respect to wildland fire) and Texas having the lowest overall sensitivity. The figure on the right panel shows a radar plot showing the different major components of the sensitivity contributing factor, namely, demographic (blue), ignition causes (red), and the environmental index (yellow) for the selected 14 states of the US used in this study.

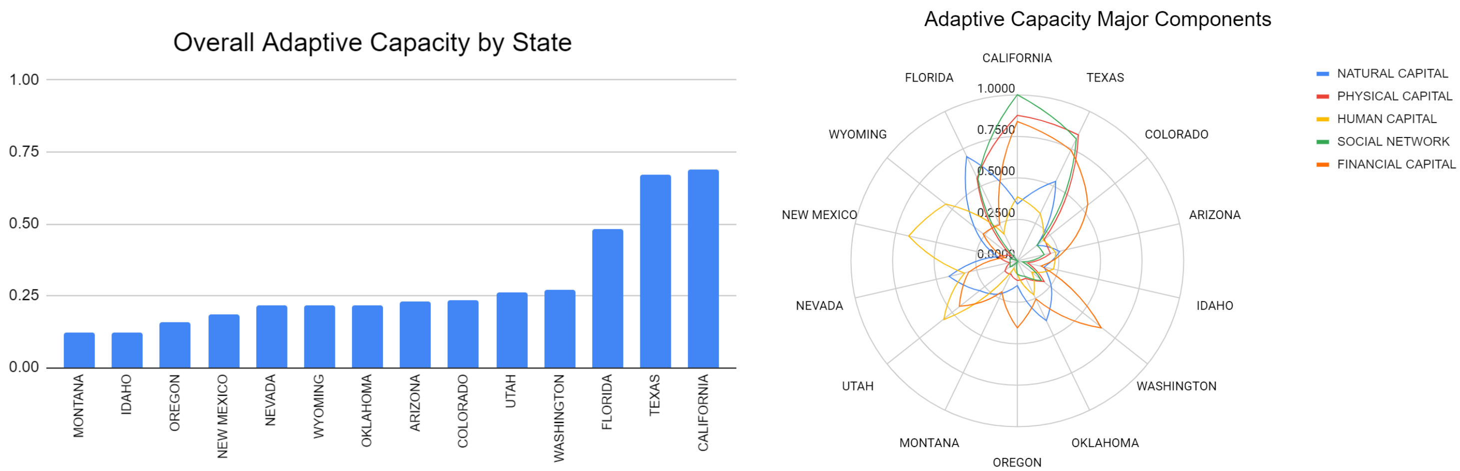

Figure. 7 Figure on the left panel shows histogram with the overall adaptive capacity of the 14 selected states in the US with California having the highest adaptive capacity (with respect to wildland fire) and Texas having the lowest overall adaptive capacity. The figure on the right panel shows a radar plot showing the different major components of the adaptive capacity contributing factor, namely, natural capital (blue), physical capital (red), human capital (yellow), social network (green), and the financial capital (orange) for the selected 14 states of the US.

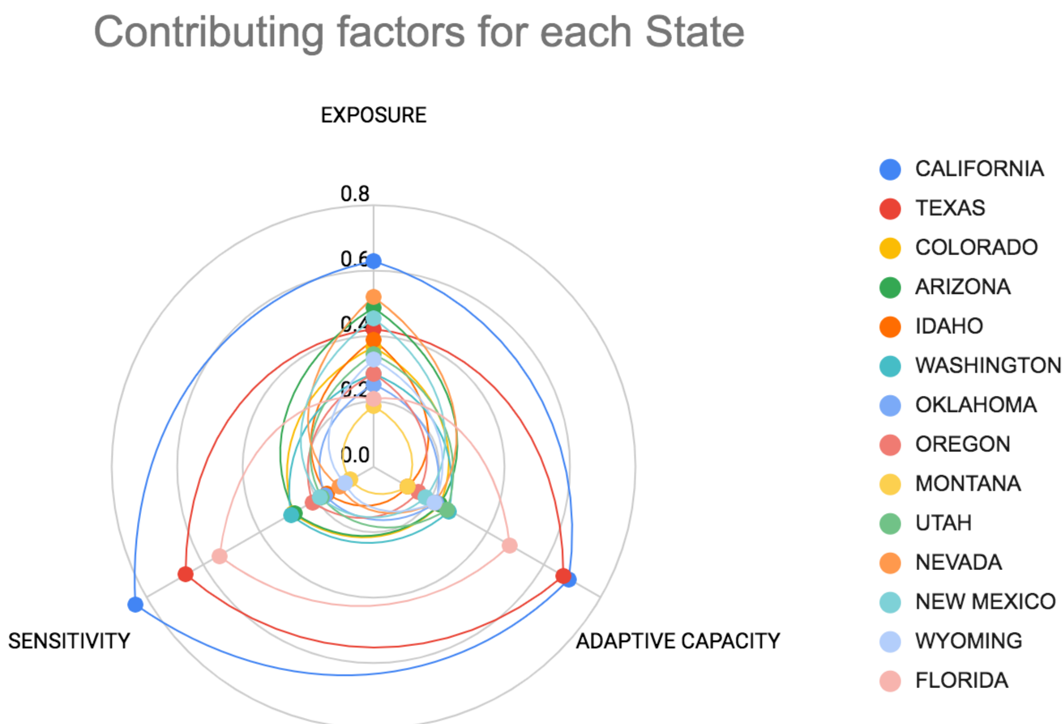

Figure. 8 Radar plot showing the overall contributing factors (exposure, sensitivity, and adaptive capacity) for the selected 14 states of the US analyzed.

Appendix

Table A1: Total area (acres) burnt for each State during the 2018 and 2019 year, obtained from the *Wildfire Risk Report, (2019*)

State	Total area burnt in 2018 and 2019 (acres)
California	1 823 153
Nevada	1 001 966
Oregon	897 262
Oklahoma	745 097
Idaho	604 481
Texas	569 811
Colorado	475 803
Utah	438 983
Washington	438 833
New Mexico	382 344
Wyoming	279 242

Table A2. The Kaiser- Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity results for each contributing factor of exposure, adaptive capacity, and sensitivity

Contributing Factor	Major Components	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Barllett's Test of Sphericity
Exposure	Wildfires	0.5	0.11
	Topography	0.5	0.351
	Weather	0.488	0
	Weather Extreme Events	0.5	0.264
Adpative Capacity	Natural Capital	0.612	0.101
	Physical Capital	0.613	0
	Human Capital	0.5	0.37
	Social Network	0.5	0
	Financial Capital	0.5	0.434
Sensitivity	Demographic	0.788	0
	Ignition Causes	0.5	0.004
	Environmental Index	0.5	0.04

Table A3. A matrix loading table, showing each indicator variable for the exposure contributing factor and its respective loading into each major component (wildfires, topography, weather, and weather extreme events)

Exposure Component Matrix				
Indicators	**Wildfires**	**Topography**	**Weather**	**Weather Extreme Events**
Number of wildfires	0.85			
Number of acres burnt	0.85			
Mean height above sealevel		0.797		
Highest elevation		0.797		
Annual average wind speed			0.166	
Annual average humidity			0.968	
Annual Average precipitation			0.974	
Average number of days with 0.1 inch or more precipitation a year			0.748	
Annual average temperature			0.39	
Number of extreme wildfires				0.813
Number of extreme heat occurences				0.813

Table A4. A matrix loading table, showing each indicator variable for the adaptive capacity contributing factor and its respective loading into each major component (social network, natural, physical, human, and financial capital)

Adpative Capacity Component Matrix					
Indicators	**Natural Capital**	**Physical Capital**	**Human Capital**	**Social Network**	**Financial Capital**
Acres of forest	-0.654				
Water area	0.831				
Area of lakes	0.847				
Miles of public road		0.874			
Number of major airports		0.964			
Number of households with a computer		0.981			
Number of households with broadband internet connection		0.977			
Number of People per household			0.794		
Number of timber/wood laborers			-0.794		
Number of Firefighters				0.998	
Number of first responders (EMTs)				0.998	
Median Household Income					0.783
Number of fire management assistance grants					0.783

Table A5 A matrix loading table, showing each indicator variable for the sensitivity contributing factor and its respective loading into each major component (demographic, ignition causes, and environmental index)

Sensitivity Component Matrix			
Indicators	**Demographic**	**Ignition Causes**	**Environmental Index**
WUI area	0.985		
Number of house within WUI zone	0.993		
Population at risk in WUI zones	0.994		
Population Density	0.906		
Housing units	0.991		
Number of camping sites		0.926	
Number of smokers		0.926	
Annual PDMI			-0.882
Annual AQI			0.882

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