

Chapter 3

Estimating Migration Impacts of Wildfire: California's 2017 North Bay Fires



Ethan Sharygin

Abstract This chapter examines a cluster of wildfire conflagrations that hit northern California during October 2017, which resulted in significant loss of housing units (6874 residential structures destroyed or damaged). To assess the magnitude of the migration response and network of destinations, a method to estimate migration drawing from a proxy universe of households with students enrolled in public schools was proposed, using data on school exits and re-enrollments from a longitudinal student database. The analysis finds that a small minority of households affected by the fires moved out of the area. Out of nearly 7800 persons displaced by the central fire complex in one city, this study estimated fewer than 1000 changed neighborhoods; of those, fewer than 500 moved out of Sonoma County. These findings are applicable to other wildfires and localized disasters where a substantial portion of housing is lost but public infrastructure in the region remains intact.

Keywords Wildland-urban interface · Wildfire · Natural hazards · Migration · Administrative data

3.1 Introduction

This chapter examines a cluster of wildfire conflagrations that hit northern California during October 2017, which resulted in significant loss of housing units (6874 residential structures destroyed or damaged). The magnitude of migration response was unknown, as was the timing and the network of possible destinations. This chapter provides a standard theoretical framework for understanding fire disasters: their frequency and locations most at risk. It also presents an overview of the 'October 2017 Fire Siege' and the conditions which precipitated the fire followed by a discussion into possible approaches to estimating population impacts. A method is proposed to estimate migration drawing from a proxy universe of households with students enrolled in public schools using data on school exits and re-enrollments from a

E. Sharygin (✉)

Population Research Center, Portland State University, Portland, OR, USA

e-mail: sharygin@pdx.edu

© The Author(s) 2021

D. Karácsonyi et al. (eds.), *The Demography of Disasters*,

https://doi.org/10.1007/978-3-030-49920-4_3

longitudinal student database. The analysis finds that a small minority of households affected by the fires moved out of the area. Out of nearly 7800 persons displaced by the central fire complex in one city, this study estimated that fewer than 1000 people changed neighborhoods; of those, fewer than 500 moved out of Sonoma County. These methods and findings are applicable to policies and policy research regarding future wildfires and localized disasters where a substantial portion of housing is lost but public infrastructure in the region remains intact.

Section 3.1 of this chapter discusses the growth of wildfire risk in California over the last and next century. Section 3.2 provides background on the Central Sonoma-Lake-Napa Unit (LNU) Complex fires, in particular the largest, the Tubbs fire in Sonoma County. Sections 3.3 and 3.4, the size of the displaced population is estimated, and previous research on estimating migration discussed. The ‘school enrollment proxy method,’ a new method of estimating migration, is described along with the results. The closing section outlines limitations of this approach and identifies directions for future research.

3.2 Background

3.2.1 *Wildfire Hazard in California*

Disasters are a major part of the Californian experience. Throughout American expansion into California, earthquakes, floods, fire, and other catastrophes have played an important role in defining life in the state. A tragic standard was set by the 1906 San Francisco earthquake and ensuing fire that followed, which destroyed 28,000 buildings, displaced at least 200,000 residents, and killed between 500 and 3000 people. Flooding in Los Angeles in 1938 destroyed 5600 buildings and caused over 100 deaths. Earthquakes at Loma Prieta in 1989 and Northridge in 1994 injured thousands and caused billions of dollars of damage. Wildfires in Berkeley during 1923 and then Oakland in 1991 destroyed thousands of residences and emphasized wildfire as a constant threat in urban and suburban parts of the state.

Disasters can be broadly classified into two types of looming threats. Gradual-onset disasters include droughts, sea level rising, global warming, while sudden-onset disasters would include fires, floods, and earthquakes. Sudden-onset threats are especially important for applied demographers to anticipate and prioritize due to their disruptive and chaotic aftermath and the essential role that demographic data can play in the government response. Sudden-onset disasters have immediate consequences, including mass mobilizations of people and resources.

This paper presents a case study from a series of wildfires in late 2017 that displaced more than 10,000 people in Sonoma County in the State of California. This event presented an exceptional challenge to account for the population of each county and city as of January 1, 2018 and to estimate the size of the affected population and the relocation patterns of people displaced by the fires.

While migration responses to wildfire are the focus of the present research, a broader agenda on disaster demography should consider sequelae of disasters and differential vulnerability (see Chaps. 4, 6 and 10). In the example of wildfires, smoke plumes may have a significant public health impact. Equity concerns are also important. Climate change is expanding the geography of risk and changing the demographic profile of the affected populations (see also Chap. 8). No longer limited to remote areas or vacation homes, vulnerability to wildfire in particular, may be reversing from a progressive to a regressive hazard (Davies et al. 2018; Baylis and Boomhower 2018).

Even though California is one-third forested, many of these forests are in poor health due to a combination of factors that including climate change and inadequate, misguided, or uncoordinated forest management policy. Abatzoglou and Williams (2016) found that climate change was responsible for half of the increase in aridity in Western US forests between 1966 and 2016 and that without climate change the cumulative area burned by fires would be just half of what has occurred between 1984 and 2016. Climate change is expected to continue to increase the frequency and intensity of fires (Keyser and Westerling 2017; Moghaddas et al. 2018).

More than 40% of California housing stock is in areas at heightened risk of fire damage, where housing abuts forest, referred to as the wildland–urban interface (WUI; Hammer et al. 2007). The hills, forests, and peripheries of cities and towns are desirable areas, both for builders and potential residents attracted to their natural amenities. Housing growth in WUI areas in California grew by approximately 20% each decade during 1990–2010, compared to 10% each decade for non-WUI areas even though the WUI accounts for just 10% of land area (Radeloff et al. 2018). This has contributed to more problematic forests due to fire suppression efforts and also exposed an increasing number of residents to increased fire risks.

3.2.2 Conditions of the 2017 Fire Season and the LNU Complex Fires

The year 2017 marked a record fire season in California, with 436 significant fires that burned more than 630,000 ha (CDFFP 2019). Yet, the records set during the fire season of 2017 have already been surpassed. Fires during 2018, notably the Carr fire near the city of Redding and the Camp fire which razed the city of Paradise, were the deadliest (93 confirmed fatalities) and most destructive (650,000 ha) in the state's history. This increase has necessitated the development of a robust toolset for estimating demographic impacts of disasters.

The LNU Complex fires comprised of the Tubbs, Nuns, Atlas, and several other fires deserves special mention. These three conflagrations occurred during October 2017 and in close to each other in the WUI. Nauslar et al. (2018) state that these fires 'pushed the bounds of conventional fire wisdom with the extreme rates of spread, size, and timing.' They affected four counties, but Sonoma County bore the brunt

of the population and housing impacts. They affected four counties, but Sonoma County bore the brunt of the population and housing impacts.

Sonoma County is located north of San Francisco, along the California coast of the Pacific Ocean. The county has a great deal of climatic variation, according to elevation and proximity to the ocean. Parts of the county close to the ocean remain cool and moist year-round and can be foggy most days from late afternoon until morning. Inland areas have a more typically Mediterranean climate, with hot, dry summers and cool, wet winters. The Northern Coastal Range of mountains runs on either side of the Sonoma Valley. Its abundance of variable microclimates lends itself well to viticulture, with California's first wineries established in the area in the 1850s. Santa Rosa is the largest city in Sonoma County and was home to 178,000 of the county's 504,000 residents in 2017 (CDOF 2018).

The region had suffered the effects of severe drought since 2011—possibly the worst drought in more than 1000 years (Griffin and Anchukaitis 2014). These conditions contributed to a record high total of 129 million dead trees in the state as of late 2017 (USFS 2018; Guerin 2017; Buluç 2017). In total, the state's tree mortality survey counted 147 million tree deaths during 2010–2018. A normal average would be 1 million tree deaths each year. However, 62 million deaths were recorded in 2016 at the peak of the drought.

As of October 2016, 83% of the state was in drought, and 21% of the state was in 'exceptional' drought status, the most severe category. The first months of 2017 saw high rainfall, which mitigated drought conditions. Most of the precipitation of the 2016–17 season fell during January and February, marking the state's wettest winter and the second-wettest year since records began in 1895 (Di Liberto 2017). The rain fell so fast that it caused flooding throughout the state and damaged the nation's tallest dam, Oroville Dam. The state's drought declaration had been in place since 2014 and was lifted in April 2017. The immense volume of rain was a welcome reprieve to depleted reservoirs but also promoted the growth of shrubs and grasses that typically wither during the hot, dry summer and become fuel for more intense fires (Dudney et al. 2017). Recent research found that the connection between wet weather and fire activity in California has broken down completely during the second half of the twentieth century, as the effect of growth and fuel buildup during rainier seasons created greater fire hazards within the context of increased annual temperatures (Wahl et al. 2019).

The state's seasonal wind patterns are another factor in making California especially susceptible to fires late in the year. Late summer winds, known regionally as the Santa Ana or Diablo winds, can occasionally bring fast hot winds that exacerbate fires. These winds may grow more intense as a result of climate change, although the effect is debated (Jin et al. 2015; Mass and Ovens 2019). These late summer or fall winds were a factor in all of the state's most destructive WUI fires and have long been recognized as 'a wind of bad augury [...] at this season of the year' (Russell and Boyd 1923).

It was during one such windy evening on October 8, 2017 that a small fire ignited near the town of Calistoga, a city of approximately 5000 in Napa County. The state had effected a 'red flag warning' which alerts the public to heightened fire

hazard conditions. Warm air at 32 °C combined with strong winds with peak gusts of 175 km/h. Weather stations in the hills around Santa Rosa recorded windspeed exceeding the ninety-ninth percentile as well as relative humidity below the second percentile (Nauslar et al. 2018). At the 9:44 pm local time, a resident of Calistoga reported a fire in the vicinity of Tubbs Road. Within six hours of the report, numerous fires in the region had grown into major conflagrations, collectively termed the LNU Complex (Fig. 3.1). The Tubbs fire, while not the largest of these, was the most destructive. It moved out of the WUI into urban Santa Rosa and surrounding communities.

Embers carried by strong winds ignited cascading spot fires that complicated rescue efforts by making it impossible to track the extent of the fire during the period of its most rapid expansion overnight. The fire spread uncontrolled during the night and reached the city limits of Santa Rosa by 1 am on October 9. Although

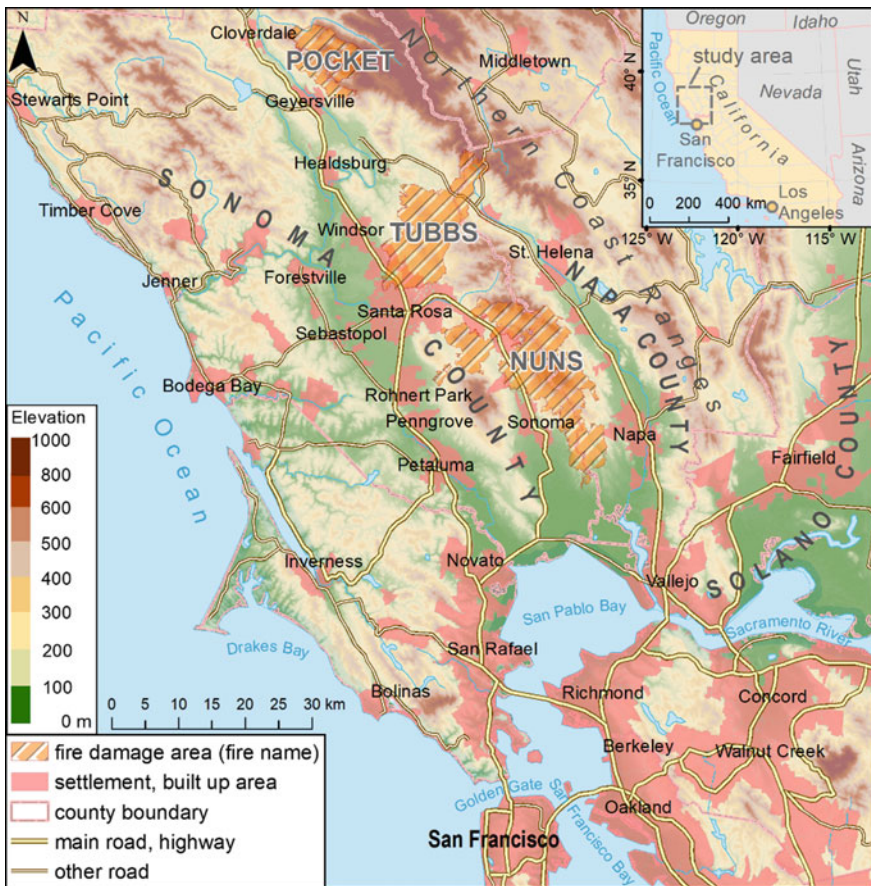


Fig. 3.1 Central LNU Complex fires in Sonoma County (Author: Sharygin, cartography by Karácsonyi)

Table 3.1 Characteristics of Sonoma County, Santa Rosa City and Tubbs fire perimeter

| Geography | Total population | N Households | | | Owner-occupied share of housing | Median household income |
|-----------------|------------------|--------------|----------------------------|-----------------------------|---------------------------------|-------------------------|
| | | Total | With 1 or more child (<18) | With 1 or more senior (65+) | | |
| Sonoma | 500,943 | 190,058 | 54,398 (27%) | 62,770 (33%) | 0.603 | 71,769 |
| Santa Rosa | 174,244 | 64,709 | 19,641 (30%) | 19,958 (31%) | 0.531 | 67,144 |
| Tubbs Fire Zone | 33,431 | 12,590 | 3,514 (28%) | 4,774 (38%) | 0.727 | 98,479 |

it was not fully contained until October 31, the urban destruction caused by the fire peaked within 24 h before winds died down. The Tubbs fire eventually burned almost 15,000 ha and destroyed 5636 structures, of which 4651 were residential. Collectively, the LNU Complex fires consumed more than 5000 housing units in Sonoma, Napa, and Solano counties (Hawks et al. 2017).

The following analysis focuses on impacts in Sonoma County, where the Tubbs fire displaced the greatest number of residents. The city of Santa Rosa lost 3081 housing units, representing approximately 5% of the city's housing stock (CDOF 2018). The city was already facing a housing shortage before the fire: with an overall vacancy rate of just 4.2% in 2017 (1.6% vacancy for rental units), and with 6.5% of housing units defined as 'overcrowded' (more than one resident per room).¹ Table 3.1 provides additional characteristics of Sonoma County, the city of Santa Rosa, and the fire-devastated areas.

The census block groups affected by the Tubbs fire had fewer renters as a share of households and higher average income. Households in the fire zone were also more likely to have at least one person in the household over the age of sixty-four, but the difference in the share of households with children was not found to be statistically significant.

3.3 Estimating Population Impacts From Housing Data

3.3.1 Role of Housing in Population Estimates

This section will investigate ways in which the statistics of destruction presented in the previous section could be translated to population and migration data necessary to plan a recovery effort. The State of California Demographic Research Unit produces

¹U.S. Census Bureau; ACS 2017 5-year SF, table DP04. Retrieved 1 April 2019 from <https://factfinder.census.gov>.

population estimates for July and January of each year. The methods of accounting for population change include housing data that enters into the calculation in several ways. Annual estimates for January 1 are produced via complimentary top-down and bottom-up estimation steps. The headline state population is estimated using a cohort component method (Swanson and Tayman 2012), in which the total population is determined by the last known population² accounting for births, deaths, and migration. Net migration is composited from different datasets for different age groups that include school enrollment; tax returns, driver's licenses, and immigration data; and pension and health insurance data.

County population estimates are produced by ensemble averaging (Clemen 1989). The first piece of the ensemble is a composite method in which different methods are used to estimate the size of the population of different age groups (Bogue and Duncan 1959). For example, births and school enrollment inform estimates of the size of the child population; driver's licenses, deaths, and tax information for the adult population, and administrative records including pension and health insurance data are the primary source of information about change in the population age 65 and older. The second piece is a 'ratio correlation' regression-based method, which predicts the county's total population as a function of covariates such as the county birthrate, housing stock, and labor force (Schmitt and Crosetti 1954). The third piece of the ensemble is a cohort component model, in which births, deaths, and net migrants from federal administrative data are included as measured by the U.S. Census Bureau. These three models are combined into the model (as equally weighted averages, although the weights could be specified differently) to produce a single county estimate, which is translated into a county share of the total state population and applied to the state total number estimated above.³

The populations of each of California's 539 city and county jurisdictions that include 482 cities, unincorporated parts of 57 counties, as well as the city and county of San Francisco, were estimated using a housing unit method (Swanson and Tayman 2012), which relates the total population to the number of housing units, the persons per household, and the vacancy rate. An advantage of the housing unit method is that, as an accounting identity, the only source of error is in the estimation of the

²Generally, this would be the last decennial Census, post adjustments.

³A small set of 14 counties with population below 65,000 is incremented (births) or decremented (deaths) from the last decennial census only, without an attempt to estimate net migration.

parameters. However, the parameters can be extremely challenging to monitor and update due to data constraints, especially for small areas. Change in the population that live in group quarters⁴ can be accounted for exclusively from administrative data.

The housing unit method and the ratio correlation method both rely on housing stock to adjust population counts. In the case of the housing unit method, the effect of loss in housing stock could be offset by updated vacancy and density constants. However, in the wake of a sudden-onset disaster, there may be no data with which to update the persons per household or vacancy rates, even if the data on housing unit change are rapidly updated and very high quality. The ratio correlation method can be even more vulnerable, depending on whether housing is part of the equation. A large shock in the form of housing stock loss would mechanically produce a significant drop in the population of Santa Rosa and Sonoma County. Qualitative accounts from reportage on the fire suggested that many displaced people stayed in proximity to the fire area, anticipating a return to their land after cleanup and reconstruction. The higher income and homeownership rates in the area are consistent with this notion.

3.3.2 Estimating the Number of Displaced Persons

To estimate the size of the displaced population in Sonoma County, we tested two approaches. In the immediate aftermath, without data on the precise location or addresses of destroyed housing, we interacted the total number of destroyed housing units inside the county boundaries with the persons per household most recently estimated for the city, weighted by the occupied share of housing.

In late October 2017, the state fire agency published a report on damage from the Tubbs Fire (Hawks et al. 2017), in which fire affected addresses and land parcel numbers were published along with assessments of the extent of the damage to the building and the building type (residential, commercial, or outbuilding). From this list, we generated a distribution of damaged and destroyed residential structures by census block group, which was used to weight block group level household size estimates from the American Community Survey (ACS), an annual household survey.⁵ Results for estimated population displacement using these two methods are presented below in Table 3.2. Despite the more careful use of block group specific housing tenure and vacancy rate data, the two alternatives are within 1% of each other; for this study, we adopted the simpler calculation that resulted in the count of 11,521.

⁴Group quarters include residential care facilities, hospitals, school dormitories, military barracks, prisons and jails, and other shared living arrangements.

⁵Geocoding of fire addresses was performed using the Census Bureau geocoding service, with manual geocoding of 296 records that returned no matches.

Table 3.2 Estimates of the population displaced by the Tubbs fire: Sonoma County, October 2017, **a** 2017 DOF housing and population estimates (Table E-5). **b** 2013–17 American community survey (Tables B25002, B2510)

a

| Geography | Residential structure loss | Vacancy rate | Persons per household | Displaced persons |
|-----------------|----------------------------|--------------|-----------------------|-------------------|
| | <i>A</i> | <i>B</i> | <i>C</i> | $A * (1 - B) * C$ |
| Sonoma County | 1,569 | 0.083 | 2.59 | 3,726 |
| Santa Rosa City | 3,081 | 0.038 | 2.63 | 7,795 |
| Total | 4,650 | | | 11,521 |

b

| Block group | Residential structure loss | | Rental share of occupied housing | Occupied units | Persons per household | | Displaced persons |
|-------------|----------------------------|---------|----------------------------------|----------------|-----------------------|----------|-------------------------------|
| | Freq. | Percent | | | Owned | Rented | |
| | <i>A</i> | | <i>B</i> | <i>C</i> | <i>D</i> | <i>E</i> | $D * C * (1 - B) + E * C * B$ |
| 152100.1 | 131 | 2.8 | 0.39 | 395 | 1.74 | 1.70 | 226 |
| 152400.1 | 169 | 3.6 | 0.11 | 947 | 2.50 | 1.36 | 402 |
| 152400.3 | 397 | 8.5 | 0.47 | 942 | 1.80 | 1.30 | 538 |
| 152400.4 | 642 | 13.8 | 0.15 | 980 | 2.90 | 2.54 | 1,828 |
| 152400.5 | 503 | 10.8 | 0.00 | 630 | 2.89 | 0.00 | 1,454 |
| 152502.1 | 2 | 0.0 | 0.35 | 614 | 2.65 | 3.62 | 6 |
| 152600.1 | 500 | 10.8 | 0.13 | 570 | 2.24 | 4.20 | 1,180 |
| 152600.5 | 169 | 3.6 | 0.16 | 526 | 2.12 | 1.41 | 241 |
| 152701.1 | 276 | 5.9 | 0.18 | 461 | 2.53 | 3.49 | 649 |
| 152701.3 | 35 | 0.8 | 0.19 | 387 | 2.50 | 1.83 | 83 |
| 152702.2 | 98 | 2.1 | 0.67 | 481 | 2.16 | 2.78 | 252 |
| 152702.3 | 315 | 6.8 | 0.06 | 368 | 2.16 | 2.13 | 665 |
| 152702.5 | 8 | 0.2 | 0.31 | 216 | 2.84 | 2.36 | 22 |
| 152801.1 | 219 | 4.7 | 0.58 | 531 | 2.55 | 2.49 | 551 |
| 152801.2 | 401 | 8.6 | 0.19 | 412 | 2.78 | 3.97 | 1,206 |
| 152801.3 | 275 | 5.9 | 0.35 | 403 | 2.13 | 4.15 | 740 |
| 152801.4 | 166 | 3.6 | 0.18 | 250 | 2.60 | 4.72 | 496 |
| 152801.5 | 207 | 4.5 | 0.22 | 296 | 2.67 | 2.38 | 540 |
| 152905.1 | 92 | 2.0 | 0.44 | 482 | 2.21 | 2.43 | 212 |
| 152906.1 | 1 | 0.0 | 0.40 | 1,326 | 2.80 | 2.95 | 3 |
| 153807.2 | 21 | 0.5 | 0.09 | 1,016 | 2.93 | 2.50 | 57 |
| 154100.4 | 23 | 0.5 | 0.49 | 357 | 2.57 | 4.19 | 63 |
| Total | 4,650 | 100.0 | | | | | 11,414 |

3.3.3 *Estimating Migration*

Having prepared an estimate of the population displaced by the loss of their home, we then needed to devise a system that could accurately model where people moved. In doing so, we analyzed how many remained in the same city, moved elsewhere in the county or state, or left the state altogether. We considered the literature from other efforts to assess disasters, as well as the methods used by other U.S. states.

An inspiring account came from the state of Florida in the aftermath of Hurricane Andrew in 1992, where a publicly funded telephone and field survey provided updated information on vacancy rates, persons per household, and population in transitory locations such as hotels and motels. This survey data provided rapid and accurate new inputs to the classical housing unit method (Smith 1996). However, costs and logistical challenges mean that this approach has not gained traction. Also, there are reasons why it might not succeed in all contexts. For instance, the accuracy of the approach depends on how many likely destinations of displaced people are captured. In the case of Hurricane Andrew, or indeed the Tubbs fire, this approach showed great promise because the housing losses were substantial but small relative to the regional housing capacity. In other cases where these conditions do not hold, a survey may not be practical or effective. A new data collection effort may not always be feasible, but there are many other private and public data sources were considered as shown in Table 3.3.

The US Census Bureau has worked with the US Federal Emergency Management Agency (FEMA) to collect data on persons registered with the agency to receive disaster assistance. In the case of wildfire, the extent of federal operations is determined by whether the federal government declares a ‘major disaster,’ ‘emergency,’ or a ‘Fire Management Assistance Declaration.’ The 2018 Camp Fire was declared a major disaster; however, the 2017 LNU Complex fires were only given the latter designation, limiting the extent of federal assistance and the accuracy of federal data. Residents affected by the LNU Complex fires had limited time to register with FEMA for grants or loans that support uninsured or underinsured residents. In addition, many homeowners may have opted to rely on private insurance. In Sonoma County, FEMA approved just 3200 registrations, and ultimately, only 119 households received temporary housing relocation assistance, leaving major gaps in the coverage of FEMA data for this disaster (Morris 2017; Schmitt 2019).

The US Postal Service provides change of address (COA) data with names and addresses of individuals, families, and businesses who have filed a change of address for mail delivery through a service called NCOALink. Postal service address data are the backbone of the US Census Bureau’s Master Address File, a putative master list of all living quarters in the USA. The NCOALink product is the most comprehensive source of household moves, but it is not a panacea, due to several limitations. The data are licensed for the purpose of updating mailing lists, and for privacy reasons cannot be queried without an extant mailing list which includes a name and address. From cadastral datasets, we generated a database of names and addresses associated with properties in the burn area, but the names of those with legal title to affected land

Table 3.3 Sources of data on migration

| | Data source | Coverage | Notes |
|----|---|---|--|
| 1 | FEMA Assistance | Registered persons or households | Requires national disaster declaration; confidential data |
| 2 | USPS NCOALink | Registered changes of address | Requires names and addresses; no data for temporary moves |
| 3 | ID, drivers license, or vehicle registrations | Drivers or ID holders; vehicle owners | Delayed registration of address changes. Potentially longitudinal, but confidential data difficult to access |
| 4 | Public health insurance/pension data | Beneficiaries | Varying coverage and rapidity of updates according to each program. Potentially longitudinal, but confidential data difficult to access |
| 5 | Traffic measurements | Drivers | Difficulty of parsing traffic data and relating to total population |
| 6 | Social media (Twitter, Facebook) | Users | Without adjustment, limited representativeness of selected population; difficulty of parsing data |
| 7 | Wastewater | Households using municipal sewer system | Missing population living in transitional locations or septic tanks; difficulty collecting and parsing/interpreting data |
| 8 | Solid waste | Households using municipal solid waste collection | Missing population living in commercial buildings (e.g. apartments and hotels); difficulty collecting and parsing/interpreting data; indirect relationship to disaster migration |
| 9 | Historical migration patterns (census/survey) | All persons | Geographic scale may be limited; historical data may not be representative of disaster migration patterns |
| 10 | Mobile phone movement | Mobile phone users | Rapid updates, but expensive, proprietary data source |
| 11 | Remote sensing | All structures | Potentially high cost of imagery and other sensor data; indirect relationship to disaster migration |

(continued)

Table 3.3 (continued)

| | Data source | Coverage | Notes |
|----|-------------------------------|----------------------------|---|
| 12 | Utilities (e.g. electric/gas) | Utility customers | Missing population living in transitional locations; difficulty of accessing and parsing/interpreting data. Limited longitudinal data |
| 13 | HUD Point-in-Time Count | Homeless | Conducted yearly or biennially |
| 14 | Voter registration rolls | Registered voters | Delayed registration of moves. Potentially longitudinal, but confidential data difficult to access. Representativeness issues |
| 15 | Credit Bureau Headers | Persons with credit files | Expensive, proprietary data; licensing issues |
| 16 | Tax data | State or federal taxpayers | Delayed registration of moves and publication of data. Generally not available at small geographies |
| 17 | Public education enrollment | Public school students | Longitudinal, but potentially limited representativeness; confidential data |

parcels will not give complete coverage. For example, cadastral datasets will include apartment and rental housing addresses and landlords' names, but not the names of individual tenants. In addition, historical metadata are not attached to moves. In other words, a search of COA within the past 18 months would return the most recent address only, not a sequence of moves if more than one move occurred. Another limitation is that temporary COA, for example, a hold mail or temporary change of address order may be filed with the postal service for up to one year, but these temporary orders are not searchable via NCOALink. People change residence for many reasons, and a blanket query of addresses in a disaster perimeter will overstate out-migration (as well as missing possible moves into undamaged housing in the area). For these reasons, NCOALink would be valuable only when a specific list of destroyed addresses and associated names are available.

Government programs such as public pensions, medical insurance, cash or in-kind transfer programs, and other entitlements may be a source of migration data. Their coverage will vary according to the socioeconomic characteristics of the area affected by the disaster, and the ability or willingness of the agencies involved to share data with the appropriate geographic specificity. These data were not available for this study, but in the future, they should be explored further. Agencies that collect such data ought to give thought to ways in which they could be made available for demographic studies without violating laws regarding privacy and disclosure of sensitive information. There are a variety of administrative data sources that may be

useful resources, but they share the drawback that the populations that participants in these programs may be few and highly selected relative to the total population. Still, some of these programs may enable estimation of population migration more rapidly than other sources, and it may be possible to statistically control for some aspects of population selectivity.

We pursued leads from the available data sources, and research into the use of new data is an area of continuing activity. For the LNU Complex fires, we eventually gravitated toward the use of public education enrollment data. We considered that public education is more representative than other government programs of the general population, while still capturing data in a timely manner as relocated families re-enroll their children in school. California, like many other US states, received federal grant funding to produce a student longitudinal data system (SLDS). In California, the SLDS program is called CalPADS and assigns individual identifiers to each student. The program records all enrollment activity such as transfers to other public schools or transfers out of the public school system (to private schools or out of state). Bias still exists: the behavior of families with children enrolled in Santa Rosa schools may not be representative of the decisions made by people in other living arrangements (living alone or with others in households without children, or in group quarters). On balance, these data offered a superior balance of timeliness, completeness, and representativeness compared to the alternatives.

3.4 Student Enrollment Proxy Method For Estimating Migration

Previously, in Sect. 3.2, the displaced population (N) was estimated at 11,521. To model new locations for this population, we focused this study on developing a methodology to use longitudinal student enrollment data in order to calculate a rate of migration of students in Sonoma County and extrapolate from their behavior to the wider population. To this end, the following data were collected.

1. Fire perimeter (GIS; or, geocoded housing loss registry).
2. Census block group boundaries (GIS)
3. Census block group population and housing characteristics
4. School attendance zones (GIS)
5. Student enrollment data by campus, including:
 - a. Total enrollment in October 2017 by grade (or age).
 - b. Enrollment changes by school campus of origin and destination.

Fire perimeter polygons were downloaded from the state's fire agency. Census block group boundaries and data were collected from IPUMS-NHGIS (Manson et al. 2018). School attendance boundaries were obtained from the School Attendance Boundary Survey (SABS), a program of the national department of education and the US Census Bureau (Geverdt 2018). We used the SABS polygons to determine which

Table 3.4 Student transfers (*N* = 211) by destination: Sonoma County school districts; 1 Oct-31 Dec 2017

| Many (>20) | <i>N</i> | (%) | Some (5–20) | <i>N</i> | (%) | Few (<5) | <i>N</i> | (%) |
|---|----------|-------------|--|----------|------------|--|----------|------------|
| <i>San Jose—San Francisco—Oakland CSA</i> | | | <i>Sacramento-Arden Arcade-Yuba City CSA</i> | | | <i>Bakersfield MSA</i> | | |
| Total | 138 | 65.4 | Total | 18 | 8.5 | Kern | 3 | 1.4 |
| Alameda | 3 | 1.4 | Sacramento | 10 | 4.7 | <i>Fresno-Madera CSA</i> | | |
| Contra Costa | 4 | 1.9 | Placer | 2 | 1.0 | Fresno | 2 | 1.0 |
| San Francisco | 1 | 0.5 | Nevada | 4 | 1.9 | <i>Stockton MSA</i> | | |
| Santa Clara | 1 | 0.5 | El Dorado | 2 | 1.0 | San Joaquin | 2 | 1.0 |
| Napa | 3 | 1.4 | <i>Los Angeles-Long Beach-Riverside CSA</i> | | | <i>Modesto MSA</i> | | |
| Marin | 10 | 4.7 | Total | 13 | 6.2 | Stanislaus | 2 | 1.0 |
| Solano | 8 | 3.8 | Los Angeles | 7 | 3.3 | <i>Visalia-Porterville MSA</i> | | |
| Sonoma; of which | 108 | | Riverside | 1 | 0.5 | Tulare | 1 | 0.5 |
| Other city | 51 | 24.2 | San Bernardino | 3 | 1.4 | <i>Salinas MSA</i> | | |
| Santa Rosa | 56 | 26.5 | Ventura | 2 | 1.0 | Monterey | 1 | 0.5 |
| Balance of County | 1 | 0.5 | <i>Clearlake μSA</i> | | | <i>San Luis Obispo-Paso Robles MSA</i> | | |
| | | | Lake | 16 | 7.6 | San Luis Obispo | 1 | 0.5 |
| | | | <i>Redding MSA</i> | | | <i>Red Bluff μSA</i> | | |
| | | | Shasta | 8 | 3.8 | Tehama | 1 | 0.5 |
| | | | <i>Ukiah μSA</i> | | | | | |
| | | | Mendocino | 5 | 2.4 | | | |

Source CalPADS

Totals may not be equal due to rounding

schools’ attendance areas included census block groups that experienced housing losses from the fires, by calculating the percentage overlap between the fire perimeter and school attendance zones. In Sonoma County, we ultimately selected 41 schools, spread over six school districts. We received from the state education department a tabulation from CalPADS data of school level enrollment change data for these districts, whose coverage areas included all block groups where a significant amount of housing was lost. The data we received consisted of total student transfers that occurred between October 1, 2017 and December 31, 2017 that were reported to the department as of March 2018. The report includes the number of transfers for every unique origin–destination pair of schools, along with the destination school city and county summarized in Table 3.4.⁶

⁶Due to a processing error, we did not receive out of state transfers, only transfers to other schools in California.

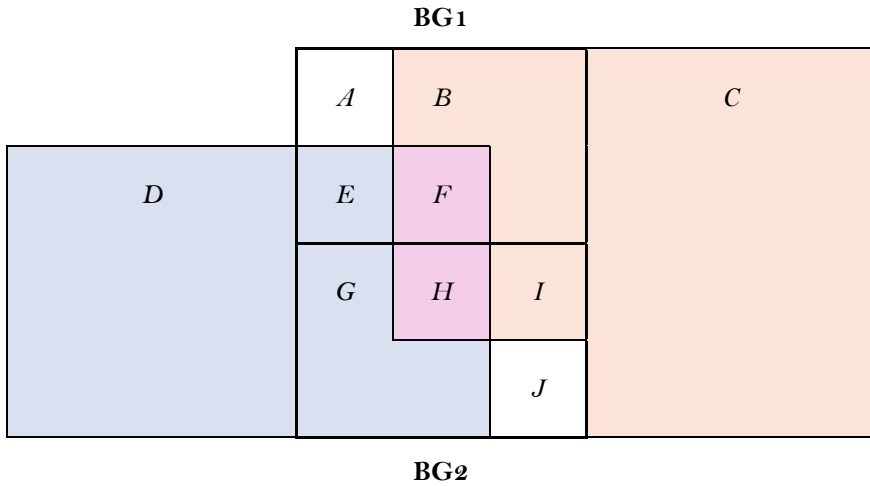


Fig. 3.2 Calculating migration universe for school enrollment proxy model. *Note* labels refer to the entire area inside the intersection of fire/school/block group boundaries

In total, the data indicated that there were 211 transfer students out of schools serving homes in the burned area. The majority of the 211 transfer students did not move far: over half of withdrawn students re-registered at other schools in Santa Rosa or other jurisdictions in Sonoma County. Other significant destinations (circa 5% of transfers) were Lake, Marin, and Sacramento counties. The next step was to follow up by identifying the population at risk of these moves, to estimate a migration rate for the general population based on the total number of displaced students.

I proposed a *school enrollment proxy method*, in which the percentage overlap is calculated between each school’s attendance zone, census block group, and fire area shown in Fig. 3.2.

In Fig. 3.2, the area $B + C + F + H + I$ (written hereafter as $BCFHI$) is bounded by the fire area, and $DEFGH$ is defined by the school attendance boundary. Two census block groups are represented above where $BG1 = ABEF$, and $BG2 = GHIJ$. Area A is in neither the school attendance zone nor the fire area. B is the fire area, but not the school attendance zone. E and F are in the school attendance zone, but only F is within the fire area. The total number of households inside areas F and H was estimated using a GIS analysis. This revealed households whose migration trends can be followed in the school enrollment data. The above is an extreme example. In most cases, there was an insignificant amount of area in a given block group that was not captured by the school attendance zone. For this reason, the simplifying assumption was made such that $H \approx HI$ and $F \approx FB$.

To estimate the population at risk of migration, we further needed to assume which portion of the total enrollment of each school lived in the households in the intersecting areas. To do this, we used student enrollment data at each school by grade, which are regularly published online by the education department (students’ ages are

withheld from these data for privacy reasons).⁷ At the block group level, we compared with data on school enrollment by grade from the latest five-year ACS to estimate the number of children in the block group whose household moves should be captured in the enrollment change data.⁸ For example, if school boundary *DEFGH* represents an elementary school, the migration universe or population at risk of migration is the total number of children in BG1 enrolled in elementary school, weighted by the share of households in BG1 that are inside block group zone *F*. To estimate the latter, we adopted the equal area weighting method of areal interpolation, under which the share of BG1 land area in zone *F* also approximates the zone's share of housing units. Student enrollment by school could be used to update ACS data from previous years or to estimate student counts in their absence. The resulting estimate of population at risk is shown below in Table 3.5.

This novel approach relies on a geocoded structure damage/loss inventory, which may not be readily available for other types of disasters. Perimeter data are more readily available for a variety of disaster events. However, a perimeter-only method without structure losses by block group greatly overestimates housing units lost since it implicitly assumes that burned area in any given block is equally likely to have consumed housing as not (which is unrealistic and usually counter to the goal of fire suppression). We tested the effect of generating a perimeter-based estimate by comparing the housing loss estimates from perimeter-only method to the known total housing loss. This process identified all block groups that intersected the fire perimeter (46 compared to only 22 block groups identified in the geocoded loss data). Interacting the share of the area of each of these block groups inside the fire perimeter with the housing stock produces an overestimate of 10,490 housing units lost. Weighting the estimated impacted students by the ratio of an independent standard results in what is likely an undercount of the displaced student population ($N = 1293$), but a useful point of comparison (Table 3.6).

The migration proportion of Sonoma students can now be calculated by:

$$\text{Migration rate} = N \text{ movers}(211) / N \text{ at risk } (1740) = 12.13\%$$

We assume that all transfers were the result of fire related displacement, and that there were no moves in due to the fire, which may result in an overestimate of net migration attributable to the fire. In estimating the student population, the equal area weighted interpolation assumption implies homogeneity within the block group. Results will be biased if block group average characteristics do not accurately describe the characteristics of lost housing units. For example, we implicitly assume that destroyed homes were equally likely to contain students as standing homes in the same block group.

There are caveats in the approach as it is currently formulated. A significant source of uncertainty is whether the rate of migration we estimated for students

⁷CDE Data Report Office. <https://www.cde.ca.gov/ds/sd/sd/>.

⁸ACS 5-year 2013–17. “School enrolment by detailed level of school for the population 3 years and over” (B14007).

Table 3.5 Estimating population at risk of migration from ACS survey data

| Block Group | Enrolled students, by grade | | | Housing lost (share of total) | Student population at risk of move |
|-------------|-----------------------------|-----|------|-------------------------------|------------------------------------|
| | K-6 | 7-8 | 9-12 | | |
| | A | B | C | D | (A + B + C) * D |
| 1521001 | 60 | 5 | 18 | 0.332 | 28 |
| 1524001 | 84 | 82 | 202 | 0.178 | 66 |
| 1524003 | 0 | 0 | 0 | 0.366 | 0 |
| 1524004 | 231 | 63 | 142 | 0.655 | 286 |
| 1524005 | 52 | 62 | 241 | 0.798 | 283 |
| 1525021 | 228 | 72 | 114 | 0.003 | 1 |
| 1526001 | 112 | 0 | 57 | 0.828 | 140 |
| 1526005 | 60 | 14 | 36 | 0.229 | 25 |
| 1527011 | 109 | 21 | 53 | 0.521 | 95 |
| 1527013 | 94 | 21 | 59 | 0.090 | 16 |
| 1527022 | 123 | 10 | 39 | 0.204 | 35 |
| 1527023 | 72 | 8 | 69 | 0.838 | 125 |
| 1527025 | 101 | 8 | 8 | 0.037 | 4 |
| 1528011 | 88 | 0 | 6 | 0.412 | 39 |
| 1528012 | 152 | 18 | 45 | 0.973 | 209 |
| 1528013 | 198 | 28 | 21 | 0.647 | 160 |
| 1528014 | 48 | 0 | 37 | 0.664 | 56 |
| 1528015 | 96 | 66 | 21 | 0.699 | 128 |
| 1529051 | 43 | 20 | 24 | 0.191 | 17 |
| 1529061 | 392 | 167 | 209 | 0.001 | 1 |
| 1538072 | 312 | 112 | 323 | 0.019 | 15 |
| 1541004 | 91 | 38 | 77 | 0.052 | 11 |
| Total | | | | | 1,740 |

applies equally to the non-student population. Households without children may be more or less likely to relocate depending on their age, housing tenure, length of time in the area, and employment. Of those that migrate, they may be less likely than households with children to remain in the region. Migration of families with children could also be underestimated, for example, children may have commuted from new residences back to their original schools to avoid the stress of changing schools. If households without children in school are more likely to relocate, then these results are biased toward underestimating the impact of the fire on out-migration.

To generate new estimates for January 1, 2018, we follow the usual steps for the housing unit method and county estimates ensemble. However, we deviated from usual practice in that we keep the housing lost from the disaster in the housing stock when the models are run. After generating counterfactual estimates this way,

Table 3.6 GIS-only method for displaced student population from fire zone

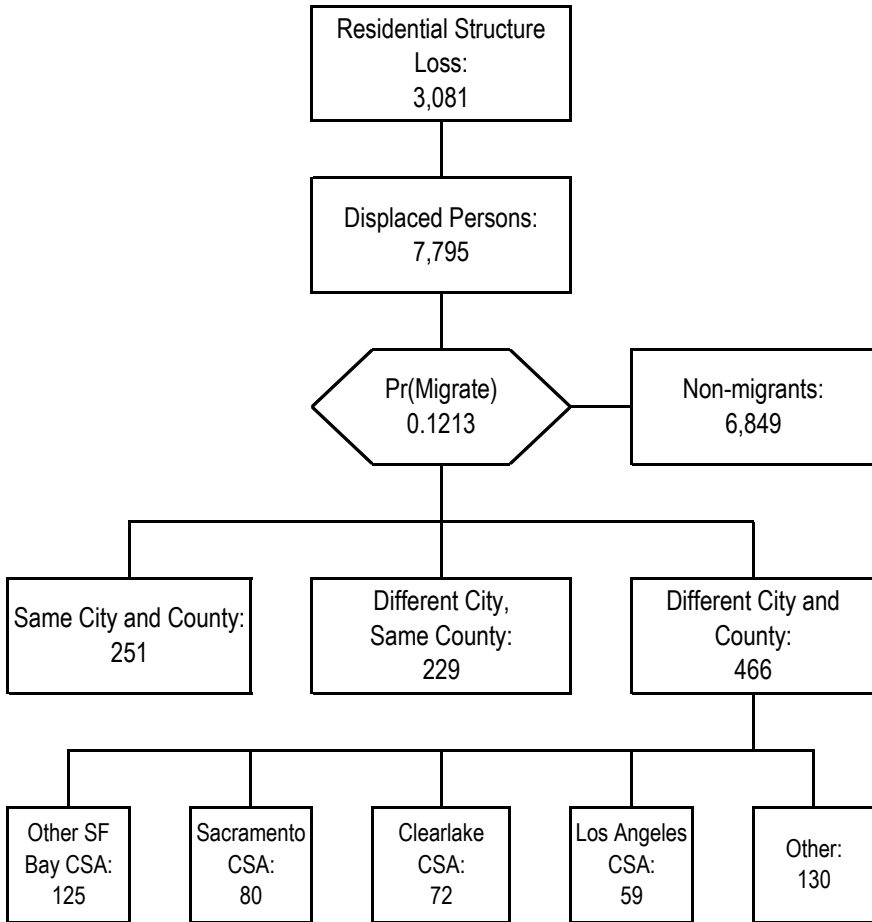
| Block Group | Share of BG Area inside Fire perimeter | Housing units | Student population (K-12) |
|-------------|--|-----------------------|---------------------------|
| | <i>A</i> | <i>B</i> | <i>C</i> |
| 1501001 | 0.450 | 610 | 64 |
| 1501003 | 0.034 | 272 | 38 |
| 1502023 | 0.745 | 450 | 115 |
| 1502024 | 0.545 | 803 | 200 |
| 1503032 | 0.002 | 504 | 135 |
| 1503063 | 0.489 | 902 | 257 |
| [...] | | | |
| | Independent estimate | Modelled housing loss | Weighted exposure |
| | | $B * A$ | $C * A * (D/E)$ |
| 1501001 | | 275 | 13 |
| 1501003 | | 9 | 1 |
| 1502023 | | 335 | 38 |
| 1502024 | | 438 | 48 |
| 1503032 | | 1 | 0 |
| 1503063 | | 442 | 56 |
| [...] | | | |
| Total | $D = 4650$ | $E = 10,490$ | 1,293 |

we account for the disaster impacts separately. We then define the population at risk of migration for each jurisdiction where population estimates are needed. In this case, example results are shown below in Table 3.7 for the city of Santa Rosa. We apply the migration probability to the population at risk of migration and then assign migrants to new destinations according to the distribution of destinations in the student enrollment change data.

3.5 Conclusion

The results suggest that most Santa Rosa residents did not move out of the city: according to our analysis, only 695 or 9% of displaced persons crossed jurisdictional boundaries in this case and most often to nearby cities or unincorporated areas in the same county. The estimation framework is intended to be generalizable to any origin–destination dyad data, as long as the geographic data can be used to estimate a population at risk. The methodology we presented may be suited to timely assessment of the population impacts of disasters that occur in countries with a well-developed public infrastructure. The effort we made would not have been possible without

Table 3.7 Net migration estimates for fire displaced population of Santa Rosa, Sonoma County



the ability of government institutions to produce and share reliable data about the emergency, as well as high quality small area data from the ACS and longitudinal records from the public education system.

We propose that the housing stock destroyed by disasters should be handled carefully by population estimation methods that rely on housing stock. One solution is to keep the destroyed housing in the model as if it was still existing and then to separately estimate and account for migration as a post-estimation adjustment (similar to the treatment of GQ population). This would improve the accuracy of the ratio correlation or other regression-based models. The housing unit method could use this approach also, but a simpler solution would be to adjust vacancy rates and persons per household to accommodate the lost housing units while keeping the population within the jurisdiction. While we anticipate that this approach can be useful for studying many disaster types, more effort should be put into developing a typology

of methods that work for a broader variety of disaster types and in other state and country contexts.

Future work on this methodology should focus on identifying systematic differences between the general and proxy population, such as students, that can be represented with data available to the model. Because our primary concern was adjusting for the very high bias toward overstatement of the number of migrants in the housing unit and ratio correlation methods, we considered these acceptable tradeoffs.

The area of Sonoma County that burned in the Tubbs fire in 2017 bore great resemblance to a fire of 53 years previous—the Hanly Fire of 1964. Like the Tubbs Fire, Hanly started in the hills near Calistoga; propelled by strong winds, it reached Santa Rosa city in less than 12 hours (Kovner 2013). It caused much less destruction because the WUI at that time was relatively sparsely inhabited. The fire did not halt continued growth of the population or expansion of housing continually deeper into the WUI. As the wildfire hazard increases throughout the state in coming years, continued research into methods of estimating population impacts will become increasingly in demand.

References

- Abatzoglou J, Williams AP. 2016. “Impact of anthropogenic climate change on wildfire across western US forests.” *PNAS* 113(42) 11770-11775. <https://doi.org/10.1073/pnas.1607171113>.
- Baylis P, Boomhower J. 2018. “Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters”. SIEPR Working Paper 18-044. Retrieved 1 April 2019 from <https://siepr.stanford.edu/sites/default/files/publications/18-044.pdf>.
- Bogue D, Duncan B. 1959. “A composite method for estimating postcensal population of small areas by age, sex and color.” Vital Statistics Special Report, Vol 47 No 6. Washington, DC: National Center for Health Statistics.
- Buluç L, Fischer C, Ko J, Balachowski J, Ostoja S. 2017. “Drought and Tree Mortality in the Pacific Southwest Region.” A synopsis of presentations and work group sessions from the Science and Management Symposium: “Lessons Learned From Extreme Drought and Tree Mortality in the Sierra Nevada: How Can Past Events Inform Our Approach Forward?”. Symposium held July 2017, Sacramento, CA. Retrieved 1 April 2019 from https://www.fs.fed.us/psw/topics/tree_mortality/california/documents/DroughtFactSheet_R5_2017.pdf.
- CDOF. California Department of Finance (CDOF). 2018. E-5 Population and Housing Estimates for Cities, Counties and the State — January 1, 2011-2018. Sacramento, California, May 2018.
- CDFFP. California Department of Forestry and Fire Protection (CDFFP/CalFire). Preliminary statistics from Annual Wildfire Activity Statistics Report. Retrieved 1 December 2019 from <https://www.fire.ca.gov/incidents/2017/>.
- Clemen RT. (1989) “Combining forecasts: A review and annotated bibliography.” *International Journal of Forecasting* 5(4): 559–583.
- Davies I, Haugo R, Robertson J, Levin P. 2018. “The unequal vulnerability of communities of color to wildfire”. *PLOS ONE*. <https://doi.org/10.1371/journal.pone.0205825>.
- Di Liberto T. 2017. “Very wet 2017 water year ends in California”. *NOAA Climate News*: October 10, 2017. Retrieved 1 April 2019 from <https://www.climate.gov/news-features/featured-images/very-wet-2017-water-year-ends-california>.
- Dudney J, Hallett L, Larios L, Farrer E, Spotswood E, Stein C, Suding K. 2017. “Lagging behind: Have we overlooked previous-year rainfall effects in annual grasslands?” *J. Ecol.* 105:484–495.

- Geverdt D. 2018. *School Attendance Boundary Survey (SABS) File Documentation: 2015–16 (NCES 2018–099)*. US Department of Education, Washington, DC: National Center for Education Statistics. Retrieved 1 April 2019 from <https://nces.ed.gov/programs/edge/SABS>.
- Griffin D, Anchukaitis K. 2014. “How unusual is the 2012–2014 California drought?”, *Geophys. Res. Lett.* 41:9017–9023. <https://doi.org/10.1002/2014GL062433>.
- Guerin E. 2017. “Drought kills 27 million more trees in California”. *KPCC*. Retrieved 1 April 2019 from <https://www.scpr.org/news/2017/12/12/78804/drought-kills-another-27-million-trees-in-californ/>.
- Hammer RB, Radeloff VC, Fried JS, Stewart SI. 2007. “Wildland-urban interface housing growth during the 1990s in California, Oregon, and Washington.” *Int J Wildland Fire* 16:255–265.
- Hawks S, Goodrich B, Fowler C. 2017. *Tubbs Incident Central LNU Complex (CALNU 010045) Damage Inspection Report*. Sacramento, CA: California Department of Forestry and Fire Protection (CDFFP/CalFire).
- Jin YF, Goulden M, Faivre N, Veraverbeke S, Sun F, Hall A, Hand M, Hook S, Randerson J. 2015. “Identification of two distinct fire regimes in Southern California: implications for economic impact and future change”. *Env Res Lett* 10(9). <https://doi.org/10.1088/1748-9326/10/9/094005>.
- Keyser A, Westerling A. 2017. “Climate drives inter-annual variability in probability of high severity fire occurrence in the western United States”. *Environmental Research Letters* 12(6). <https://doi.org/10.1088/1748-9326/aa6b10>.
- Kovner G. 2013. “Redwood Empire fire history remains visible in wild spots”. *Santa Rosa Press-Democrat*, September 14, 2013. Retrieved 1 April 2019 from <https://www.pressdemocrat.com/news/2217177-181/redwood-empire-fire-history-remains>.
- Manson S, Schroeder J, Van Riper D, Ruggles S. 2018. *IPUMS National Historical Geographic Information System: Version 13.0* [Database]. Minneapolis: University of Minnesota. 2018. <https://doi.org/10.18128/D050.V13.0>.
- Mass C, Ovens D. 2019. “The Northern California Wildfires of 8–9 October 2017: The Role of a Major Downslope Wind Event”. *Bull Am Met Soc*. Feb 2019: 235–256. <https://doi.org/10.1175/BAMS-D-18-0037.1>.
- Morris JD. 2017. “Northern California fire victims must register for FEMA, SBA assistance by Monday”. *Santa Rosa Press-Democrat*, December 9, 2017. Retrieved 1 April 2019 from <https://www.pressdemocrat.com/news/7732075-181/northern-california-fire-victims-must>.
- Moghaddas J, Roller G, Long J, Saah D, Moritz M, Star D, Schmidt D, Buchholz T, Freed T, Alvey E, Gunn J. 2018. “Fuel treatment for forest resilience and climate mitigation: a critical review for coniferous forests of California.” California Natural Resources Agency. Publication number: CCCA4-CNRA-2018–017.
- Nauslar N, Abatzoglou J, Marsh P. 2018. “The 2017 North Bay and Southern California Fires: A Case Study”. *Fire* 1(1), 18; <https://doi.org/10.3390/fire1010018>.
- Radeloff V, Helmers D, Kramer H, Mockrin M, Alexandre P, Bar-Massada A, Butsic V, Hawbaker T, Martinuzzi S, Syphard A, Stewart S. 2018. “Rapid growth of the US wildland-urban interface raises wildfire risk”. *PNAS* 115 (13):3314–3319. <https://doi.org/10.1073/pnas.1718850115>.
- Russell G, Boyd A, eds. 1923. *The Berkeley fire: dedicated to the people of Berkeley who have proved themselves great hearted in giving, courageous in losing, and clear eyed in building toward a safer future*. Berkeley, CA: Lederer, Street & Zeus Co.
- Smith SK. (1996): *Demography of Disasters: Population Estimates after Hurricane Andrew*. Population Research and Policy Review, vol. 15, pp. 459–477.
- Schmitt R, Crosetti A. 1954. “Accuracy of the ratio-correlation method for estimating postcensal population.” *Land Economics* 30:279–281.
- Schmitt W. 2019. “FEMA extends housing aid for fire survivors as Santa Rosa offers home loans to eligible Coffey Park fire victims”. *Santa Rosa Press Democrat*, March 21, 2019. Retrieved 1 April 2019 from <https://www.pressdemocrat.com/news/9412262-181/fema-extends-temporary-housing-for>.

- Swanson D, Tayman J. 2012. *Subnational Population Estimates*. The Springer Series on Demographic Methods and Population Analysis. Springer Netherlands. <https://doi.org/10.1007/978-90-481-8954-0>.
- U.S. Forest Service (USFS). 2018. "2018 Tree Mortality Aerial Detection Survey Results". Retrieved 1 April 2019 from https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd609295.pdf.
- Wahl E, Zorita E, Trouet V, Taylor A. 2019. "Jet stream dynamics, hydroclimate, and fire in California from 1600 CE to present". *PNAS* 116(12):5393-5398. <https://doi.org/10.1073/pnas.1815292116>.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

