THE IMPACT OF NATURAL DISASTERS ON SCHOOL CLOSURE

by

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To my beloved family and friends.

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LIST OF ABBREVIATIONS

$: Dollar

U.S.: United States

USA: United States of America

PUMA: Public Use Microdata Area

EM-DAT: Emergency Events Database

PTSD: Post-Traumatic Stress Disorder

°C: Celsius

FEMA: Federal Emergency Management Agency

%: Percent

TV: Television

FRPM: Free Reduced-Price Meals

CA: California

NC: North Carolina

LA: Los Angeles

IPUMS: Integrated Public Use Microdata Series

IRB: Institutional Review Board

PA: Public Assistance

IA: Individual Assistance

NSLP: National School Lunch Program

AFDC: Aid to Families with Dependent Children

SSI: Supplemental Security Income

GA: General Assistance

NCES: National Center for Education Statistics

ANOVA: Analysis of the Variance

OLS: Ordinary Least Squares

ES: Elementary school

MS: Middle school

HS: High school

NCES: National Center for Education Statistics

ABSTRACT

Despite the fact that natural disasters have always existed, the number and intensity of natural disasters have increased. Progress has been made in preparing for natural disasters, but the consequences are still severe. This study takes on the task of identifying the features that make schools more vulnerable to natural disasters. Using a simple OLS (N=387) the study analyzes the effect of natural disasters on school closures. Using six different disasters as our study area, we capture different demographic and socioeconomic features of a school impacted by natural disaster at different geographic levels: the individual school, the school district, and the Public Use Microdata Area (PUMA). The regression results show that factors such as increased disaster severity, higher levels of poverty, and larger numbers of at-risk individuals within a PUMA have significant positive associations with an increase in the number of days a school closes. At a practical level, understanding the impact of a disaster on school closure can depend on multiple factors and is important for local, state and federal governments. Policies must be implemented by local communities throughout the nation to increase community resilience. By understanding vulnerability factors adequately, their impact on school closure can be mitigated by increasing appropriate preparedness, efficient recovery strategies, evacuation strategies, and interpersonal awareness. Climate change and its effects, present and future, is a major concern for the whole world. Our efforts to understand and seek solutions to prevent and limit the damages rendered by natural disasters are critical to an effort to reduce the impacts of climate change in the U.S. and other affected countries.

Key words: Natural disasters, school closure, education, days out of school

INTRODUCTION

The United States has great geographic diversity. This, unfortunately, plays a role in a variety of frequent natural disasters that the country suffers from annually. Over the past 30 years, there have been over 53 natural disasters in the United States. Those disasters include hurricanes, floods, tornadoes and wildfires.

A natural disaster can provoke not only an economic shift, but also a demographic shift. The number of casualties can go over 16,000 per event. Normally, economic losses accompany human casualties. For example, in 2016, the total estimated U.S. losses reached $46 billion. There were multiple events costing more than $10 billion such as the Louisiana flooding in august 2016 or Hurricane Matthew from October 5th to 10th of 2016. Severe thunderstorms that year inflicted the highest economic losses among all the disasters in 2016, which cost about $20 billion. They represent more than 40% of the total estimated losses from disasters occurring in 2016(Benfield, 2017; Smith, 2017).

Disasters are also linked to psychological distress. After a disaster, people may have to reallocate, may have lost their relatives, their home, or income, or may live in fear of a possible upcoming disaster. All these factors cause stress. Most of the research on disasters has focused on adults, businesses, and communities. However, a serious consequence is the long-lasting impact on schools and schoolchildren. After a disaster, schools, which are a vital part of the community are affected. This means that children do not have classes for, sometimes, long periods of time. Some children are reallocated to other schools, while others may be forced to start homeschooling.

As an example, Hurricane Katrina struck the United States in August 29, 2005 inflicting damages estimated to be around $125 billion. There were approximately 25,000 storm evacuees and 971 fatalities in Alabama, Florida, Georgia, Louisiana and Mississippi(CNN Library, 2019). Five years later, the Children's Health Fund (2016) reported, as mentioned in "The devastating effect hurricane Katrina had on education"(Wade, 2017), that 40% of the children in affected families did not have stable housing. Another 20% remained emotionally distressed and 34% had been held back in school. It means that children missed class during the disaster and for a duration after the disaster. In that same article, Wade (2017) mentions that Reckdahl (2015) wrote, "probably numbering in the tens of thousands—missed weeks, months, even years of school after Katrina"(Wade, 2017).

Katrina is but one example of the damage that disasters can inflict on school systems and children. Location of the school system can exacerbate the damage. Each geographic zone has different demographic and economic characteristics. Therefore, the varying levels of resources and the task of recovery from disasters will differ for each school. Additionally, disasters inflict different degrees of destruction on each school. The time of recovery will also vary due to such differences.

The objective of this study is to determine the effect of socioeconomic vulnerability on school closures after a natural disaster. This study will concentrate on the impact that school demographics such as race and community economic characteristics such as poverty rate have on the number school days lost after natural disasters that occurred in 2018 in California and North Carolina. We test the following hypotheses: 1. The severity of the disaster will increase the days out of school; 2. Schools with high levels of poverty will be closed more days; and 3. Increasing the number of vulnerable population within a PUMA will increase the number of days out of school. In addition, we control for the characteristics of the students within the schools and the characteristics of the environment of the schools that based on the literature are thought to contribute to the vulnerability of the schools.

CHAPTER 1. BACKGROUND AND LITERATURE REVIEW

1.1 Background

This section aims to provide a background on the natural disasters that happened all around the world, and their consequences.

1.1.1. What is a natural disaster?

The consequences of natural disasters have been investigated mainly by economists, sociologists and political scientists. EM-DAT, the international disaster database defines a disaster as “a natural situation or event which overwhelms local capacity and/or necessitates a request for external assistance”. In order for an event to be categorized as a disaster and be entered into the EM-DAT database, at least one of the following criteria must be met: 10 or more people are reported killed; 100 people are reported affected; a state of emergency is declared; or one can also account for disaster costs at the micro level (especially households)(Below, 2006). For economists, natural disasters are a “set of complex chain of events that can disrupt both the local economy and, in severe cases, the national economy”(Kliesen, 1994). For sociologists, disaster events are unique historic episodes(Drabek, 2005). Drabek (2004) defined a disaster as “. . . an event in which a community undergoes severe such losses to persons and/or property that the resources available within the community are severely taxed”(Drabek, 2004).

Currently, EM-DAT has registered valuable information of over 23,000 disasters out of which around 62.5% are natural and 37.5% are technological disasters. The number of worldwide disasters date from 1900 to the present day. The different disasters are droughts, earthquakes, extreme temperatures, floods, landslides, mass movements (dry), storms, volcanic activities and wildfires. The information is collected from different sources which are UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies(Below, 2006; CRED, 2019). The impact and frequency of each type of disasters will be discussed later on.

For each disaster reported one can find different type of information. One may find the following information concerning disasters: a unique disaster number for each disaster event (DISNO), country, disaster generic group, disaster subgroup, disaster main type and sub-type, date (start and end), total deaths, injured, homeless and affected, total affected, and estimated damages. The main goals of gathering this quality and valuable data is to aid humanitarian organizations at both the national and international level, to help decision makers for disaster preparedness and to provide an objective basis for vulnerability estimate and priority setting. It is the international and most important publicly available source of disaster data(Guha-Sapir, Hoyois, & Below, 2016).

1.1.2. Worldwide natural disasters reported since 1900 to 2018

Figure 1 and Figure 2, from EMDAT(EMDAT, 2017, 2019), indicate the number of natural disasters that were recorded from 1900 to 2018 including floods, wildfires and other events. In Figure 1 these natural disasters are categorized by type and includes both weather and non-weather-related disasters. As Figure 1 shows, the number of recorded natural disasters has been increasing slowly between 1900 and 1963, it went from 5 in 1900 and 41 in 1963. However, after 1963, the increase has been more drastic until 2000 where it reached 411 natural disasters recorded. The year with the most disasters was 2005 with 432. After that year there was a gradual decrease. In 2018 the number of disasters was 282. Globally, 3.9 billion people, or about half the worldwide population, were potentially exposed to natural disasters in 2018. If we were taking into account, the regions where natural disasters struck more than once in 2018 there would be 10.7 billion people exposed to natural disasters(CRED, 2019).

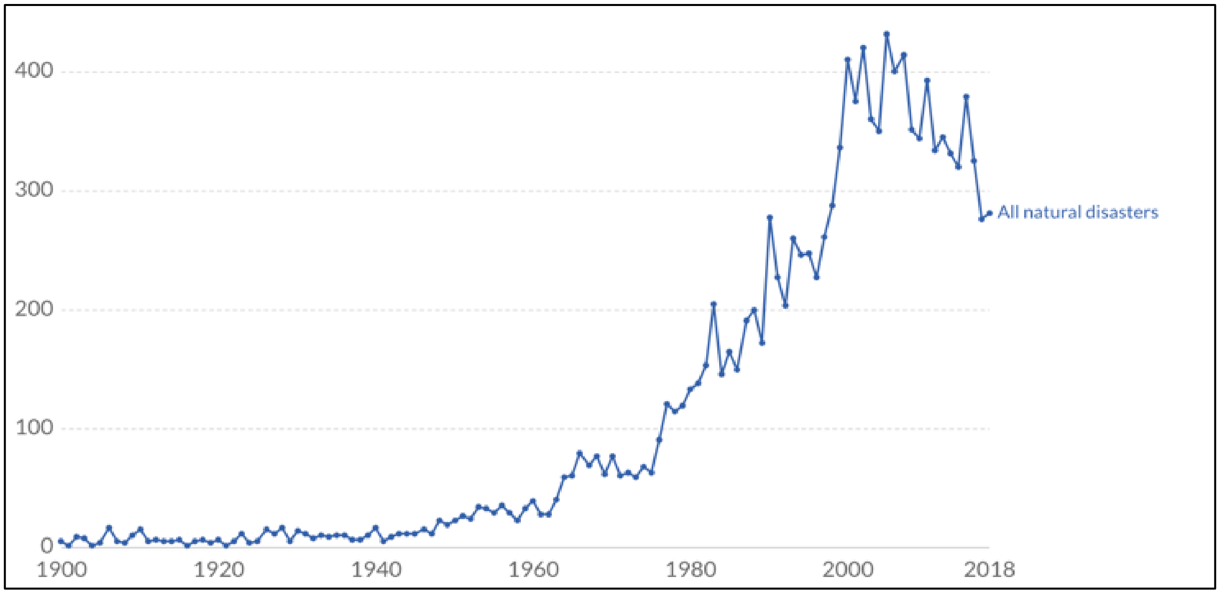

Figure 1: Number of recorded natural disaster events, all natural disasters (source: EMDAT, 2019)

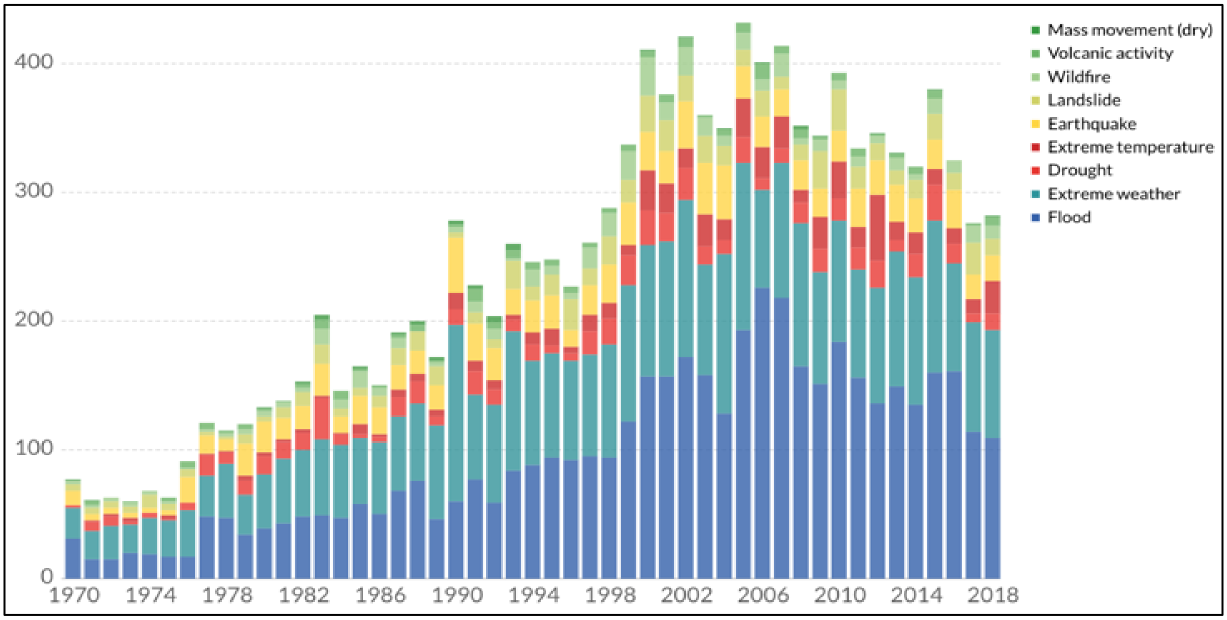

Figure 2: Global reported natural disaster by type (source: EMDAT, 2017)

As Figure 2 shows, the natural disasters that occurred between 1900 and the 2018 were either droughts, earthquakes, extreme temperatures, floods, landslides, mass movements (dry), storms, volcanic activities and wildfires. The two most predominant disasters are extreme weather and floods. Added together they represent at least 75% of the natural disasters each year.

In terms of extreme weather, there were several incidents reported each year between 1900 and 2018. The number of those disaster incidents has been increasing throughout the years, until it reached its peak of 137 disasters in 1990. After 1990, the number of disasters has stayed high varying between 66 and 130. Extreme temperatures however were not common during the period between 1900 and 1977, where no incidents were reported. Up until 1999, the pattern showed a slow increase. However, in 2000, the number of extreme temperatures incidents increased fourfold. In the following years, the number of this type of disaster varied until reaching 51 incidents in 2012. In 2013, this number dropped to 14. In 2018, there was 84 extreme weather and 25 extreme temperature disasters recorded.

Floods, unlike extreme weather, had years in which no disasters were reported like 1912-1914, 1921-1924, etc. After 1947, there were no more years that would escape floods. Between 1900 and 1963, the number of floods stayed low at an average of 3.9 per year and the maximum year being 13 floods. In 1964, it tripled and then it just continued to increase. In 2006, there were 218 flooding disasters, and the following years it decreased. In 2018, there were 109 disasters. With regard to landslides, the number of incidents between 1909 and 2018 varied between 0 and 32, with 2010 being the year with the highest number of landslides incidents reported.

Concerning earthquakes, the number of this disaster per year varies from one and 14 between 1900 and 1975. After 1975, there has been an important increase whereas the number of disasters went from four in 1975 to 20 in 1976 and by then gradually increased to 42 in 2004 and then decreased to 20 in 2018. Droughts slowly increased from 1900 to 2018. Figure 2 shows that 1983 was the year with the most droughts, 32. In 2018 there was 13 droughts.

Mass movements and volcanic activity are rare. Between 1900 and 2018 there were only 33 years where one or more incidents of mass movements being reported. The highest number of mass movements were reported in 1992 and 1993. The highest number of volcanic activity incidents was 12 in 2006.

Concerning wildfires, 30 was the number of incidents being reported in 2000, which was also the highest number of wildfires incidents being reported. Between 1911 and 2018 there were only 16 different years out of 62, with 10 or more wildfires being reported. The other years the average is around 2-3 wildfire reported per year. We can notice that the number of wildfires reported per year is increasing over time.

Overall, in 2018, flooding was the type of disaster with the highest number of occurrences in the world. However, natural disasters do not affect the world evenly, and in 2018, Asia is a continent that suffers tremendously from those. Out of the 315 disasters incidents that took place in that same year, the damage was not the same depending on the geographical zone. Indeed, 45% of the incidents struck Asia(CRED, 2019).

1.1.3. The causes of those natural disasters

Many weather and climate extreme events result from climate variability that can be related to natural or human causes. For the last 27 years, the world's oceans have been retaining 60% more heat each year than research teams had previously predicted. Therefore, the world has warmed with an increase of approximately 0.6 degrees in the mean surface temperature over the past century(Cane et al., 1997; Guha-Sapir et al., 2016; Mufson, Mooney, Eilperin, & Muyskens, 2019). Our planet is now more sensitive than ever to greenhouse gases than in the past. Those gases are part of natural processes that, using the sun's warmth, keep the temperature of the earth livable, at approximately 15ºC, for the flora and fauna that populate it. This effect is called the "greenhouse effect”(Ramamasy & Baas, 2007).Hence, for a million years the temperatures have been oscillating between hot and cold. However, since the 1970s, the increase in temperature is not only the result of natural causes, but also human activity. One such activity took place during the Industrial Revolution era, which was marked by the significant use of machines and tools to help perform task. This sudden increase in machine use resulted in heightened amounts of greenhouse gases in the atmosphere leading to an increase of heat retention and therefore higher temperatures on the surface of the planet. This effect is called the “enhanced greenhouse effect”(Ramamasy & Baas, 2007; USCGS Science of changing the world, n.d.).

In other words, the world is now facing a climate change issue, which has an impact on the risk of natural disasters(Cockburn, 2018; Field & Intergovernmental Panel on Climate Change, 2012; Gabbatiss, 2017; National climate assessment, 2018; Than, 2005; Van Aalst, 2006). First, the increase of the temperature makes the water vapor evaporate into the atmosphere. This becomes fuel for more powerful storms to develop. Hence, we are subjected more often to droughts and more intense storms. Second, the increase of temperature warms up the atmosphere and the ocean surface temperatures. These increased temperatures turn out to increase wind speeds in tropical storms. Finally, due to the increased atmospheric temperatures, glaciers and the sea ice in the Arctic Ocean are melting at a faster rate, which increases the sea level. As a consequence of this, more locations, particularly coastal communities, are exposed at higher level to the power of the sea and to the erosive forces of waves and currents. That would indeed explain the increase in the number of incidents of extreme weather events, including droughts, flooding, and heatwaves for the past(USCGS Science of changing the world, n.d.). The United Nations Intergovernmental Panel on Climate Change warns that there will be major consequences and catastrophic changes if the average temperature of the earth increases by 2°C(Mufson et al., 2019; United Nations, 2019).

1.1.4. The consequences of natural disasters

1.1.4.1. Human Impacts

Besides deaths, disasters may or may not result in other human impacts, such as people being injured either physically or emotionally (psychological shock), being subjected to trauma, illness, or homelessness either due to their houses being completely destroyed or severely damaged. Those people may eventually seek out assistance for their basic needs(EMDAT, 2019). This section will describe each consequence, starting with the death casualties. Figure 3 and Figure 4 summarize the number of people who died due to disasters from 1900-2018. This includes death from all-natural disasters mentioned for Figures 1 and 2.

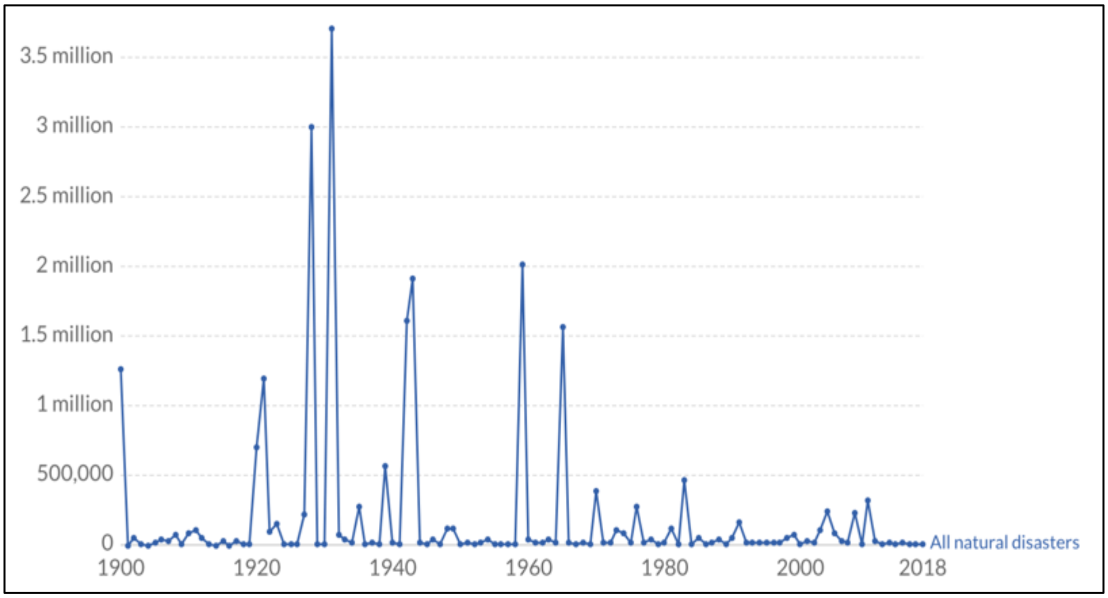

Figure 3: Global natural disaster death rates, All-natural disasters (source: EMDAT, 2018)

As Figure 3 shows, between 1900 and 2018, there have been seven years with a high death rate due to disasters. In 1900, the EMDAT (2018) recorded 1.27 million of deaths. In 1921, there were 1.2 million. In 1928, this number was more than double with 3.0 million; 1931 was the worst year ever, with the number of casualties being recorded as 3.71 million. This means that within just 10 years from 1921, the number of casualties drastically increased. However, the upward trend was not permanent, as in 1942 and 1943, there were 1.61 million and 1.91 million of casualties, respectively. In 1959, the EMDAT recorded 2.0 million casualties and 1.56 million casualties in 1965.

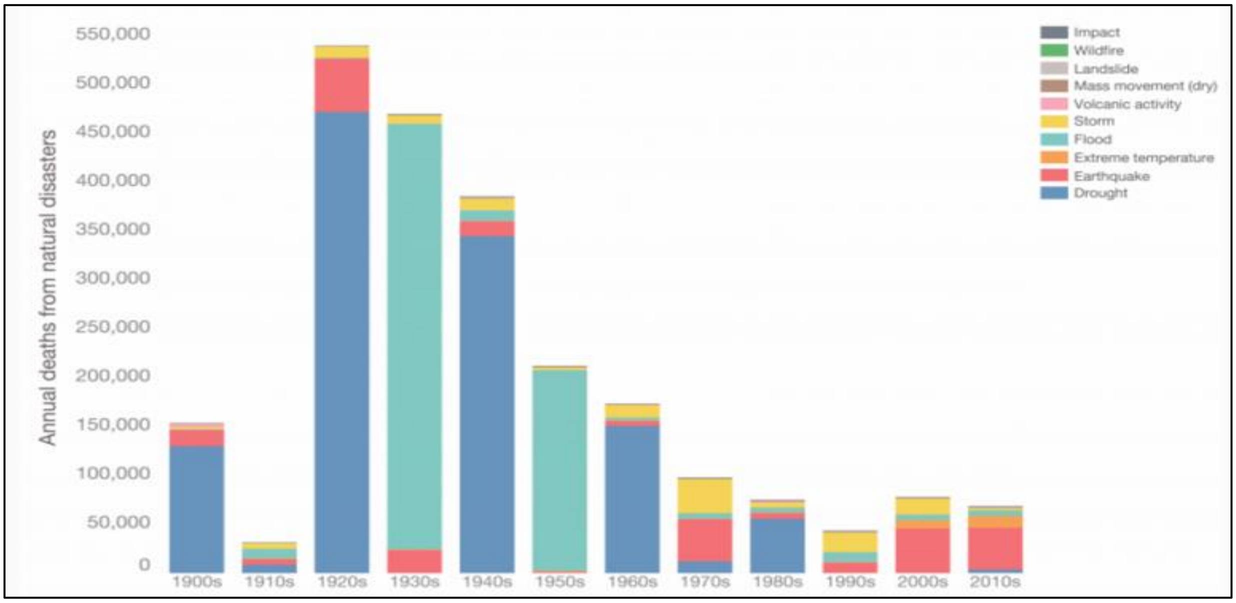

Figure 4: Global annual death rate from natural disasters, by decade (source: EMDAT,2017)

In Figure 4 the annual average of deaths per decade are categorized by type of natural disasters. Overall, Figure 4 shows that the types of disasters that have the highest mortality rates over the decades are floods and droughts. However, for the last two decades it was earthquakes that brought about the most casualties(EMDAT, 2017). The top two deadliest disasters in 2018 were two earthquakes, both in Indonesia(CRED, 2019).

Natural disasters not only have an impact on human mortality rate. Figure 5 provides a visualization of the number of people who were displaced internally by natural disasters. "Internally displaced persons" represents all the people that were displaced within a country.

The country with the most internally displaced persons due to natural disasters in 2017 was China, with 4.47 million cases. China is followed by the Philippines and then Cuba with 2.53 million and 1.74 million cases, respectively. The United States comes in the fourth with 1.69 million cases and is followed by India with 1.35 million cases. Somalia, Bangladesh and Vietnam have displacement cases ranging between 500,000 and 1 million cases. The rest of the world had less than 500,000 cases(EMDAT, 2018).

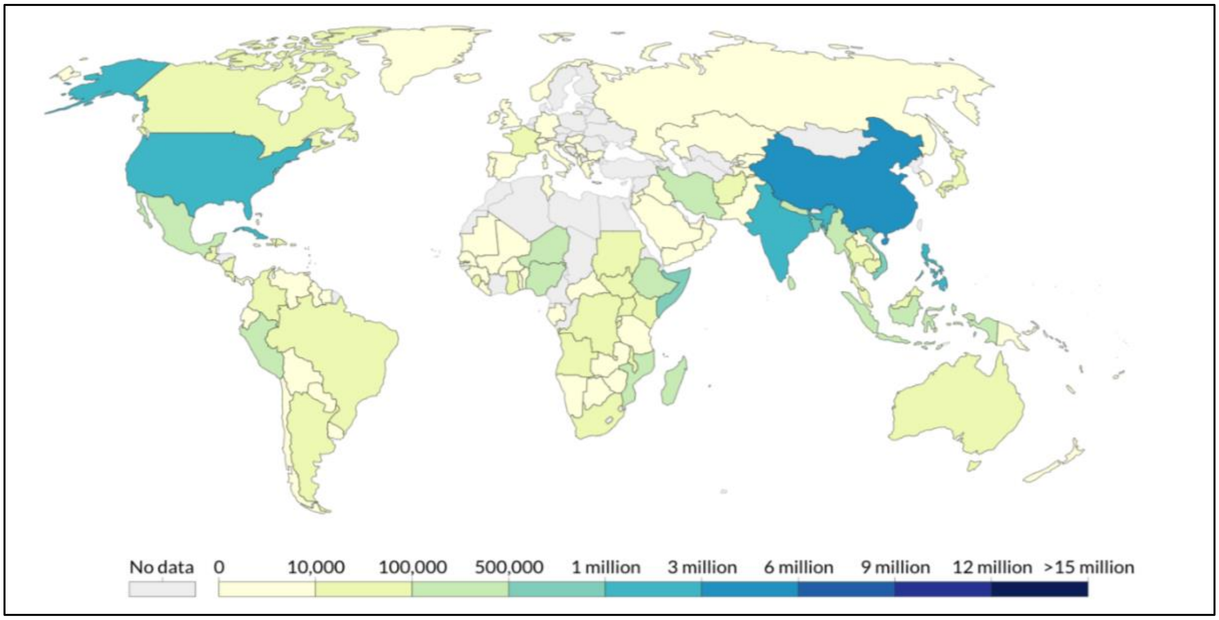

Figure 5: Internally displaced persons from natural disasters, 2017 (source: World Bank, 2017)

Other significant impacts on the population are "injured, affected and left homeless". According to *Our World in Data(Ritchie & Roser, 2019)*, injured is defined as "people suffering from physical injuries, trauma or an illness requiring immediate medical assistance as a direct result of a disaster." Affected is defined as "people requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance." And homelessness is defined as "number of people whose house is destroyed or heavily damaged and therefore need shelter after an event." The disasters that have affected the most people are droughts, floods and storms. In 2018, the flood in India affected 23.2 million people, and this disaster affected the highest number of people that was ever recorded(EMDAT, 2018). Figure 6 is a visualization of the total number affected by natural disasters from 1903 to 2018. We define "total affected" as the combination of injured, affected and left homeless(EMDAT, 2018).

As Figure 6 shows, 2002 was the year with the highest number of *total affected* in the population with 658.05 million people. The number of left homeless in 2002 was 354,875 individuals which represents 0.054% of the total affected population. There were 52,633 individuals injured, which represents 0.008% of the total affected population. The majority, 657.65 million individuals, were affected and represent 99.94% of the total affected population. The second highest number of total population affected by disasters with 433.86 million people was

2015. In that year, there were 619,992 cases (0.14%) of left homeless, 128,471 cases (0.03%) of injured and 433.11 million (99.82%) of affected individuals. The year that had the most cases of injured was 2004 by far, with 1.88 million cases, which made up of 0.85% of the total affected people, which amounts to 221.42 million. Compared to the other years, 221.42 million of total affected cases is just the average. Hence, the number of injured do not make up a big portion in the total number of affected. For the number of people left homeless, 1998 was the year with the most damages, reaching 29.42 million. This represented 8.58% of the total of affected people, which was 342.84 million in 1998. In general, the number of people affected has the most weight in human impacts. We can observe that the number of total affected individuals has escalated since 1965(EMDAT, 2019).

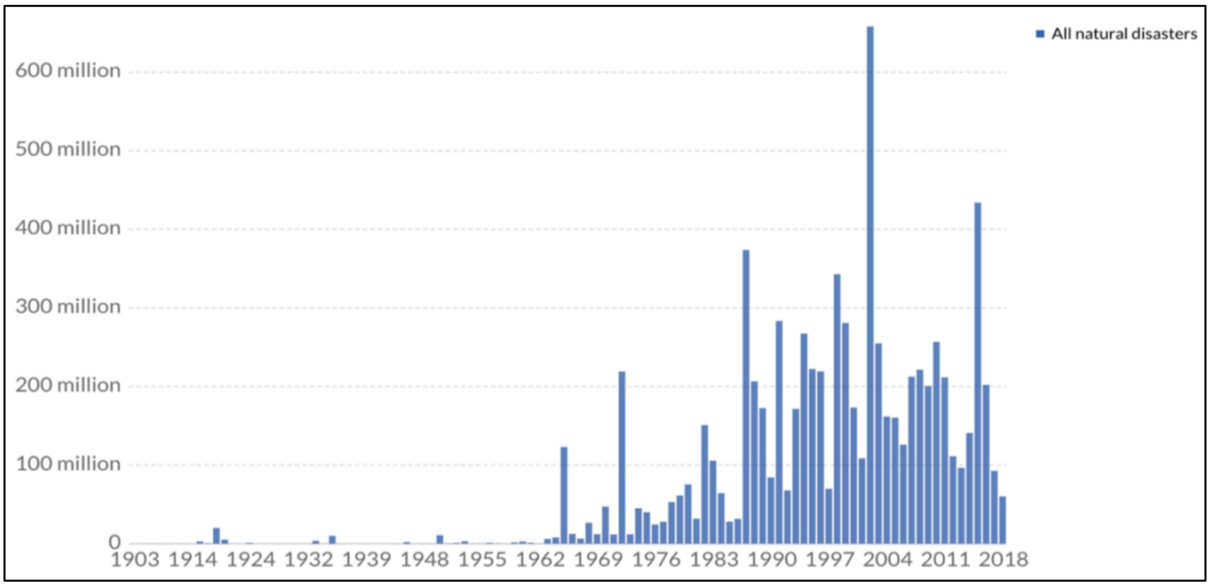

Figure 6: Number of people affected by natural disasters, All-natural disasters (source: EMDAT, 2019)

Finally, since disasters are traumatic events, it is important to take into account the mental health consequences, such as the post-traumatic stress disorder (PTSD), one of the most studied, frequent and debilitating health issue that some survivors may experience. Galea, Nandi, and Vlahov (2005) suggest that for the direct victims, the prevalence of PTSD is 30-40%. The prevalence is approximately 10-20% for rescue workers and 5-10% among the general population. These ranges tend to vary depending on the severity of the disaster and the characteristics of the individuals. The prevalence of PTSD will increase if the disaster causes more casualties and property destruction. The prevalence of PTSD will also increase if the individual is a direct victim of the disaster, a women, a person with low social support, someone with pre-existing or concurrent psychiatric disease and persons who have previously experienced traumatic events or some forms of stressors(Galea, Nandi, & Vlahov, 2005).

In 2018, 11,804 deaths were recorded and over 68 million people were affected by the natural disaster's events recorded in the world. Similar to the regions affected; the burden related to human casualties was not shared equally with 80% of the deaths and 76% of the people affected were in Asia. In that same year, earthquakes were responsible for 45% of the deaths, followed by flooding with 24%. With regard to the number of people affected, flooding was responsible for half of the total, followed by storms with 28%(CRED, 2019).

1.1.4.2. Economic losses

After a natural disaster strikes, there are short-term and long-term impacts. Figure 7 represents the economic losses from natural disasters from 1980 to 2018 in current US$.

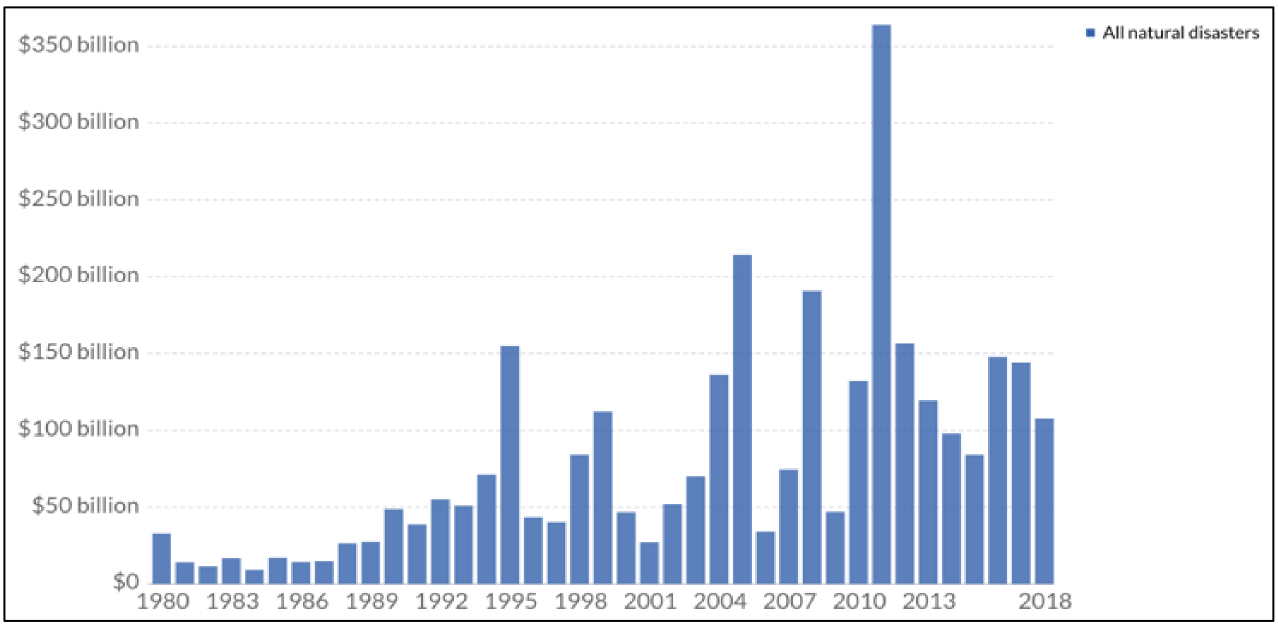

Figure 7: Global damage costs from natural disasters, All-natural disasters (Source: EMDAT, 2018)

As Figure 7 shows, between 1980 and 2018, the economic damage due to natural disaster has increased. Until 1994, the economic losses increased slowly, moving from $32.87 billion to $71.13 billion. In 1995 it reached the peak at $154.97 billion. Earthquake disasters turned out to be the most destructive type of disaster, bringing about $101.29 billion of damages. The next year, economic losses dropped to $43.33 billion and then increased again through 1999, when it reached $112.25 billion. The following two years (2000-2002), economic losses dropped to $27.07 billion and then drastically increased, reaching $214.21 billion in 2005. Extreme weather events caused $184.79 billion of damages that same year. The next peak occurred in 2008 with $190.85 billion of damages. Again, earthquakes caused the most damage, which required $85.8 billion to cover the destructions. The next peak with an important economic loss was in 2011 with $364.09 billion. Once again, earthquakes were the major cause of damages, which amounted to $230.3 billion. Floods came second with $70.76 billion of damages, then came extreme weather events with $50.87 billion. Between 2012 and 2018, the economic losses due to disasters stayed high, varying between $84.12 billion and $156.69 billion. Floods and extreme weather were the major cause of economic losses(EMDAT, 2018).

Figure 8 represents the global economic damage from natural disasters, differentiate by disaster category, in US$ per year. Overall, from Figure 6 we can observe that the severity has been increasing over time due to more extreme weather events(EMDAT, 2019). In the short run, the economic loss is related to homeowner and insurance companies. In the long run, the regional economic growth slows down for decades. Communities need to rebuild all the destructions such as bridges, roads, utilities, buildings, etc. The financial burden for those uncovered by insurances was vast, which led to bankruptcy for some, while some others had to move out of the area (Amadeo, 2019).

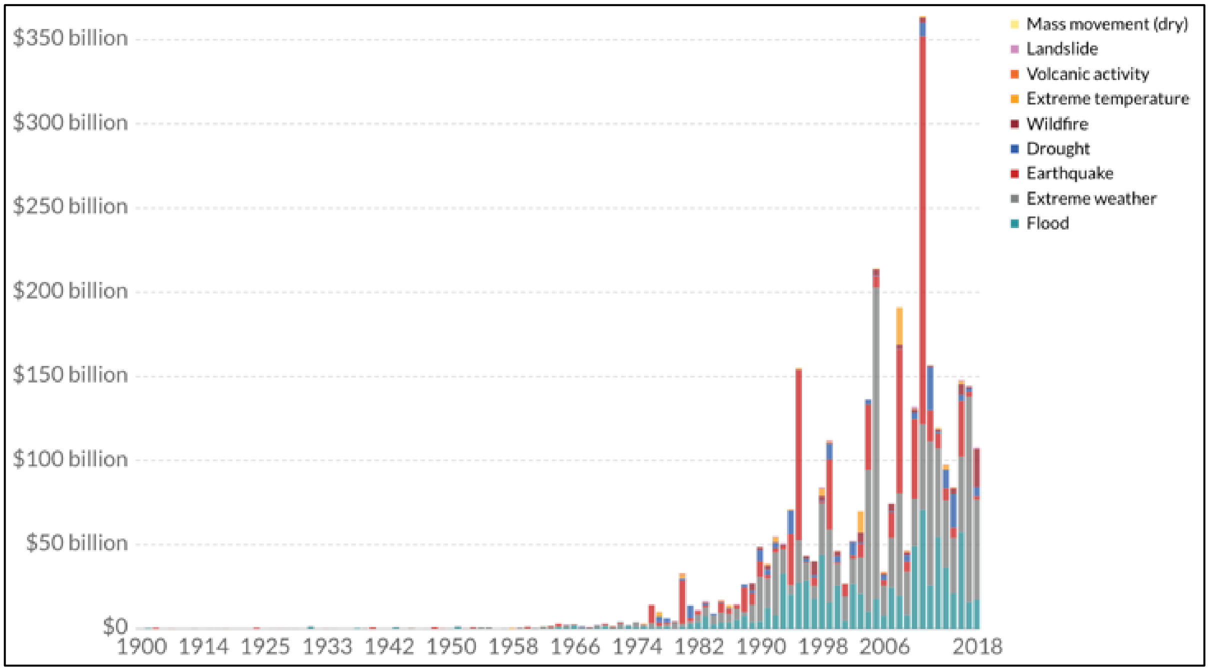

Figure 8: Economic damage by natural disaster type (source: EMDAT, 2019)

1.1.5 Focus of natural disasters in the US in 2018

1.1.5.1. United States situation

Global warming does not affect the world evenly, and the United States is a country that suffers tremendously from it. An analysis of the Washington Post(Mufson et al., 2019) found that more than 1 in 10 Americans, which is approximately 34 million of people live in regions affected from global warming. Important cities such as New York City and Los Angeles are regions whose average temperatures have risen rapidly in recent years. Alaska, a state known for its cold weather has warmed up at the fastest rate. Meanwhile, Rhode Island is the first state in the U.S whose average temperature has increased 2°C, closely followed by New Jersey, Connecticut, Maine and Massachusetts. All in all, 71 counties in the United States have crossed the 2°C mark(Mufson et al., 2019).

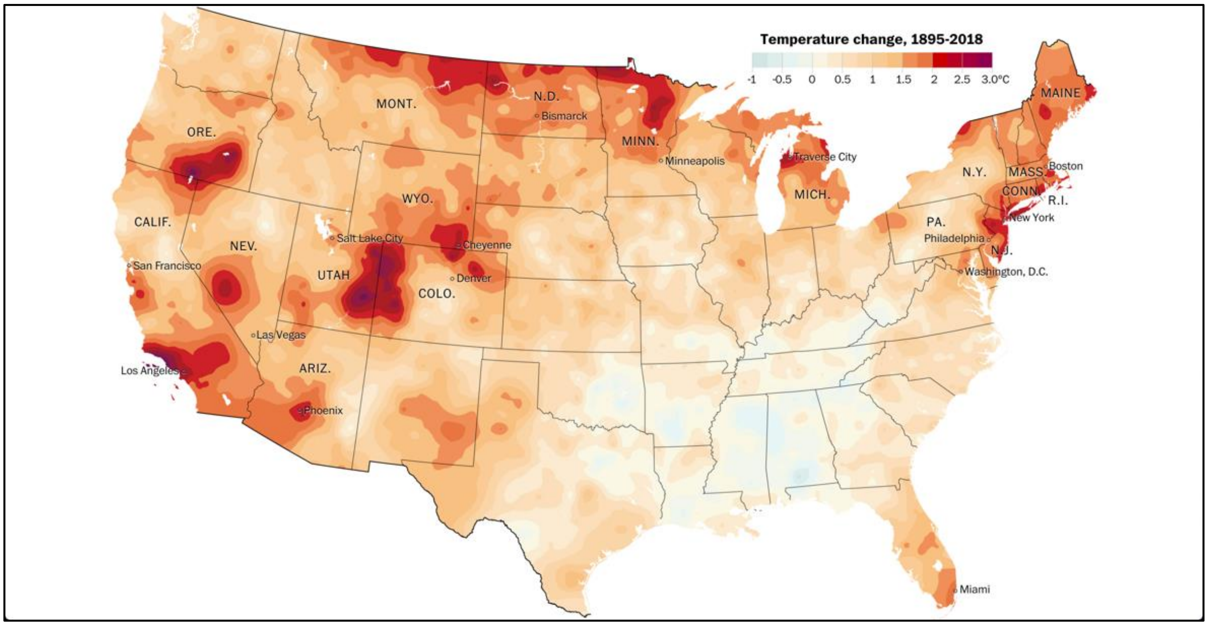

Figure 9: Temperature change, 1895-2018 (source : NOAA, 2018)

The National Oceanic and Atmospheric Administration(NOAA, 2018) did not provide data for Alaska and Hawaii for this time period. However, as Figure 7 shows, there are many different geographical zones within the country that are marked in deep red and red. The areas that reached the increase of more than 2°C in their average temperature are the high-altitude deserts in Oregon, parts of the western Rocky Mountains that nourish the Colorado River, and some counties along the northeastern shore of Lake Michigan. Next to the Canadian border, a few places ranging from eastern Montana to Minnesota are warming up at a worrying rate. In the South, however, there are some regions such as Mississippi and Alabama that have not warmed up.

In 2018, The United states was the country with the third most natural disasters in the world, after China and India. In total, there were 19 incidents. In that same year, it was also the country that suffered from the most economic losses due to disasters. The California wildfire season was the most costly disaster in the world, which brought about economic losses of around $16.5 billion. It was also one of the deadliest disasters since the 1940s, the Camp Fire incident took away 88 lives in 18 days. Hurricane Michael and Hurricane Florence were the second and third most costly ones, with economic losses of $16 billion US and $14 billion, respectively(CRED, 2019). Because of the number and severity of the disasters that struck the U.S. those past years, there have been many precautions put in effect to assist the population in dealing with those incidents.

1.1.5.2. What is the Federal Emergency Management Agency?

Although disasters have existed in the United States since the beginning of time, the Federal Emergency Management Agency (FEMA) was only established in 1979 by President Jimmy Carter. Before 1979 it would take the U.S. Army Corps of Engineers to control the major damages and more than 100 agencies to provide insurance(Grabianowski, 2019). Therefore, FEMA was created to provide communities in the U.S. information, warnings and prevention techniques to help people with preparedness in a pre and post disaster situation. Within those disasters there are natural disasters (fires, floods, etc.), national security concerns (terrorist attacks) or environmental concerns (toxic contamination). In a post disaster situation, FEMA are the first to respond and to assist the victims in uncertain situations(Civic Lab, n.d.).

In the 1990's FEMA became a cabinet-level agency where the aim was to cover every disaster. According to Grabianowski, FEMA "performed homeland security functions". However, the terrorist attack that occurred on the September 11th, 2001 showed that FEMA was not entirely prepared to deal with those situations. Therefore, they had to coordinate with border security, intelligence and law enforcement agencies(Grabianowski, 2019).

FEMA came to be part of the Department of Homeland Security in 2003. Coordinating with the Red Cross and other volunteer organizations, FEMA helps families handle the situations they are going through. Families may face destroyed homes, work places, loss of transportation and may have injured, missing and/or dead loved ones. The first help they will provide covers all the basic needs (water, food, medical care…) and information (location of care centers…)(Grabianowski, 2019).

Divided in ten regional offices, FEMA collaborates with the states within their region to better respond in a post disaster situation. They have 2600 people working full-time within the entire country and 4000 people ready to take action whenever a disaster occurs(Grabianowski, 2019). Because of the number and severity of the disasters that strike the population of the United States, part of the American tax dollars is devoted to FEMA.

1.1.5.3. The disaster aid: Where is the money placed?

When a community is affected by a natural disaster, the incident can be declared an emergency state by the President of the United States. This status releases different federal aids that can either be attributed to individuals, nonprofit organizations, or public agencies. Federal assistance depends on the type and severity of the disaster, such as the economic and human losses it begets(Amadeo, 2019a). The help that federal assistance provides can cover a range of different areas, including in assistance efforts, coordinating assistance efforts, providing technical and advisory assistance, and distributing supplies and emergency assistance. If the incident is considered a major disaster, further help and more specific provisions are provided, including repairing and restoration of federal facilities, removal of debris, housing assistance, unemployment assistance, emergency grants to assist low-income migrants and seasonal farmworkers, food coupons and distribution, relocation assistance, crisis counseling assistance and training, community disaster loans, emergency communications, and emergency public transportation(Liu, 2010).

In his book review published in 1971, using data on economic behaviors in disaster situations, Christopher M. Doughty(Doughty, 1971) stated that it would usually take three years for a community that suffered from an incident to recover. The first reason for this slow process of recovery is the absence of a functioning transportation system and communications networks, and later (in wealthy nations) by labor scarcity. Therefore, the organizations or officials responsible for the release of federal aid have numerous priorities and matters that require their attention. Kellenberg and Mobarak (2011) showed that natural disasters have important economic impacts on both the government and the individuals. Once a disaster strikes, every destroyed building must be replaced in order to maintain the activities of the city. Also, individuals, especially those newly affected by a disaster will have the tendency and incentive to purchase insurance in order to prevent possible future disasters. The average insurance amount is reported to be $6,505, which is equivalent to 23.7% of the average income level(Kellenberg & Mobarak, 2011).

Different articles focus on Hurricane Katrina, that struck the United States in 2005(Garber, Unger, White, & Wohlford, 2006; Groen & Polivka, 2008; The Labor Market Impact, 2006). The major topic of those papers is the employment change after Hurricane Katrina in the sectors that suffered the most. They focused mainly on the employment situation and employment recovery. Therefore, demographical impacts, economics losses, psychological distress are the major concerns of research after a natural disaster. However, a topic that few have researched is usually unspoken of and unknown to most is the long-lasting impacts on school children/students.

1.2 Literature Review

1.2.1 Natural disasters and education

Education is a topic of high priority in a country. High educational level favors high rate of development. This leads to high productivity level of a country. It explains why high level of education is often linked to the prosperity of developed countries(NEA, 2013). Besides, schooling gives people the tools to prepare us in everyday life, such as the capacity to be literate, numerate, to have critical thinking and social skills, etc.… It also builds up of skills such as confidence, teamwork, inspiration, etc.(Enotes, 2019; Sarahn, 2014). Therefore, in a situation where schools unpredictably close and the daily routine of the students is disrupted, the main concern should be the reopening of schools. Most of the sates in the United States, including California and North Carolina states, require a minimum number of instructional days set at 180 days(Education Commission of the states, 2018).

1.2.1.1. Educational system after disasters

The American Academy of Pediatrics (2015) and the American Psychological Association (2010) indicated that the fastest way to restore the wellbeing of parents and children is via school. Reopening the schools helps facilitate the fastest return to normalcy and daily routines for disaster victims. It provides a support system to help young persons to cope more constructively after an incident. Re-entering a classroom provides predictable routines (with a schedule) and clear expectations. Teachers will also help the victims to deal with a traumatic situation, understanding and providing the children an important support. This is particularly important since we know that children represent a highly vulnerable population. Hence their level of symptoms after a trauma such as a natural disaster is more likely higher than for adults. The investigation of Prinstein, et al. in 1996 was the first one to show that children, more frequently reported receiving coping assistance (a "naturally occurring strategies that parents, teachers, or peers use to help children with the process of coping with a disaster and possibly identify strategies that are particularly helpful in facilitating their recovery") in the form of reinstituting familiar roles and routines(Barenbaum, Ruchkin, & Schwab-Stone, 2004; Barrett, Barron Ausbrooks, & Martinez-Cosio, 2008; Meier, O'Toole, & Hicklin, 2010; Prinstein, La Greca, Vernberg, & Silverman, 1996).

1.2.1.2. Effect of displacement due to the natural disasters

The majority of post-disaster recovery research has focused on evacuee well-being, especially children. Many studies(Barrett et al., 2008; Pane, McCaffrey, Kalra, & Zhou, 2008) examined what happens to children who are displaced and what happens to the academic functioning of the new school environments where they are transferred to. Barrett et. Al. (2008) research on the student relocation into new schools after Hurricane Katrina struck in 2005. This natural disaster caused damages that forced thousands of families to flee the area. Unexpectedly, some students actually preferred their new school, as they found it more welcoming. With the data collected from the Louisiana Department of Education, Pane et al. (2008) showed that many students were transferred to a better performing school after Hurricanes Katrina and Rita in 2005. Those same children turn out to have higher achievement. They also showed that the negative effects of displacement on achievement were small overall. However, it tends to increase when the amount of time children spend out of school and the number of schools transitions the student experiences increase.

1.2.1.3. Educational attainment

Attention has also been placed on the consequences that disasters have on the educational attainment of children both inside and outside the U.S. Research that focus on developing countries such as those of Groppo and Kraehnert(Groppo & Kraehnert, 2017) revealed that extreme weather events have severe negative consequences on the educational attainment of children in Mongolia. Two extreme weather events were studied: the 1999–2002 triple dzud and the 2009/2010 dzud. “dzud” is the name they give in Mongolia for exceptionally harsh winter that cause mass livestock mortality, thus it is a type of extreme weather event. Using a difference-in-differences approach, their results showed that dzud intensity and livestock mortality are directly linked to completion of basic education, negative impact on the completion of basic education while dzud intensity and livestock mortality is more important. For the 2009/2010 dzud, there is no age or gender-specific effects. The major consequences are the effects that winter disasters have on children through losses in household assets and income.

For the studies pursued within the United States the majority of post-disaster recovery research has focused on the impacts on school achievement in the United States. Acquiring important academic concepts and skills, such as critical thinking, reading skills, writing skills, etc., can be compromised by unscheduled school closure. This, eventually, may contribute to a frail academic achievement in the future(Duncan et al., 2007).

Marcotte and Hemelt(Marcotte & Hemelt, 2008) conducted a survey to demonstrate the impacts of school closures on student performance. Their research showed that losing school days due to unscheduled closings had negative effects on the performance on state assessments. Reasons that lead to kids not attending school are teacher absences, shortened school years, length of school year across states within the U.S. and weather events. In this study, they examined the impacts of snowfall on student performance in Maryland. The data was collected from the Maryland State Department of Education (MSDE) and from Maryland public schools. The results showed that the higher the number of days out of school, the higher the impact was. This, perhaps is due to the possibility that the teachers may need to cover the materials again, owing to interrupted studying schedule. A similar study was conducted by Goodman(Goodman, 2014). However, he demonstrated that school closure due to snowfall did not show any relationship with achievement, whereas an absence did cause a negative impact on students' achievements. This was due to an interruption of the school program, which the teacher would have to adjust in the case of a school closure. While in the case of an absence, it was a delay in the material. It did however mention that there was some relationship between school closures and math achievement. However, this was true for poorer schools and in younger grades only.

1.2.2. Features of a school that increase its vulnerability

1.2.2.1. The rurality of an area

In rural areas where there are relatively fewer inhabitants, it takes more time to receive aid and assistance to cope with a disaster. This is because they are farther away from distribution centers and resources like hospitals, fire departments, police stations(Haskins, Barney, & Paudel, 2019). According to Neal (2005), every aspect of the aid process whether financial, legal, material, is more costly, even under normal circumstances.

1.2.2.2. Vulnerable population

Within an area, different groups of individuals are differently abled to respond to natural disasters. Those categorized as at-risk groups will not respond the same ways as those not at-risk. At-risk groups can include elderly people, people with disabilities, pregnant women, minorities and others. At-risk groups are groups that do not cope with disasters like everyone else due to physical or psychological disadvantages and hence won't respond and recover like everyone else. About 47.5 million people with disabilities in the U.S. may have a slower response time to disasters or may be unable to take appropriate response steps(Bethel, Foreman, & Burke, 2011). They will have special needs during and after the disaster(Hoffman, 2009; Mace, MD et al., 2018a).

1.2.2.2.1. Elderly persons

In a research on assessing long terms impacts of a natural disaster, Kilijanek and Drabek (1979) report multiple findings related to the long-term impacts on the elderly. They cite some studies(Bell, 1976; White & Haas, 1975) that indicate that most of the studies support the idea that the impact of disasters is greater for the victims who are least prepared or able to cope with them, thus elderly. They also note other researches(Dynes, 1970; Friedsam, 1962; Lang & Lang, 1964; Moore, 1958) that showed that during the recovery phases of disasters, the elderly tends to be slower in responding to the full extent of their losses. According to the study conducted via Kilijanek et Drabek, (1979), one out of every five elderly victims did not receive aid from any kind of help sources. For those who received aid, only 8% were assisted by five or more sources while for victims of 39 years old or younger it reaches 32%. Also, older victims use less insurance of any other type of economic sources in recovery compare to younger people except for house insurance. To continue with the comparison, they tend to have more "problems" using the different types of insurance less often. However, looking in the long-term negative impacts, elderly do not seems to have physical or mental health problems compared to the other elderly, non-victims. Thus, in the short-term, elderly are more vulnerable than younger victims. The more elderly living in the area, the more the area itself will be vulnerable to disasters and hence, take more time in the recovery process(Kilijanek & Drabek, 1979).

1.2.2.2.2. Individuals with disabilities

This at-risk groups may have a disability that won't allow them to perceive critical information when it is the most needed. Therefore, in a case of emergency a deaf person, for example, may not hear an alert on the radio or a blind person may not read headlines flashing on a TV. A person in a wheelchair may not able to evacuate or someone with a mental disability may not understand the situation or its severity. There are many other examples. Either way they may not be able to react adequately and follow the instructions as required whenever a natural disaster strikes. Also, in the past, some health care providers have determined that individuals with disabilities are of a lower priority than others because treating them is more difficult or complicated(Hoffman, 2009; Mace, MD et al., 2018b, p. 2). For example, in 2006, Marcie Roth of the National Spinal Cord Injury Association heard reports that American Red Cross shelters were refusing access to people with disabilities. Later inquiries confirmed that the American Red Cross implemented a policy to refuse shelter access for people with obvious disabilities(National Council on Disability (U.S.), 2006). Therefore, those who experience disabilities may not only have difficulty helping themselves but also may have more trouble getting assistance.

1.2.2.2.3. Pregnant women

This group faces greater risks to their health and the health of their babies in a situation of stress, danger and panic. Catastrophic events such as natural disasters are a type of stress that can cause pregnancy problems(marchofdimes, 2012). Those who survive a disaster will live through a situation of stress that is not recommended for pregnant women. According to the March of Dimes (2012), stress can trigger "trouble sleeping… headaches, [loss of] appetite or overeating. High levels of stress that continue for a long time may cause health problems, like high blood pressure and heart disease." Some women who experience stress during pregnancy may deliver their babies early without having access to medical care. According to Hoffman, "this increases the risk of complications such as underweight infants or infant mortality." Disaster may also restrict access to a woman's specific medication such as prenatal vitamins(Hoffman, 2009). Therefore, pregnant women need special attention in a case of a disaster.

1.2.2.2.4. Minorities

More recent research such as those of Esnard *et al.* (2018) focused on the features of schools affected by disaster. Their objective was to identify what made a school more vulnerable than another based on their location, downtime, student composition, and exposure to climate-related hazards. This research only used data related to Hurricane Ike. The study examined sixty counties of southeast Texas. They used four demographic variables: percent Hispanic, percent White, percent Black, percent Other (Asian and Native American) and one socioeconomic variable which was the percent of economically disadvantaged. The model used was the Poisson or negative binomial model. The results showed that the coefficient on percent Hispanic was the only demographic characteristic that had a significant association with the number of days closed. Whereas, an increase in the percentage of Hispanics students versus White students was associated with a decrease in the number of school days closed. Hence the race do seem to have an influence in the number of days a school closes.

1.2.2.2.5. Others

Other at-risk groups that we can identify in a case of an emergency such as a natural disaster are children, prisoners, undocumented workers, and individuals with language barriers. Most of those groups are dependent on others, whether to their legal custodian for children, to governmental authorities for prisoners or to any person who understands the situation for individuals with language barriers(Hoffman, 2009). There are other issues to consider. In the case of undocumented workers many hesitate to turn to authorities for any aid at all because they fear prosecution for immigration violations and those who do are only eligible for short-term noncash assistance after an emergency. Children are more susceptible to panic in a case of an emergency and guardians are often more concern with immediate safety rather than emotional consolation. Prisoners who are not able to move freely, are required to rely on the decisions of their wardens who do not always prioritize prisoner safety first. A lack of language-specific resources causes problems beyond evacuation for non-English speaking residents. For each of these groups, it is more difficult to evacuate, seek medical care, or obtain food, shelter, and supplies by themselves which makes them more vulnerable than others(Morey, 2012).

1.2.2.3. The resources of the area

Lai et al. (2019) also conducted research on how schools differ in their academic recovery after direct exposure to disasters. The data came from 464 Texas public schools directly exposed to the Hurricane Ike in 2008. Using a growth mixture modeling, it was shown that economic disadvantage was a risk factor. Therefore, schools with higher rates of economically disadvantaged students were more likely to fall in the Low-Interrupted versus High-Stable trajectories. The following figure shows those two school academic recovery trajectories identified in this research.

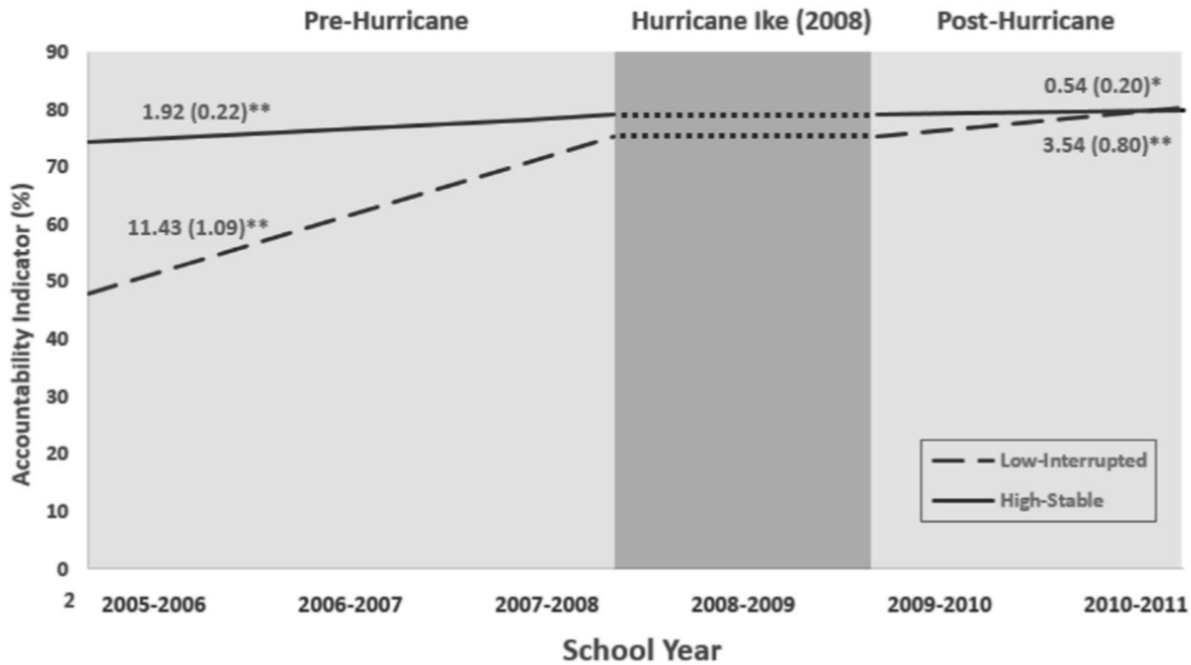

Figure 10:Trajectory Plot of the Two School Academic Recovery Trajectories (source: Lai et al, 2019)

On one hand, low-interrupted school academic recovery trajectory indicates an increasing level of academic performance up until Hurricane Ike where is studently interrupted. This drastic change is represented by an abrupt change in the slope of the curve after Hurricane Ike. On the other hand, the high-stable school academic recovery trajectory indicates that the academic performance stays relatively stable in spite of Hurricane Ike, in a parallel format as before, the slope of the curve pre- and post-Hurricane will not differ.

In the Scientific American an article released on July 2017(Boustan, Yanguas, Kahn, Rhode, & The Conversation US, 2017) examine the natural disasters by location. We save that poverty rates increases by one percentage point in areas hit by severe disasters. That suggests that rich individuals, with enough resources to move away from areas facing natural disasters, are migrating out and the other part of the population is left behind. Disaster Technical Assistance Center (U.S.), issuing body. (2017) cite many studies that found that people in poverty, with low incomes, and with less education to be less prepared for disasters (Turner, Nigg, et Paz, 1986 ; Vaughan, 1995 ; Fothergill et Peek, 2004 ; as cited in Disaster Technical Assistance Center (U.S.), issuing body., 2017). This lack of preparedness may relate to the high cost of being prepared for a disaster. Hence, people living in poverty cannot afford buying insurances, strengthening a home for greater earthquake resilience, etc…(Palm & Carroll, 1998 as cited in Fothergill et Peek, 2004). Despite the progress in preparing for natural disasters, the research suggests that the poor population will face growing exposure to natural disaster activity(Boustan, Kahn, Rhode, & Yanguas, 2017).

1.3. Objective of this thesis

As previously mentioned, as the number of natural disasters in the world, and more specifically in the United States, rises the necessity to adapt to natural disasters risks becomes crucial. We want to evaluate the impact of disasters on education to help with preparedness. The states of California and North Carolina require a minimum number of instructional days set at 180 days(Education Commission of the states, 2018). We assume that if students attend school for less than 180 days, they will not meet the requirements to be prepared for the following school year. Therefore, we conclude that these factors will result in a negative impact on the children's education. Hence, we will evaluate the impact on education via the number of days a school closes after a natural disaster. Therefore, this study focuses on the impact of the disasters on school closure.

Because natural disasters strike at different levels of severity in different parts of the country, the consequences on school closure differ. On one hand, among the disasters, the damages will vary since each disaster differs from their type, their length and their geographic location. On the other hand, the vulnerability of each area will not be the same. Every school differs from each other via different parameters such as their composition and their resources. For instance, the population of the school will differ by race, gender, household, wealth, etc. Therefore, this article analyzes what variables influence the vulnerability of a school after a natural disaster. Gathering information from different types of disasters, including fires and hurricanes, this research focuses on how the characteristics of the schools' area and school demographics affect the amount of time children spend out of school after a natural disaster.

1.4. Specific Research Question and Hypotheses

The literature review shows that in the context of natural disasters caused mainly by climate change, social institutions, specifically schools, are often a secondary concern in recovery efforts.

Yet, the quality of education often enables a child's ability to succeed. School teaches social skills, literacy, critical thinking and builds students confidence. However, little research has been done in terms of the impact of natural disaster on education. Hence, our research question asks, how do the characteristics of the schools' area and school demographics affect the amount of time children spend out of school after a natural disaster? In order to look into that research question, we stated three hypotheses, based on the literature review we were able to collect. The three hypotheses are features captured at three different levels: at a disaster level, at a school level, and at a PUMA level.

The severity of a disaster depends on its cause (natural, man-made), magnitude, length, surface it strikes, number of people it affects, structures it damages or destroys, number of casualties, death, injured(Hasani, El-Haddadeh, & Aktas, 2014). Hence, when the severity of a disaster increases the time and cost for the recovery process increases, so it takes more time for victims to return to their daily routine. The severity of the disaster will be measured by the length of a disaster. Looking into the severity of a disaster gives an indication on the impact of this characteristic of a disaster on school closures.

Hypothesis 1: The severity of the disaster will increase the days out of school

In the United States, individuals with low socioeconomic status are more likely to live in homes that are more vulnerable to the impact of disasters. The often lack of resources to migrate out of the risky areas, to afford insurance and to strengthen their homes for things like greater earthquake resilience and preparedness. These individuals will face growing exposure to natural disaster activity since they are more likely to live-in high-risk areas. They may experience more material losses, less protection from disasters, and perhaps greater damage to or even destruction of their homes. Hence poor populations are greater affected by natural disasters. This increases the vulnerability of schools as well(Boustan, Kahn, et al., 2017; Fothergill & Peek, 2004). The poverty level of the students within a school will be measured by the percent of students eligible for Free-Reduced Price Meals (FRPM) within a school. Looking into the percent of students receiving FRPMs within a school gives an indication on how this characteristic of a school has an impact on school closures.

Hypothesis 2: The poverty level of the students within a school will increase the days out of school

Vulnerable populations will have special needs during a natural disaster. Without appropriate preparation, vulnerable individuals may not be able to evacuate as instructed, reach points of distribution for medical care, understand written or verbal communications during an emergency, or find suitable housing if their residences are destroyed during a disaster(Hoffman, 2009). The percentage of vulnerable populations within a PUMA will be measured by the percentage of individuals receiving welfare income within a PUMA. Looking into the vulnerable individuals in a PUMA gives an indication on how this characteristic of the community or neighborhood has an impact on school closures.

Hypothesis 3: The number of vulnerable individuals within a PUMA will increase the days out of school

1.5. Contribution

This research looks at the impact of 6 different disasters striking in 2018. Within those disaster we have two types: fires and flooding. All the other research mentioned in the literature review looked into the impact of only one disaster at a time and into one county at a time. By looking at six different disasters we can better measure how the severity of a disaster impacts the number of days out of school. Also, this research leads to the realization of a dataset that gathers information for the number of days out of school for 387 observed schools located in 27 different school districts. The data of the independent variables, which examine the hypothesis of this paper was gathered at the school level, school district level and PUMA level, which are the smallest scales available, combining pre-existing datasets and additional work. Hence, this research examines which variables influence the vulnerability of a school after a natural disaster using specific information on the characteristics of the school location. Previous studies also focused on the vulnerability of certain groups of people with regard to disasters, but not how those at-risks groups have an impact on the area, and subsequently the educational system. This research studies the impacts that the number of people receiving welfare income may have on the days out of school to verify if the proportion of the at-risks groups has an impact on school closure.

CHAPTER 2. DATA AND METHODS

2.1. Study area

Over the past 30 years, there have been over 53 natural disasters in the United States. Those disasters were mainly hurricanes, floods, tornadoes, and wildfires.

2.1.1. Identification of disasters

2.1.1.1. Criteria of selection

For this paper, we first had to identify the study area. We only focused on disasters classified under "major disaster declaration". For a disaster to be classified as major disaster declaration, the President of the United States has to declare it. This status releases different federal aid to alleviate damages or suffering caused by the disaster. For this study we want to determine if the severity of the disaster increases the number of days children spend out of school. One way to evaluate the severity of the disaster is via the amount of aid associated to the incident, the choice of the incident had to be made out of those declared "major disaster declaration".

This study is focused on disasters that occurred in 2018. Since we were calling schools, we focused on disasters happened in 2018 to help our correspondents in looking up the information while it was recent. Finally, we wanted data from different type of disasters. Out of the wide range of possibilities we focused on floods, because in 2018 it was the type of disaster with the highest number of occurrences in the world(CRED, 2019). We also focused on fires since in 2018 this happened both the costliest in the world and the deadliest in the world since 1940s. In California, the 8,500 fires that happened in 2018 burned more than 1,893,913 acres making 2018 one of the most destructive seasons ever recorded. Finally, we focused on hurricanes because in 2018, the second and third most costly disasters were hurricanes(EMDAT, 2019). In this study we were only able to study fires and floods.

We used the Federal Emergency Management Agency(FEMA, 2019) which provides a complete list of all the natural disaster considered "major disaster declaration", by their year and type. We targeted incidents holding the previous criteria. We then targeted the geographical area they struck in order to, later on, narrow down the schools affected by those incidents. The incidents used in this study depend on the data we were able to collect. Hence, our dataset gathers information for 387 schools located in 27 different school districts from 6 disasters that happened in 2018: five fires in California and one hurricane in North Carolina. Each disaster chosen for this research has a different degree of severity with different outcomes. Table 1 resume all the disaster that we focused on for this study.

Table 1: Disasters the study focuses on

Name of the disaster	Type	Date	Location
Thomas Fire	Fire	December 4th, 2017 - January 12th, 2018	Ventura and Santa Barbara counties in California
Woolsey Fire	Fire	November 8th, 2018 - November 21st, 2018	Ventura and Los Angeles counties in California
Hill Fire	Fire	November 8th, 2018 - November 21st, 2018	Ventura county in California
Camp Fire	Fire	November 8th, 2018 - November 25th, 2018	Butte county
California Wildfires and High Winds	Fire	July 23rd, 2018 September 19th, 2018	Shasta and Lake county in California
North Carolina Tropical Storm	Hurricane	October 10th, 2018 - October 12th,2018	Alamance, Brunswick, Caswell, Chatham, Dare, Davidson, Davie, Forsyth, Granville, Hyde, Iredell, McDowell, Montgomery, Orange, Person, Randolph, Rockingham, Stokes, Surry, Vance and Yadkin

2.1.1.2. Description of the disasters in the study

2.1.1.2.1. Thomas Fire

The Thomas Fire disaster that struck Ventura and Santa Barbara Counties in the United States started on December 4, 2017. According to a report released on March 13, 2019 by The Star, the fire might have started in two different spots and merged later on. The disaster spread throughout Southern California, burning down 281,893 acres and destroying 1,063 structures, mostly homes leaving numerous families homeless. It also claims the life of a 70-years old lady and a 32-years old firefighter (a California Department of Forestry and Fire Protection engineer). Over a quarter million people in Southern California Edison were out of power. Due the quality of the air, dangerous concentrations of smoke and particulates, people were recommended to stay inside, avoid driving in risky areas and drink loads of liquid. Dozens of school districts closed their schools and the university of California, Santa Barbara postponed final exam by a month. The fire was finally contained on January 12, 2018(Diskin, 2019; Morain, 2018). Figure 11 represents the location and surface of the Thomas fire.

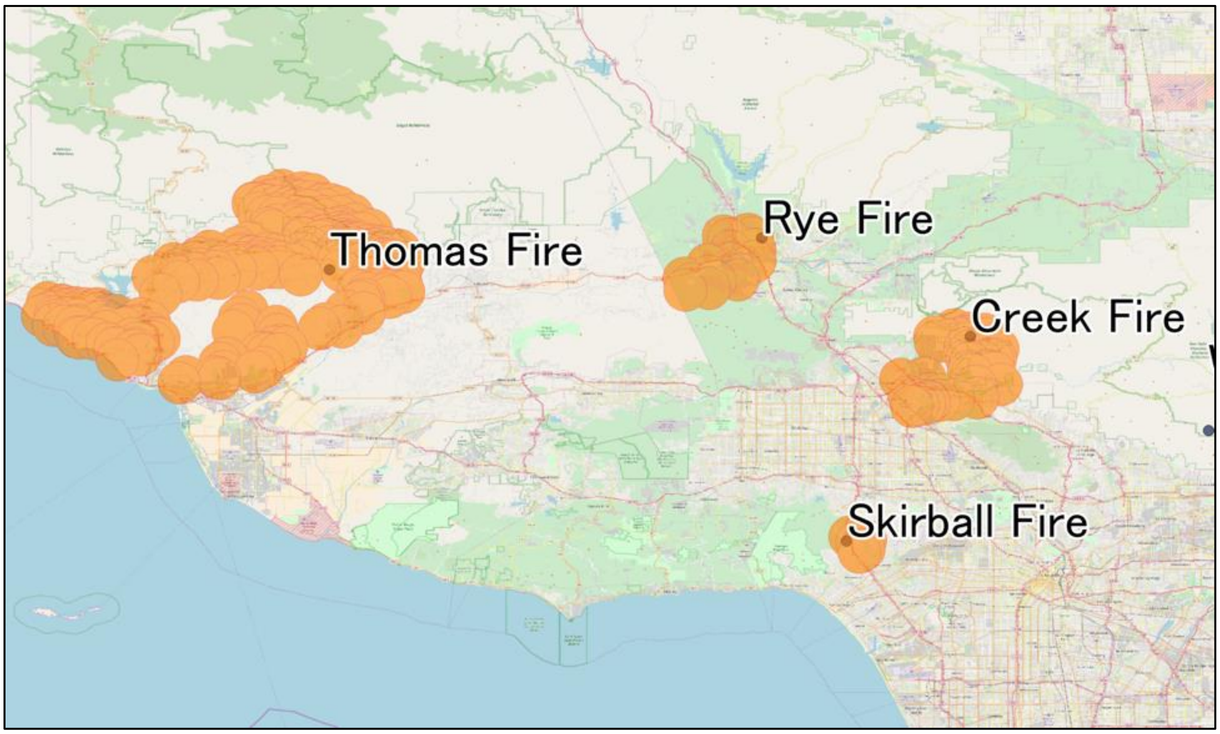

Figure 11: Map of Thomas fire and adjacent fires
(source: USDA Forest Service, Remote Sensing Application Center, 2017)

2.1.1.2.2. Woolsey Fire

The Woolsey Fire broke across Ventura county and Malibu in Los Angeles county, between November 8th and 21st, 2018, forcing 200,000 people to leave the area. Because of the dry weather and extreme winds, the fire was shoved in a southerly direction on the first day and it spread over 35,000 acres destroying everything in its path(Cosgrove, Newberry, Nelson, & Mejia, 2018). This resulted in 88% of the National Park Service acres within the park boundary being burned. Many other parks were severely damaged such as: National Park Service; California State Parks; the Mountains Recreation and Conservation Authority; and the Santa Monica Mountains Conservancy.

The Woolsey fire was the harshest park fire ever recorded in its history(National Park Service, 2019).

2.1.1.2.3. Hill Fire

While Woolsey fire was destroying everything in its way, the Hill fire was burning across the Santa Rosa Valley at the same time. Starting in Hill Canyon Road, this fire consumed 4,531 acres in Ventura county. There were no fatalities or severe injuries reported. However, fire officials reported four destroyed homes and two damaged one. Unlike Thomas and Woolsey fires, this fire may have been due to "human activity"(abc7.com, 2018). Figure 12 indicates the location of the Hill fire and the Woolsey fire and the area they struck.

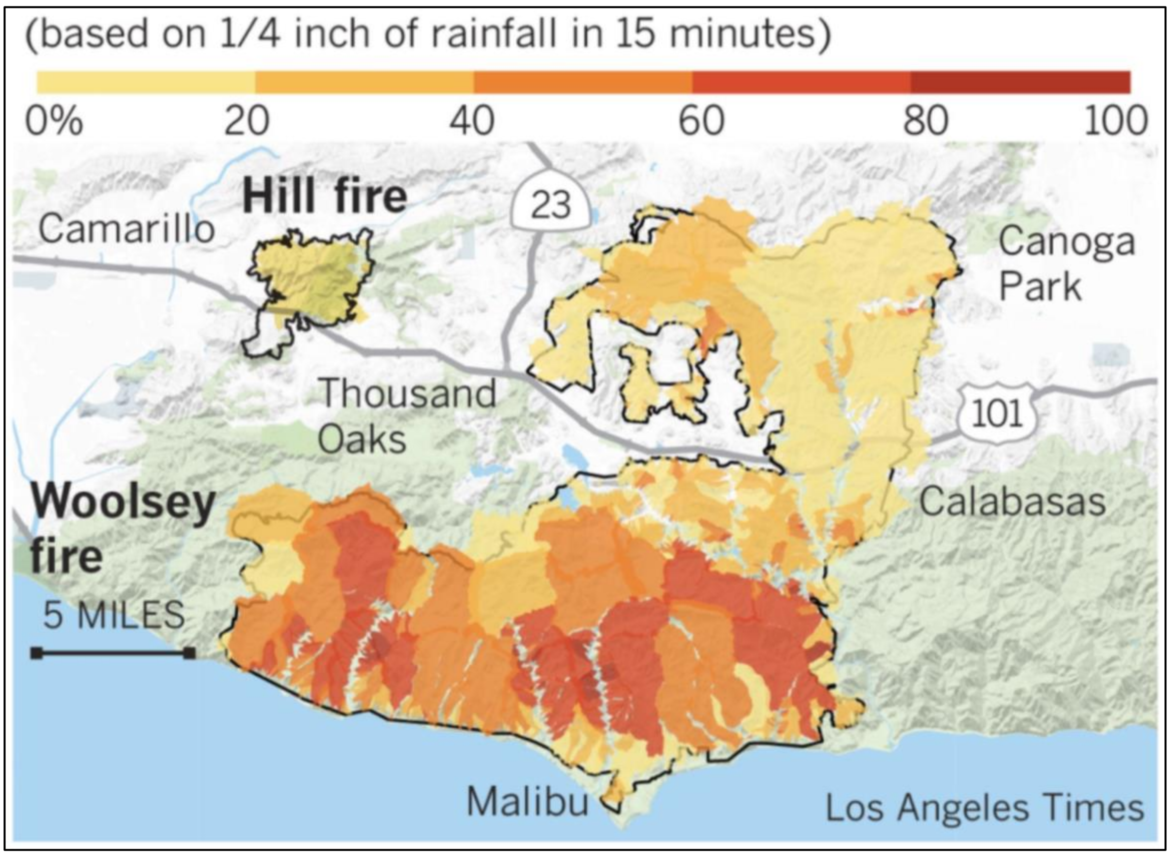

Figure 12: Likelihood of debris flow (source: Kim et Simani, 2018)

2.1.1.2.3. Camp Fire

If the Woolsey fire was the worst park fire, the Camp fire, which struck in that same period of time, between November 8th and 25th, 2018, was the deadliest one ever recorded in history. The outcome of this disaster: 85 lives lost; 14,000 residence burned down; 153,000 acres burned; thousands of people displaced and 1,000 firefighters to contains the fire. The tragedy lasted 17 days in total. The origin of the fire was the Sierra Nevada foothills, and all the conditions gathered were favorable for the fire to spread rapidly: high temperatures; windy; low humidity; and arid vegetation(Wootson Jr., 2018). The California Department of Forestry and Fire Protection investigator determined that the fire started due to electrical transmission lines(Mohler, 2015). Figure 13 shows the location of the Camp fire and the area affected.

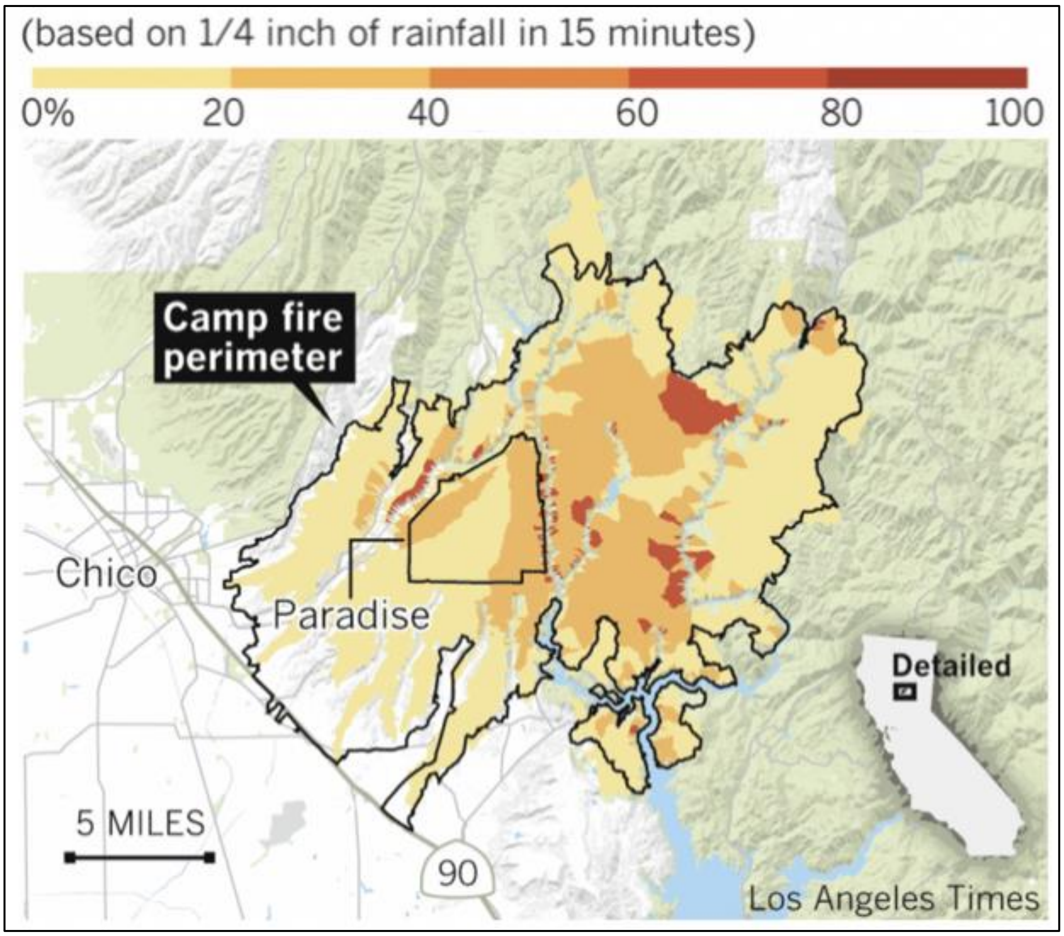

Figure 13: Likelihood of debris flow (source: Kim et Simani, 2018)

2.1.1.2.4. California Wildfires and High Winds

The California Wildfires and High Winds incident that occurred between from July 23rd and September 19th of 2018 affected two counties: Shasta and Lake counties in California. The fire in Shasta county started in a rural area northwest of Redding about 200 miles north of San

Francisco. It spread quickly and, in a few hours, 600 acres were burned down. The outcome was 1,100 homes threatened and 4,000 residents under evacuation orders(Associated press, 2019).

2.1.1.2.5. North Carolina Tropical Storm

The North Carolina Tropical Storm that happened between October 10th and October 12th of 2018 was the third-most intense hurricane to make landfall in the United States. Alamance, Brunswick, Caswell, Chatham, Dare, Davidson, Davie, Forsyth, Granville, Hyde, Iredell, McDowell, Montgomery, Orange, Person, Randolph, Rockingham, Stokes, Surry, Vance and Yadkin where all the counties affected(FEMA, 2019). Also called Hurricane Michael, the top winds reached 155 mph. The major consequences in North Carolina were the 39 individuals that perished by October 22 and the people left with no power which was more than 1 million customers. The economic loss to cover wind and surge damages was between $3 and $5 billion (National Weather Service, 2018 ; Amadeo, 2019).

In the database every one of those disasters is classified by its type, so either as a fire or as a hurricane. Therefore, in our database we collected data for five fire disasters and one hurricane.

2.1.2. Identification of the counties, school districts, and schools in the database

The first step was to identify the counties affected by the disasters mentioned above. The second step was to identify all the school districts in the counties and each school in the school districts. We used Education Bug (2019), which is a complete list of educational resources updated whenever there is a major event on the site or within their company. Education Bug (2019) provided a full list of school districts per county and schools per school districts.

2.1.3. Identification of the PUMAs

Public Use Microdata Areas (PUMAs) are geographic areas that provide information for an area at a smaller scale than at the county level. It is the smallest geographic unit available in the census. Each PUMA is defined by a code. It gives more specific and detailed insights on the area each school is situated. Therefore, in rural areas where the population is less dense, PUMAs tend to be larger areas. However, if it is an area with a high density of people, such as urban areas, there might be more than one PUMA within the same region. These geographic areas help to capture the environment in which individuals interact. Hence, a county may contain more than one PUMA code. In order to get information per PUMA, we used secondary data collection from the Integrated Public Use Microdata Series (IPUMS) database, the world's largest individual-level population database(Ruggles, Fitch, Magnuson, & Schroeder, 2019). Before extracting data from IPUMS USA we first had to identify the PUMA codes relevant for our dataset.

2.1.3.1. Identifying the PUMA codes relevant for our dataset

In order to get the information only for the PUMAs we are interested in, we had to determine the PUMAs code for each school collected in our current database. In order to do that we used the 2010 census PUMA reference map from the United States census bureau website.

2.1.3.1.1. For the state of California

For California, the code of the state was 06. Then the PUMA number would range from 101 to 11300. Within one county there can be more than one PUMA. For California we only focused on Ventura, Butte and Shasta counties. Ventura county counted for 6 PUMAs (11101, 11102, 11103, 11104, 11105 and 11106), Butte county for 2 PUMAs (600701 and 600702) and Shasta county for only 1 PUMA (608900). Then we would use the school districts to target which PUMA would correspond to each school.

When the area had a population too dense and the PUMAs were too close to each other's, like Ventura, we had to use Google map, 2010 census PUMA reference map and the address of the schools individually to identify in which area to classify them. The following two pictures represent a PUMA reference map, that indicates all the existing PUMA in Ventura, while the second Figure is a screen shot of that same area but in google map. Hence, for the schools in Ventura we would look the school up in Google map before attributing the PUMA code. Figure 14 represents the PUMA reference map of Ventura county.

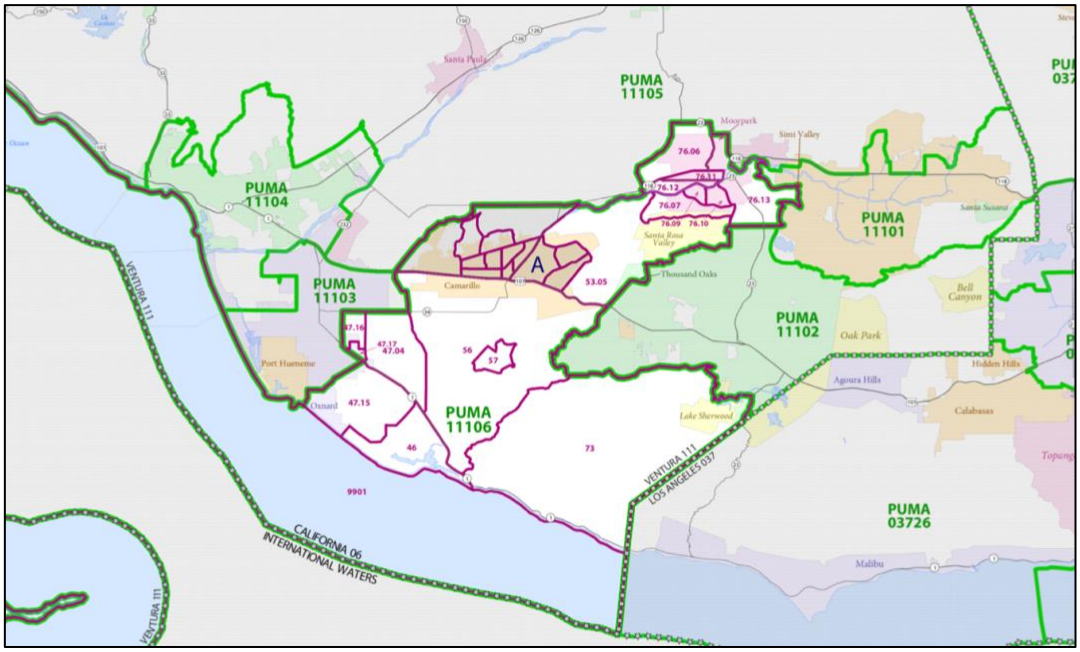

Figure 14: 2010 CENSUS - PUMA REFERENCE MAP: Ventura County (source: United States Census Bureau, 2010)

As we can see in Figure 14, a county like Ventura can count six PUMAs in a very small area. Within those six PUMAs there are 19 school districts and 193 schools. Therefore, in order to identify correctly the PUMA to each school we used Google Map. Figure 15 is a screenshot of Ventura county in google map.

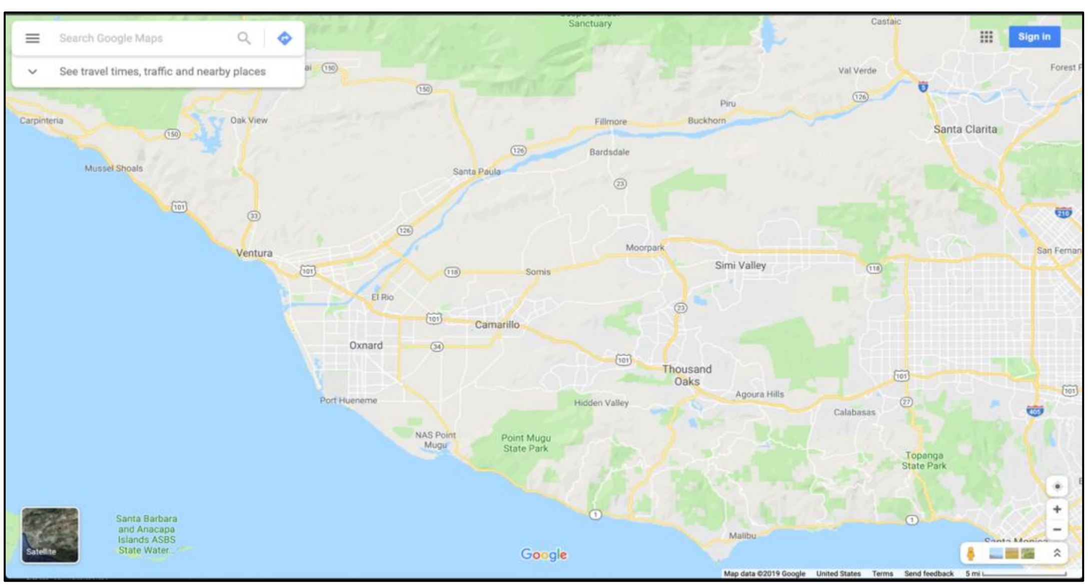

Figure 15: Screenshot of Google map: Ventura County(Google, n.d.)

Figure 15 represents the exact same zone than Figure 14 but in Google maps. Thus, to find the PUMA of a school we would enter the name of the school in the area “search Google maps”. Google maps would indicate the exact localization of the school and with the help of both maps, and the routes we when able to attribute the PUMA to the school.

2.1.3.1.2. For the state of North Carolina

For North Carolina, the code of the state was 37. Then the PUMA number would range from 100 to 5400. For North Carolina we only focused on Chatham county and it counted for only one PUMA: 01500. Figure 16 represents the PUMA reference map of Chatham county.

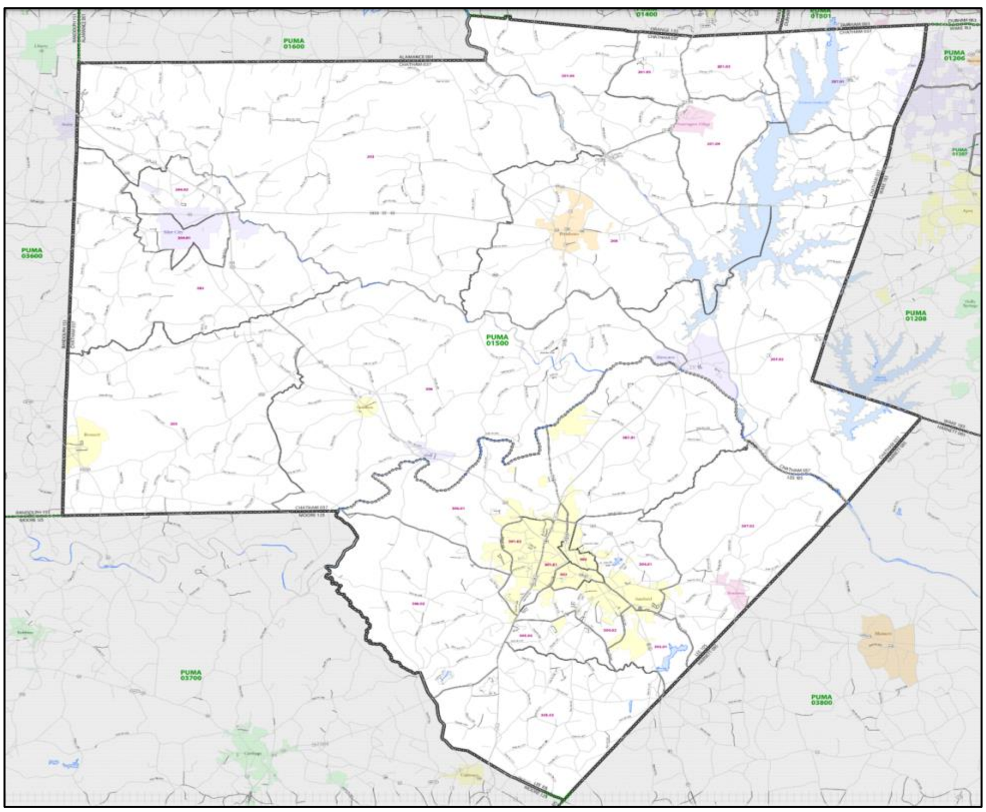

Figure 16: 2010 CENSUS - PUMA REFERENCE MAP: Chatham & Lee Counties (source: United States Census Bureau, 2010)

As Figure 16 shows, in this situation one PUMA two counties. Therefore, identifying the PUMA for each school was easier since all schools are already match with the county they are located in. Thus, all the schools in Chatham county have the same PUMA code.

2.1.3.2. Extracting the data

Therefore, once we identify the PUMA that we needed for the current database, we were able to drop all the other PUMAs we were not using for our current database. We ended up having the following number of information for each PUMA and for each year. As shown in the Table 2, the database includes 34,499 of individuals leaving in all PUMAs.

Table 2: Number of observations per PUMA, per year

PUMA codes	2015	2016	2017	TOTAL
701	999	947	993	2939
702	970	973	969	2912
1500	937	1015	1048	3000
11101	991	991	1008	2990
11102	1181	1287	1273	3741
11103	1355	1437	1385	4177
11104	961	947	971	2879
11105	1004	957	1060	3021
11106	1222	1179	1198	3599
8900	1754	1754	1733	5241
TOTAL	11374	11487	11638	34499

2.2. Data collection

The data were collected in two different ways, using secondary and primary data collection. Primary collection corresponds to a survey of school officials conducted by phone. Secondary collection corresponds to all the data collected via internet. This section describes the variables chosen, why we chose them, and how the data was acquired. To begin with, the following table summarizes the variables that will be used in the model.

Table 3: Variables description

Variables	Description	Level	Source
Dependent variable			
Number of days out of school (2018)	Continuous variable for the number of days a school close due to the disaster	School level	Primary data collection
Key independent variables			
Length of the disaster (2018)	Continuous variable, indicator of the severity of the disaster. Calculated as the sum of days between the day the incident starts and ends.	Disaster level	FEMA
% of students eligible for Free-Reduced Price Meals (2018)	Continuous variable. Indicator of socioeconomic vulnerability. Calculated as the sum of the students coded as eligible for free or reduced-price meals	School level	California Department of Education and North Carolina Department of Public Instruction
% of individuals receiving a welfare income (2017)	Continuous variable. Indicator of socioeconomic vulnerability. Calculated as the sum of the individual receiving a welfare income. It includes federal/state Supplemental Security Income (SSI) payments to elderly (age 65+), blind, or disabled persons with low incomes. Aid to Families with Dependent Children (AFDC) and general Assistance (GA).	PUMA level	IPUMS USA
Demographics Indicators of socioeconomic vulnerability.			
% of Hispanics, % Blacks and % other (includes % American Indian or Alaska, and % Asian or Pacific Islander) (2018)	Continuous variable. Ethnicity categories of the students are in percent per school.	School level	Education Bug

Table 3 continued

% of females (2018)	Continuous variable. The percent of females in the school.	School level	Education Bug
Type of school (2018)		School level	Education Bug
% of individuals receiving a retirement income within a PUMA (2017)	Continuous variable. Is the percent of respondent receiving a pre-tax retirement, survivor, and disability pension income.	PUMA level	IPUMS USA
Resources Indicators of socioeconomic vulnerability.			
% of individuals enrolled in public schools (2017)	Continuous variable. It indicates the percent of respondents attending public school.	PUMA level	IPUMS USA
% of individuals enrolled in private schools (2017)	Continuous variable. Indicates the percent of respondents attending private school.	PUMA level	IPUMS USA
Student/teacher ratio (2018)	Continuous variable. It represents an average of the number of students per teacher.	School district level	Education Bug

2.2.1. Dependent variable

As mentioned before, in order to measure the impact natural disasters have on education, we focused on the impact they have on school closure. Hence, the primary unit of analysis for this study, the dependent variable, is how many days children do not attend school. In order to measure this variable, we focused on the number of days for which the schools closed in 2018, after each disaster in the study. The schools included in this study are based on data availability.

We collected data using primary data collection. The data collection was done through a survey executed by phone. The goal was to reach the schools that were affected by one of the previous incidents: fire or hurricane. No funds were allocated for data collection. In order to contact the schools affected by the chosen disasters, we did background research on the states affected by the most recent natural disasters in 2018 using Federal Emergency Management Agency data(FEMA, 2019). From there we narrowed down to the counties affected. Next, we created a contact list with the names of the schools in the county, their phone number, the names of the persons in charge and their emails. The contact list included 650 schools per disaster.

Once the contact list was done, we developed a questionnaire in Qualtrics that was processed by the Institutional Review Board (IRB). The questionnaire contains seven questions. One question aimed to collect data regarding the number of days for which the schools were closed. Other questions determined if there was more than one disaster that affected the school in question, whether there was an impact on enrollment and if there were changes in the achievement on the state achievement test. The survey was conducted via phone calls. For the survey, we called over 200 schools. Several issues arose during the process. The representatives of the majority of schools either did not answer, did not have time to talk, or provided unspecific information due to a lack of time and patience. Many of the schools were also not affected at all. During the process, we resorted to directly contacting the school district since they had combined data on the schools and district. We contacted the office of education of each county and asked the school districts affected by the incidents. Thus, we could directly target the school districts affected and automatically obtain the information for each school. Some school districts would follow up via emails while others would provide the information through phone. We were only able to collect the data of the number of days out of school.

2.2.2. Independent variables

2.2.2.1. The number of days the disaster strike

The variables that can measure the severity of a disaster are either related to the length of the incident or to the aid provided by the government. In order to use the disaster aid provided, we needed the amount of the total Public Assistance Approved (PA) provided by FEMA. It is aid provided when the catastrophe that strikes goes beyond the local government's capabilities to respond or recover. It means that the damages of the disaster cannot be amended by the local government. After a disaster, a community may have to take care of debris removal, take on life-saving emergency protective measures, and restore public infrastructure in order for the population to return to their daily routine. Those obligations incur high costs for local governments, states, territories and/or some private nonprofit organizations. The Public Assistance (PA) Grant Program helps communities during the disaster recovery process(FEMA, 2019). However, we were not able to collect a specific value for each disaster from FEMA or the Governor's Office of Emergency Services of California (Appendix 3).

Therefore, we focused on the length of the disaster because we propose that the longer a disaster lasts, the more impact it will have on communities. For example, a fire that last 14 days should have more impact than one that last three days. This data was collected via secondary data collection. We counted the number of days between the day the incident starts and ends based on FEMA data. This variable is reported per disaster. Hence, since we have six different disasters, we will have six different values.

2.2.2.2. The percent of Free Reduced-Price Meals (FRPM)

In order to measure the poverty level of the schools we collected the information for the percent of eligible Free or Reduced-Price Meals (FRPM) from Kindergarten to 12th grade for the 2018-2019 school year. This variable is used to determine grant eligibility. The students who are eligible to receive FRPM based on "applying for the National School Lunch Program (NSLP), or who are determined to meet the same income eligibility criteria as the NSLP, through their local schools"(California Department of Education, 2019). This variable also includes the students who are automatically eligible for free meals.

For all the schools located in the state of California we used the California Department of Education (2019). For all the schools located in the state of North Carolina, we used North Carolina Department of Public Instruction(Public Schools of North Carolina, 2019). The North Carolina Department of Public Instruction website provides the number of free meals in one hand and reduced meals in another for the school year 2017-2018. Hence, we had to use total number of students in the school to get the percentage. Also, in order to get the percentage of free and reduced meal we add both variables together before getting the percentage. The information collected is at a school level.

2.2.2.3. Welfare (Public Assistance) income

If a geographic zone receives a significant amount of aid, it gives an indication of the economic situation of the population within this area. The variable collected for the study is welfare (public assistance) income, coded INCWELFR. It reports how much individuals receive from government public assistance programs. The assistance included are the following:

- How much federal/state Supplemental Security Income (SSI) payments to elderly (age 65+), blind, or disabled persons with low incomes.
- Aid to Families with Dependent Children (AFDC);
- General Assistance (GA). (Separate payments for hospital or other medical care not included)

The information includes the income individuals received from these sources during the previous calendar year (past 12 months). This variable gives an indication of the aid an area receives. This data was collected from IPUMS USA.

The first step was to extract the information from IPUMS USA for the variable coded INCWELFR. The second step was to count the number of individuals receiving a welfare income per PUMA in 2017. The third step was to calculate what portion those observations represent within the PUMA in 2017. This would provide what percent of the population received a welfare income per PUMA in 2017. Since we do not have the population of the PUMA, we used the number of observations recorded for each PUMA in 2017 since it is a representative sample of the number of people living in the PUMA for that year. We used the following formula to calculate this percent:

$$\text{\% of people receiving a welfare income in 2017} = \frac{\text{\# of individuals with a welfare income per PUMA in 2017}}{\text{Total number of individuals per PUMA in 2017}}$$

Therefore, using the information provided in Table 2 we calculated the percent of people receiving a welfare income within the PUMA in 2017. Those results are gathered in Table 4.

Table 4:Number of observations receiving a welfare income per PUMA, per year

PUMA codes	Number of observations in 2017	% of people receiving a welfare income in 2017
701	17	1.71%
702	28	2.89%
1500	6	0.57%
11101	10	0.99%
11102	7	0.55%
11103	27	1.95%
11104	10	1.03%
11105	11	1.04%
11106	9	0.75%
8900	37	2.14%
TOTAL	162	1.39%

2.2.3 Control variables

Data were collected at the school, school district, and PUMA levels. Control variables included demographic and economic characteristics. Demographic variables such as race and gender and economic characteristics include variables such as individuals on public assistance, teacher/student ratios.

2.2.3.1. School level

In order to identify each school in a district and their characteristics we also used Education Bug (2019). The information available and used for the model are the total number of students in the school, the number of males and females, and information on the racial diversity of the school. Concerning gender, we were able to collect a number, but we were interested in the portion it represents within the school. Hence, using the total number of students, we calculate the percent of males and females. We classify the schools by whether they are elementary, middle or high school level. Elementary schools go from kindergarten to 6th grade, middle schools go from 6th to 8th grade, and high schools go from 9th to 12th grade(Education Bug, 2019). Education Bug was up to date for the 2018 school year. Knowing the gender, race and range of age of the schools gives us an understanding of the schools' composition.

2.2.3.2. School district level

The information available and used for the model is teacher/ student ratio and collected from Education Bug. By understanding the ratio of students to teachers, we can see what kind of resources a district has. Education Bug was up to date for the 2018 school year.

2.2.3.3. PUMA level

2.2.3.3.1. Retirement income

As mentioned before, the more elderly living in the area, the more the area itself will be vulnerable to disaster and hence, take more time in the recovery process. The variable collected for the study is retirement income, coded INCRETIR. It reports how much individuals receive from government pre-tax retirement, survivor, and disability pension income.

To collect and measure the amount of people receiving retirement income, we used secondary data collection from the IPUMS USA. The smallest scale we were able to find this information was at the PUMA level. We used the variable retirement income coded INCRETIR to determine the number of people in retirement income. This data reports how much individuals receive from the government for pre-tax retirement, survivor, and disability pension income.

After extracting the information from IPUMS USA out of the 34,499 observations recorded, 4,526 received a retirement income combining 2015, 2016 and 2017. The first step to collect the data for our dataset was to count the number of individuals receiving retirement income per PUMA per year. Hence, we would have only one value to report per PUMA per year. The second step was to calculate what portion of those observations represent within the PUMA. This would provide what percent of the population received a retirement income per PUMA per year. Since we do not have the population of the PUMA, we used the number of observations recorded for each PUMA in a particular year since it is a representative sample of the number of people living in the PUMA for each year. We used the following formula to calculate this percent:

$$\% \text{ of people receiving a retirement income in 2017} = \frac{\text{\# of individuals with a retirement income per PUMA in 2017}}{\text{Total number of individuals per PUMA in 2017}}$$

We were mainly interested in 2017 but also reported results for 2016 if we wanted to look into the change over time. Therefore, using the information provided in Table 2 we calculated percent of people receiving a retirement income within the PUMA in 2017. We gathered those results in the following table:

Table 5: Number of observations receiving a retirement income per PUMA, per year

PUMA codes	Number of observations in 2017	% of people receiving a retirement income in 2017
701	121	12.19%
702	141	14.55%
1500	161	15.36%
11101	131	13.00%
11102	163	12.80%
11103	138	9.96%
11104	128	13.18%
11105	132	12.45%
11106	144	12.02%
8900	284	16.39%
TOTAL	1543	13.26%

2.2.3.3.2. Public or private school

The Council for American Private Education Number 433 released in March 2018 provides information about the new law about the Federal Disaster Aid to Help Students and Schools dictated by President Trump on February 2018. Private schools are not eligible for direct funds but are entitled to request help if they need to replace information systems, rent locations, replace tools necessary to proceed to daily routines, etc. The state has the obligation to provide a certain amount of funds for private schools to cover the cost for services and assistances. Additional assistance is also provided for displaced students. The payment of this assistance for each displaced student cannot exceed $10,000 for a child who has a disability, $9,000 for a child who is an English learner, and $8,500 for all other children. In the case of private schools, the payment may not exceed the cost of tuition, fees, and transportation expenses at the school(Cape Outlook, 2018).

On the other hand, public schools are accessible to everyone while private schools' cost on average $10,740 per year ranging anywhere from $5,330 to $25,180, according to a report from the National Center for Education Statistics (NCES)(Lindenberger, 2019). To record data for this variable we use the variable public or private school from IPUMS USA, coded SCHLTYPE, and indicates if the individual is attending school or not and whether the student is enrolled in private or public school.

In order to collect this information, we used the same four steps as for the welfare income. Thus, we looked into the number of people enrollment in private, public or not enrolled in each PUMA in 2017 and the portion it represents compared to the population of the PUMA. The information we were able to extract is shown in table 6.

Table 6: Number of observations enrolled in public or private schools or not enrolled in schools per PUMA, per year

PUMA codes	Number of individuals enrolled in public schools in 2017	Percent individuals enrolled in public schools in 2017	Number of individuals enrolled in private schools in 2017	Percent of individuals enrolled in private schools in 2017	Number of individuals not enrolled in schools in 2017	Percent of individuals not enrolled in schools in 2017
701	216	22.81%	6	0.60%	771	77.64%
702	71	7.33%	12	1.24%	886	91.43%
1500	72	6.87%	14	1.34%	962	91.79%
11101	95	9.42%	24	2.38%	889	88.19%
11102	123	9.66%	58	4.56%	1092	85.78%
11103	154	11.12%	23	1.66%	1208	87.22%
11104	95	9.78%	12	1.24%	864	88.98%
11105	101	9.53%	30	2.83%	929	87.64%
11106	145	12.10%	35	2.92%	1018	84.97%
8900	142	8.19%	33	1.90%	1558	89.90%
TOTAL	1214	10.43%	247	2.12%	10177	87.45%

2.3. Data exploration

2.3.1. Multicollinearity issues

Multicollinearity issues may bias our results. This issue arises when one or more independent variables in the model are not independent. In other words, it will violate the assumption ceteris paribus. If multicollinearity exists, if we change the value of one variable, the values of one or more other variables will also change. If the degree of correlation between variables is high enough, it can cause problems fitting the model and interpreting the results. Multicollinearity increases the standard errors of the coefficients, which makes some variables statistically insignificant when they should be significant, and vice versa. Therefore, even if we can collect different variables and have a large dataset, our results may still be biased in the existence of multicollinearity, since one or more variables can be dependent. To avoid multicollinearity, we need to remove one or more variables that are highly correlated to the others. Therefore, this section will detail the correlation coefficients of the independent variables in the dataset. Ideally, the independent variables should not be highly correlated to each other, and highly correlated to the dependent variable.

2.3.1.1. How to identify correlation

The correlation between the independent variables themselves, between the independent and the control variables and between the control variables themselves have to range ideally from 0.6 to -0.6, otherwise, the results of the model could be biased. I chose this range from the British Medical Journal website(thebmj, 2019). If the correlation is positive, it means that the two variables have a positive relationship. If one increases, the other also increases. The variables move together. While if the correlation is negative, it means that the two variables have a negative relationship. Hence, if one increases the other decreases.

2.3.1.2. Examination of the database

We examined the correlation by using the code (corr) in Stata. We established the correlation relationship for every variable in the model (Figure 17). The correlations outside the range [-0.6, 0.6] are highlighted in red. The variables with high correlation were excluded from the model.

Variables	**Days out of school**	**% FRPM**	**Days disaster strike**	**% retirement**	ln Average Income 2017	% wefare	% Not enrolled	% Private	% Public	% type of school	Student teacher ratio	Type of disaster	% Others	% Whites	% Hispanics	% Blacks	% Females	% Males
Days out of school	1																	
% FRPM	0.1929	1																
Days disaster strike	0.0985	0.0696	1															
% retirement	0.0947	-0.3598	-0.1155	1														
ln Average Income 2017	-0.3175	-0.6349	0.0402	0.2892	1													
% wefare	0.3311	0.5492	-0.0125	-0.4687	-0.8863	1												
% Not enrolled	-0.4605	0.1684	0.0759	0.2659	-0.2527	0.0204	1											
% Private	-0.4790	-0.4659	0.0576	0.1607	0.8158	-0.6780	0.0031	1										
% Public	0.6156	0.0113	-0.0989	-0.2842	-0.0666	0.2276	-0.9290	-0.3716	1									
type of school	0.0518	-0.0736	-0.0348	0.0856	0.0034	-0.0129	0.0108	0.0199	-0.0139	1								
Student teacher ratio	-0.1236	-0.1069	0.3981	-0.2592	0.3980	-0.2170	-0.1476	0.4030	-0.0222	-0.0203	1							
Type of disaster	0.1072	0.0166	0.3630	-0.4431	0.1191	0.2209	-0.3464	0.1812	0.2425	-0.0174	0.8021	1						
% Others	-0.0552	-0.2568	0.0200	-0.0996	0.2193	-0.0752	-0.2334	0.1525	0.1566	0.0371	0.1739	0.2173	1					
% Whites	0.0660	-0.7989	-0.1037	0.6387	0.4989	-0.4368	-0.1365	0.3008	0.0295	0.1256	-0.0139	-0.0802	0.1436	1				
% Hispanics	-0.0461	0.7942	0.1437	-0.6271	-0.4907	0.4455	0.1424	-0.2774	-0.0434	-0.1346	0.0885	0.1634	-0.3083	-0.9736	1			
% Blacks	0.0252	0.1120	-0.2690	0.2464	-0.2044	0.0131	0.2124	-0.2223	-0.1073	0.1082	-0.5869	-0.6354	-0.0992	0.0136	-0.1093	1		
% Females	-0.0224	-0.1049	0.0438	-0.1200	-0.0284	0.0260	-0.0472	-0.0470	0.0571	-0.1494	0.0634	0.0774	-0.0046	-0.0668	0.0797	-0.2205	1	
% Males	0.0224	0.1049	-0.0438	0.1200	0.0284	-0.0260	0.0472	0.0470	-0.0571	0.1494	-0.0634	-0.0774	0.0046	0.0668	-0.0797	0.2205	-1.0000	1

Figure 17:Correlation between the variables gathered

The log of average income in 2017 highly correlates with the percentage of individuals receiving welfare income and the percentage of individuals enrolling in private schools within a PUMA. However, the latter two variables are not highly correlated to any other variable. Log of average income in 2017 also has a strong correlation with the percentage of students eligible for a Free-Reduced Price Meal. Hence, keeping this variable would likely result in multicollinearity issues in our model, since this variable is highly correlated with many other variables. For this reason, we chose to exclude the variable log of average income in 2017 from the regression.

We can observe that the percentage of Hispanics and Whites in a school are strongly correlated with each other. Hence, keeping both of them could also result in multicollinearity issues in our model. In the work of Esnard *et al.* (2018), Hispanics is the only minority that has an impact on the number of days out of school. For this reason, we chose to keep the percentage of Hispanics within a school instead of whites.

The percentage of individuals enrolling in public schools highly correlates to the percentage of individuals not enrolled in schools. Similarly, the percentage of males in a school is strongly correlated to the percentage of females in a school. In our model, we used the percentage of individuals enrolling in public schools and the percentage of females in a school.

2.3.2. Variability of the data

The results of a regression can be biased if there is not enough variability in the data. Therefore, this section will detail the variability between the counties and the PUMAs. In order to do so, we used Analysis of variance, ANOVA. To be specific, we performed the one-way ANOVA test between each group. The null hypothesis is that the means are not statistically different from each other, which means:

$$H_0: \mu_i = \mu_j \quad (i \neq j) \text{ and } i, j \in \{1,2,3,4\}$$
$$H_1: \mu_i \neq \mu_j \quad (i \neq j) \text{ and } i, j \in \{1,2,3,4\}$$

Where μ_i, μ_j are the means of the independent variables at the PUMA level for when we examine the variability of the counties. And μ_i, μ_j are also the means of the independent variables at the school and school district levels for when we examine the variability of the PUMAs. We reject the null hypothesis if the p-value of the test is below 0.05. In this scenario, the mean of a variable in different county or PUMA would be statistically different from each other.

Table 7: County variability

Variable	F	p-value
Percent of people receiving a retirement income within a PUMA in 2017	53.77	0.00
Percent of people receiving a welfare income within a PUMA in 2017	50.64	0.00
Percent of individuals enrolled in public school within a PUMA in 2017	140.14	0.00
Percent of individuals enrolled in private school within a PUMA in 2017	48.15	0.00
Percent of students eligible for FRPM within a school in 2018	36.47	0.00
Percent of blacks within a school in 2018	33.78	0.00
Percent of Hispanics within a school in 2018	65.5	0.00
Percent of others within a school in 2018	6.47	0.00
Percent of females within a school in 2018	0.62	0.60
Type of school	1.89	0.13
Student teacher ratio	512.06	0.00

We can observe that in table 7 the p-values of ANOVA are lower than 0.05. Hence, the means of those variables for different counties are statistically different from each other. Thus, we have variability in our dataset, and the results are more likely to report the true estimates. However, the percent of females within a school in 2018 and the type of school are the two variables that have a p-value higher than 0.05. Hence, for those variables, we fail to reject H_0, which means that for those variables there is not enough variability.

Table 8: PUMA variability

Variable	F	p-value
Percent of students eligible for FRPM within a school in 2018	36.47	0.00
Percent of blacks within a school in 2018	33.78	0.00
Percent of Hispanics within a school in 2018	65.5	0.00
Percent of others within a school in 2018	6.91	0.00
Percent of females within a school in 2018	0.95	0.48
Type of school	0.87	0.56
Student teacher ratio	332.39	0.00

The results of PUMA variability shown in table 8 are the same as the results of county variability. The percent of females within a school in 2018 and the type of school are the only two variables that have a p-value higher than 0.05. Hence, for those variables, we fail to reject H_0, which means that for those variables there is not enough variability.

2.4. Model

This study examines the relationship between the dependent and independents variables and the effects each independent variable has in the same single period or point in time. Hence, we will use an ordinary least square (OLS) regression; a cross-sectional model. Except for the variables collected at the PUMA level (2017 data), all the variables of the model are collected for the year 2018. Some of the variables at the PUMA level are percent of people who receive welfare income, retirement income, and the percent of people enrolling in public and private schools. Those are the demographics variables, and hence we expect them not to change drastically after a single year. Hence, the use of those variables will unlikely invalidate the cross-sectional model.

The general model will examine the relationship between the key independent variables and the number of days out of school, taking into account all disasters. We also performed different versions of the model, incorporating PUMA fixed effect, county fixed effect, and/or studying the original model, taking into account only fire related disasters.

2.4.1. VERSION 1 : General regression for all disasters

$$\begin{aligned}
\mathrm{Days_Out_of_School_i} &= \beta_0 + \beta_1 \mathrm{Number_of_days_disaster_strike_i} + \beta_2 \mathrm{Percent_FRPM_i} \\
&+ \beta_3 \mathrm{Percent_Welfare_Income_PUMA_i} + \beta_4 \mathrm{Percent_Others_School_i} \\
&+ \beta_5 \mathrm{Percent_Hispanics_School_i} + \beta_6 \mathrm{Percent_Blacks_School_i} \\
&+ \beta_7 \mathrm{Percent_Female_School_i} + \beta_8 \mathrm{Percent_Enrolled_Public_School_PUMA_i} \\
&+ \beta_9 \mathrm{Percent_Enrolled_Private_School_PUMA_i} \\
&+ \beta_{10} \mathrm{Percent_retirement_income_PUMA_i} + \beta_{11} \mathrm{Student_Teacher_Ratio_i} \\
&+ \beta_{12} \sum_{i=1}^{3} \alpha_i Type_of_School_i + \varepsilon_i \quad (1)
\end{aligned}$$

where ε_i, is the error term. β_0 is the constant. $\Sigma_{i=1}^{12} \beta_i$ are the coefficients of the independent and control variables. Days_Out_of_School indicates the number of days the school had to close in 2018, due to the disaster(s).

For the variables related to the hypotheses, Number_of_days_disaster_strike variable indicates the number of days a disaster that occurred in 2018 strikes a school. Percent_FRPM indicates the percentage of student eligible for Free-Reduces Price Meals (FRPM) within a school in 2018. Percent_Welfare_Income_PUMA represents the percentage of individuals receiving welfare income within a PUMA in 2017. Each variable is expected to have an influence on the number of days out of school, as mentioned in the hypothesis section.

In terms of the control variables, Percent_Others_School, Percent_Hispanics_School and Percent_Blacks_School indicate the percentage of other races, Hispanics, and blacks in a school in 2018, respectively. Percent_Female_School indicates the percentage of females in a school in 2018. Type_of_School is a categorical variable, where it equals 1 if the school is an elementary school, 2 if it is a middle school and 3 if it is a high school. This variable gives us an indication of the average age of the school. Knowing the genders, races and ranges of age of the schools gives us an understanding of the schools' composition. Some groups of students may react to a disaster differently from the others due to differences in cultures or financial status. For example, the difference in race can have an implicit role on the financial status of the individuals, and hence create an impact on the number of days out of school. Percent_Enrolled_Public_School_PUMA represents the percentage of individuals enrolling in a public school within a PUMA in 2017.

Percent_Enrolled_Private_School_PUMA represents the percentage of individuals enrolling in a private school within a PUMA in 2017. Percent_retirement_income_PUMA represents the percentage of individuals that received retirement income, within a PUMA in 2017. Teacher_Student_Ratio indicates the number of children per teacher within a school district in 2018. These variables give an indication of the resources of a PUMA or a school district and hence are expected to influence the number of days out of school. We aim to study the differences between elementary, middle and high schools, so we created a categorical variable that represents the 3 different types of schools, $\sum_{i=1}^{3} \alpha_i \text{Type\_of\_School}_i$. Elementary schools are placed in category 1. Middle schools are placed in category 2. And High schools are placed in category 3. The reference are the elementary schools, since it is the dominant type of school among the observations.

We suspect that there exists heteroskedasticity in the model. Heteroskedasticity is a problem because OLS regression assumes that all residuals are drawn from a population that has a constant variance. This could result in biased standard errors and make the significance level incorrect. Hence, we performed the Breusch-Pagan & White heteroscedasticity test. The null hypothesis is that the variance of the error term is unchanged for any value of the independent value, which means:

$$H_0: \sigma_i^2 = \sigma^2 \quad \forall i$$

$$H_1: \sigma_i^2 \neq \sigma^2 \text{ for some } i$$

Where σ_i^2 is the variance of the error term for each value that the independent variables take.
We reject the null hypothesis of homoskedasticity if the p-value of the test is below 0.05. In this scenario, there is risk of heteroskedasticity.

The p-value for the test is 0.85. Thus, we cannot reject the null hypothesis. However, robust standard error is also valid for when we do not have heteroskedasticity. Thus, we used robust standard error to maintain consistency among all the versions.

2.4.2. VERSION 2: General regression with PUMA fixed effect for all disasters.

To capture the unobserved inherent differences at the PUMA level, we created dummies for each of the ten PUMAs. We chose PUMA fixed effect because it is the level that allows the most variability and even distribution of the data compared. Table 9 represents the distribution of the observations at the county and PUMA level. For the distribution within the county, 87.75% of the observations are located in Ventura county in California. For the distribution within the PUMA, the PUMA with the least observations is PUMA 608900 in Shasta county, counting with 0.52% of the total number of observations. The PUMA with the most observations is PUMA 11103 which counts for 22.22% of the total number of observations. Therefore, the distribution is more balanced.

Table 9: Distribution of the observations in the counties and PUMA

County	Number of observations	PUMA	Number of observations
Ventura (CA)	328	PUMA 11101	58
		PUMA 11102	64
		PUMA 11103	86
		PUMA 11104	29
		PUMA 11105	40
		PUMA 11106	51
Butte (CA)	41	PUMA 600701	29
		PUMA 600702	12
Shasta (CA)	2	PUMA 608900	2
Chatham (NC)	16	PUMA 01500	16

$$
\begin{aligned}
\text{Days\_Out\_of\_School}_i \\
= \beta_0 &+ \beta_1 \text{Number\_of\_days\_disaster\_strike}_i + \beta_1 \text{Percent\_FRPM}_i \\
&+ \beta_2 \text{Percent\_Welfare\_Income\_PUMA}_i + \beta_3 \text{Percent\_Others\_School}_i \\
&+ \beta_4 \text{Percent\_Hispanics\_School}_i + \beta_5 \text{Percent\_Blacks\_School}_i \\
&+ \beta_6 \text{Percent\_Female\_School}_i + \beta_7 \text{Percent\_Enrolled\_Public\_School\_PUMA}_i \\
&+ \beta_8 \text{Percent\_Enrolled\_Private\_School\_PUMA}_i + \beta_9 \text{Percent\_retirement\_2017}_i \\
&+ \beta_{10} \text{Type\_of\_School}_i + \beta_{11} \text{Teacher\_Student\_Ratio}_i + \sum_{i=1}^{10} \alpha_i \text{PUMA}_i + \varepsilon_i \quad (2)
\end{aligned}
$$

In equation 2, we examined 10 PUMAs. We wish to study the differences between those PUMAs, so we created a categorical variable that represents the 10 counties, $\sum_{i=1}^{10} \alpha_i \text{PUMA}_i$. Schools that are located in PUMA 11103 are placed in category 1. PUMA 11101, 11102, 11104, 11105, 11106, 600701, 600702, 608900, and 3701500 are placed in category 2 to 10, respectively. The reference PUMA is PUMA 11103, since it is the PUMA with the most observations. The p-value for the Breusch-Pagan & White test is 0.028. We rejected the null hypothesis and used robust standard error for this version.

2.4.3. VERSION 3: General regression with county fixed effect for all disasters.

We also perform the same model at county level, for robustness, which is represented in the Appendix 1. We analyzed the model using four counties. We wanted to study the difference between those counties, so we created a categorical variable for the four counties which is represented by the variable $\sum_{i=1}^{4} \alpha_i \text{county}_i$. The schools in Ventura would be put in category 1, those from Butte in 2, those from Shasta in 3 and those from Chatham in 4. The county of reference is Ventura, since 135 schools out of 252 schools in the database are from Ventura, this model will test if Ventura county drives the results. In other words, are the results taking into account only the observations from Ventura significantly different from the results taking into account all the schools in the database.

$$
\begin{aligned}
\text{Days\_Out\_of\_School}_i &= \beta_0 + \beta_1 \text{Number\_of\_days\_disaster\_strike}_i + \beta_1 \text{Percent\_FRPM}_i \\
&+ \beta_2 \text{Percent\_Welfare\_Income\_PUMA}_i \ + \beta_3 \text{Percent\_Others\_School}_i \\
&+ \beta_4 \text{Percent\_Hispanics\_School}_i + \beta_5 \text{Percent\_Blacks\_School}_i \\
&+ \beta_6 \text{Percent\_Female\_School}_i + \beta_7 \text{Percent\_Enrolled\_Public\_School\_PUMA}_i \\
&+ \beta_8 \text{Percent\_Enrolled\_Private\_School\_PUMA}_i + \beta_9 \text{Percent\_retirement\_2017}_i \\
&+ \beta_{10} \text{Type\_of\_School}_i + \beta_{11} \text{Teacher\_Student\_Ratio}_i + \sum_{i=1}^{4} \alpha_i \text{county}_i + \ \varepsilon_i \quad (3)
\end{aligned}
$$

Here again, we suspect heteroskedasticity. We also did the Breusch-Pagan & White heteroscedasticity test and resort to use robust standard error in the regression. The p-value of the Breusch-Pagan & White test was 0.003. Hence, we rejected the null hypothesis and employed robust standard error to correct for heteroskedasticity.

Five out of six disasters are fire related. This corresponds to 371 out of the 387 schools in the database. Thus, we wish to examine if fire disasters drive the results in versions one to three for robustness. Hence, we performed version four, five and six using the same variables and specifications as the general model (version 1), version two and version three respectively but taking into account only the schools affected by a fire. The results are shown in Appendix 2.

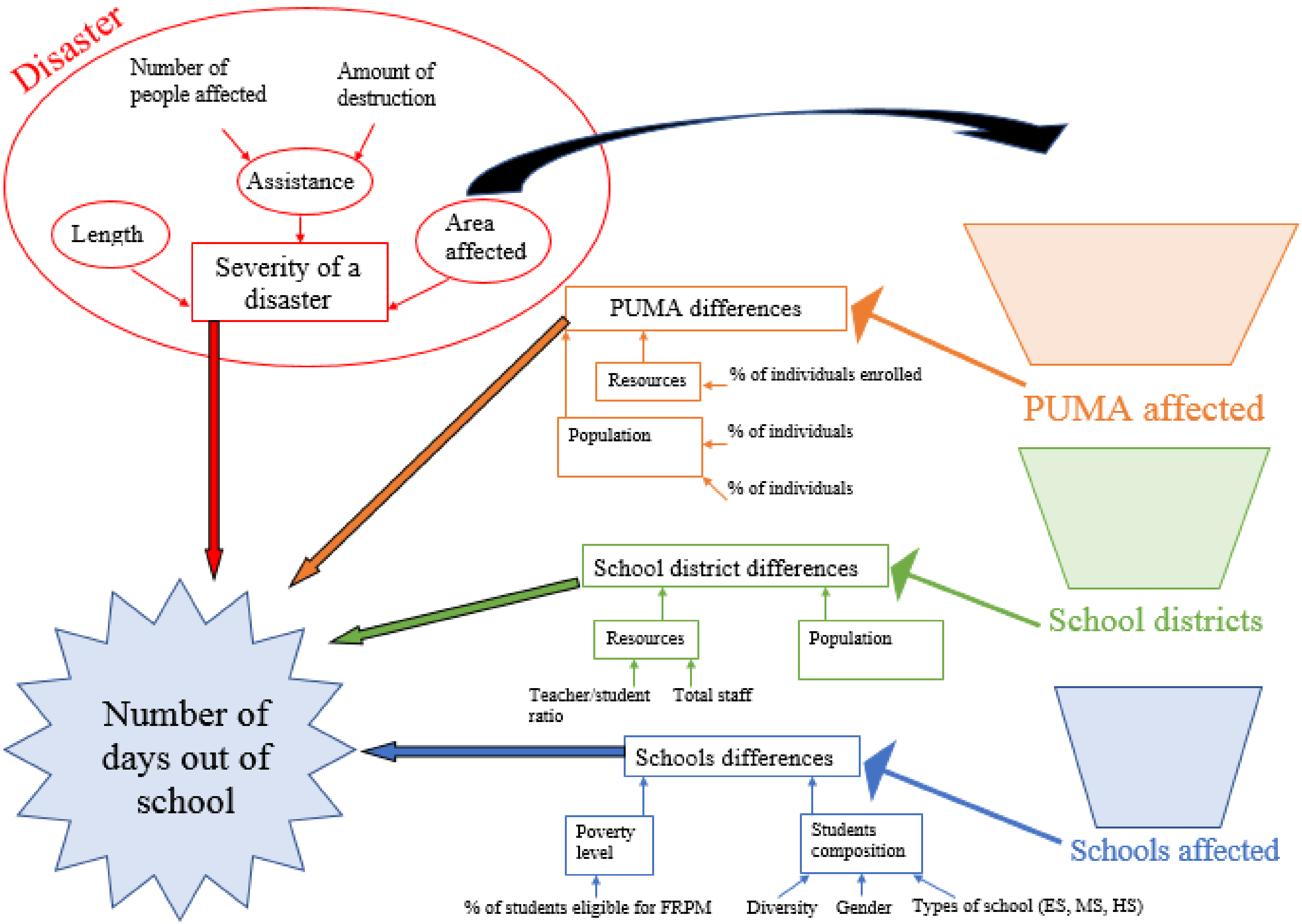

Figure 18: Knowledge map

CHAPTER 3: RESULTS

3.1. Data description

This section provides a description of the data collected for the database in order to make it more understandable and reusable by others.

3.1.1. Variables at the school level

3.1.1.1. Distribution/ location of the schools in the database

The primary unit of analysis for this study were schools, and the sample consists of public schools in the areas where the following disasters struck: the Thomas fire, the Camp fire, the Woolsey and Hill fire, the California Wildfires and High Winds, and the North Carolina Tropical Storm. The table 10 sums up the distribution of the schools and observations of our dataset based on their State, their disasters, their county, their PUMA, and their school districts. We were able to gather 387 observations from 252 schools. The reason why there are more observations than schools is that Ventura county was struck by three disasters in 2018. Hence, 135 schools out of the 193 in Ventura had to close more than once in that same year. Table 10 summarizes the structure of the data of the dataset.

Table 10: Summary of the data

State	Disaster	County	PUMA	Number of School Districts	Number of schools	Number of observations
California	Thomas, Hill and Woolsey fires	Ventura	11101	1	29	58
			11102	2	35	64
			11103	6	45	86
			11104	2	29	29
			11105	6	29	40
			11106	4	26	51
	Camp fire	Butte	600701	1	29	29
			600702	2	12	12
	California wildfires and high winds	Shasta	608900	2	2	2
North California	North Carolina Tropical Storm	Chatham	3701500	3	16	16
Total :	6	4	10	27	252	387

It is worth noting that there is a discrepancy in the table. When we look at the number of school districts in Ventura, we count 21. However, there are two school districts in Ventura that are repeated twice, since they were struck by more than one disaster. Hence, only 19 school districts are considered.

Within the 387 observations, there are 264 elementary schools, 49 middle schools and 64 high schools. The 387 observations are distributed in 4 different counties, 10 PUMAs and 27 school districts:

- ◊ Ventura is situated in California, more specifically in the South-West part of the state, on the coast. The database includes 19 school districts and 328 observations from 193 schools. The county has 55 high schools, 41 middle schools and 232 elementary schools.
- ◊ Butte county is also in California but in the northcentral part of the state, and there are three school districts, in the database, from that area. There are 41 observations from 41 schools

within this area where 11 are high schools, eight are middle schools, and 22 are elementary schools.

◊ Shasta county is a little further up than Butte county in California and the database has 2 school districts from that area. We collected data on two elementary schools from that county.

◊ Finally, Chatham county is situated in the center of North Carolina and the database includes three school districts from that area. This database contains 16 observations from 16 schools of which four of them are high schools, two are middle schools and ten are elementary schools.

3.1.1.2. Types of schools

Since the schools in the database were not all affected by the same incidents, we identified the number of elementary, middle and high schools affected by either a hurricane or a fire. We summarize this result in Table 11:

Table 11: Number of observations per type of school and disaster

Type of disaster	Elementary School	Middle School	High School	Total
Hurricane	10	2	4	16
Fire	256	49	66	371
Total	266	51	70	387

We can see that most of the school we recorded are affected by a fire disaster. This makes sense since there are more data for fire incidents than for hurricane. For the types of schools, we have 387 observations in the database, 68.73% are elementary schools, 13.18% are middle schools and 18.09% are high school. For elementary schools 96.24% of the schools collected are affected by fire incidents, for middle schools, it is 96.08% and for high schools it is 94.29%. Therefore, in total, 95.87% of the schools collected are affected by a fire incident. Out of the 5 fires in the database, the California wildfires is ranked as the most costly in the world, and the Camp fire as the most deadliest one in the U.S. since 1940.

3.1.1.3. Number of days out of school

The 387 observations that we collected come from 27 different school districts. Hence, we recorded the number of days out of school for each school. The mean and standard deviation for the variable days out of school are shown in Table 12. On average schools closed 6.47 days. But the range is wide, whereas the smallest amount of days some schools had to close was one while the maximum number of days others had to close was 24.

The following table gives the average number of days out of school for each disaster with its maximum and minimum number of days out of school.

Table 12: Average number of days out of school per disaster

Disaster	Type of disaster	Average number of days out of school	Min	Max
Woolsey and Hill Fires	Fire	2.62	1	7
California wildfires and high winds	Fire	3.00	3	3
North Carolina Tropical Storm	Hurricane	3.00	3	3
Thomas fire	Fire	6.46	1	14
Camp Fire	Fire	21.22	17	24

Table 13 indicates that the Camp fire was the disaster with the highest average of number of days out of school by far. As stated earlier Camp Fire was one of the deadliest of the United States since 1940s. The next table gives the average number of days out of school per PUMA. Table 14 shows that the average number of days change depending on the location even if the area was struck by the same disaster.

Table 13: Average number of days out of school per PUMA

Disasters	County	PUMA	Average of the number of days out of school in 2018
Thomas, Hill and Woolsey fires	Ventura	11101	1.0
		11102	4.1
		11103	4.7
		11104	13.9
		11105	8.1
		11106	2.6
Camp fire	Butte	600701	24.0
		600702	14.5
California wildfires and high winds	Shasta	608900	3.0
North Carolina Tropical Storm	Chatham	3701500	3.0

3.1.1.4. Students composition

The database also contains variables for the composition of each school such as its number of students, their gender, its diversity and their poverty level. The description of the sample is shown in table 15.

Table 14: Description of a key independent variable: the percent of Free-Reduced Price Meals and control variables related to the composition of the schools

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Students in the school	380	732.37	558.84	29.00	2844.00
Percent of Males in the school	380	51.69	3.72	35.55	72.63
Percent of Females in the school	380	48.31	3.72	27.37	64.45
Percent of Blacks in the school	380	3.24	5.99	0.00	76.00
Percent of Hispanics in the school	380	40.00	30.66	0.00	99.55
Percent of Whites in the school	380	50.23	29.15	0.20	100.00
Percent of Others in the school	380	6.75	5.59	0.00	70.00
Percent of Free-Reduced Price Meals	358	51.92	24.73	2.10	97.2

For the number of students and their gender, the average of the student population per school is 732.37 with an average of 51.69% males and 48.31% females. But, in the study this population ranges from 29 to 2844, with 35.55% to 72.63% for males and 27.37% to 64.45% for females. Concerning the variables related to the race of the student we have seven missing values for the four variables. Overall the average percent is higher for Whites with 50.23%, then Hispanics with 40.0%, Others with 6.75% and Blacks with 3.24%. But the range in which they fluctuated is almost the same from 0% - 0.2% to 70% - 100%. Finally, for the variable related to the economic level of the schools, FRPM, we have 29 missing values. On average 51.92% of the students eligible for FRPM and the values range from 2.1% and 97.2%. Concerning the type of the school 68.73% of the observations are elementary schools, 13.18% and 18.09% are middle schools and high schools respectively.

3.1.2 Variables related to the disasters

3.1.2.1. Number of days the disasters strike

As mentioned in the study area, this database contains information for six different disasters. Ventura county is the only county in the database struck by three disasters: the Thomas Fire and the Woolsy and Hill Fire. Out of the 19 school districts struck in Ventura, 12 school districts were affected by the Woolsy and Hill Fire, 18 were affected by the Thomas fire and 11 school districts were affected by both disaters. In the dataset, 236 schools (93.65%) of the schools are affected by a fire. This represents 371 observations in the entire dataset. For the length of the disaster, which is related to the severity of the disaster, the mean is 26.76 days with a minimum number of days of three and a maximum of 59. The standard deviation is 13.47.

3.1.2.2. Comparison of the number of days the disaster strike and the number of days out of school

In order to show if the schools that suffered the longest disasters also had the most days out of school, we charted the type of incident, number of days the disaster strikes and number of days the school close. From Figure 19 we can see a same incident like the Woolsey and hill Fire, the Camp Fire and the Thomas Fire are mentioned more than once. This is due to the fact that they strike different locations and therefore it leads to different consequences concerning the number of days out of schools. Thus, for the Woolsey and Hill fires, on average the schools closed for 3.75 days, ranging from 1 to 7. But, most of the schools closed only one day since it represents 75 schools out of the 141 schools (53.2%) affected by the Woolsey and Hill fires. For the Camp

Fire, 17.3 is the average number of days the schools closed, ranging from 11 to 24. In this case, most of the schools closed 24 days since it represents 29 schools out of the 41 schools (70.73%) affected by the Camp fire. For the Thomas Fire, the schools closed 9 days in average. The number ranges from 1 to 14. We can also notice that most of the schools closed only 1 day since it represent 68 schools out of the 189 schools (36%) affected by the Thomas fire.

We can also see from this graph that the california wildfires and high winds was the disaster that struck the longest with 59 days but for the two schools we were able to gather information, they only closed for three days. On the other hand the Camp fire disaster that lasted 18 days was the one with the most number of days out of school. The number of observations we have the most is for the area that closed one day.

3.1.3. Variables at the school district level

As mention above the dataset for 27 school districts. The number of schools we found per school district ranges from 1 to 58, and on average there are 14.3 schools per school district. We were able to gather the teacher student ratio for every school in the database. On average, there are 21.8 students per teacher and the standard deviation is 1.85. But this value ranges from 9.4 to 24.9 students per teacher. There are two school districts with a student teacher ratio of 24.9, both are in Ventura and affected by the Thomas fire and the Woolsey and Hill fire. There is only one school district with a student teacher ratio of 9.4, and it is in Chatham county and affected by the North Carolina Tropical Storm.

3.1.4. Variables at the PUMA level

The database contains 10 PUMAs. Ventura has 6 of them: 11101, 11102, 11103, 11104, 11105, 11106; Butte has two: 600701 and 600702; Shasta has one, 608900; and Chatham has one, 3701500. The mean, standard deviation and minimum and maximum of the variables collected at the PUMA are gathered table 18:

Table 15: Description of a key independent variable: percent of individuals receiving a welfare income and control variables related to the resources of the PUMA

Variable	Obs	Mean	Std. Dev.	Min	Max
Percent of individuals receiving a retirement income in 2017	387	12.22	1.43	9.96	16.39
Percent of individuals receiving a welfare income in 2017	387	1.21	0.60	0.55	2.89
Percent of individuals enrolled in a public school in 2017	387	11.06	3.58	6.87	22.81
Percent of individuals enrolled in a private school in 2017	387	2.40	1.18	0.60	4.56

The data is available for every PUMA, hence every school in the database. Concerning the percent of individuals receiving a retirement income it represents in average 12.22% of individuals per PUMA. However, the values for each PUMA range between 9.96% and 16.39%. In terms of individuals receiving a welfare income it represents in average 1.2% of individuals per PUMA, whereas 0.55% is the smallest percent we can find in a PUMA and 2.89% the highest. Table 19 shows all the variables at the PUMA level. This table indicates that within the different PUMAs, even from the same county their characteristics and resources are different.

Table 16: Comparison of variables at the PUMA level

County	Number of schools	Number of observations	PUMA	Average of the number of days out of school in 2018	% of individuals receiving a retirement income in 2017	% of individuals receiving a welfare income in 2017	% of individuals enrolled in public schools in 2017	% of individuals enrolled in private schools in 2017
Ventura	29	58	11101	1.0	13.00%	0.99%	9.42%	2.38%
	35	64	11102	4.1	12.80%	0.55%	9.66%	4.56%
	45	86	11103	4.7	9.96%	1.95%	11.12%	1.66%
	29	29	11104	13.9	13.18%	1.03%	9.78%	1.24%
	29	40	11105	8.1	12.45%	1.04%	9.53%	2.83%
	26	51	11106	2.6	12.02%	0.75%	12.10%	2.92%
Butte	29	29	600701	24.0	12.19%	7.10%	22.81%	0.60%
	12	12	600702	14.5	14.55%	2.89%	7.33%	1.24%
Shasta	2	2	608900	3.0	16.39%	2.14%	8.19%	1.90%
Chatham	16	16	3701500	3.0	15.36%	0.57%	6.87%	1.34%

3.2 Results from regression

In this section we present the results for the regressions we settled on which are the general regression and the regression with PUMA fixed effect taking into account all the disasters. The results for the regression with county fixed effect taking into account all the disasters can be found in appendix 1.

Table 17: Regression results

VARIABLES	(1) without fixed effects	(2) with PUMA fixed effects
Days_disaster_strike	0.100***	0.0795***
	(0.0219)	(0.0140)
P_FRPM	0.0509**	0.0190*
	(0.0203)	(0.0105)
P_welfare_2017	3.478***	3.065***
	(0.792)	(0.830)
P_Oth_School	-0.0743	-0.0103
	(0.0619)	(0.0210)
P_His_School	-0.00809	-0.0279***
	(0.0182)	(0.0103)
P_B_School	0.0330	0.00854
	(0.0274)	(0.0197)
P_F_School	0.0204	-0.0264
	(0.0602)	(0.0379)
P_Public_2017	1.361***	0.0561
	(0.0564)	(0.150)
P_Private_2017	-0.168	-18.51***
	(0.374)	(1.690)
P_retirement_2017	2.381***	-0.164
	(0.368)	(0.209)
Student_Teacher_Ratio	0.318*	0.279
	(0.172)	(0.424)
Type_of_school		
Middle School	0.379	-0.142
	(0.613)	(0.396)
High School	0.659	-0.250
	(0.557)	(0.360)
PUMA variables		
PUMA 11101		11.94***
		(1.485)

Table 17 continued

PUMA 11102		57.02***
		(3.896)
PUMA 11104		2.834
		(2.400)
PUMA 11105		27.58***
		(1.458)
PUMA 11106		24.38***
		(1.799)
PUMA 600701		-
PUMA 600702		-
PUMA 608900		-
PUMA 3701500		-
Constant	-54.11***	24.34***
	(6.794)	(7.260)
Observations	351	351
R-squared	0.665	0.868

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 1 looks into the results taking into account all the disasters of our database with and without PUMA dummies. The first hypothesis stated that the severity of the disaster would have a positive relationship with the number of days out of school. The variable that measures the severity of the disaster is the number of days the disaster strikes. In the model, this variable has a significant positive impact on the number of days out of school. If the number of days the disaster strikes increases by one unit (one day), we expect the number of days out of school to increase by 0.1 days. So, every 10 days of a disaster strike it increases the number of days out of school by 1. It is strongly significant at 1% level. We also hypothesized that the poverty level of the school will increase the days out of school. Table 20 indicates that an increase by one percent of students eligible for FRPM will increase the number of days out of school by 0.05. So, every 100 days of a disaster strike it increases the number of days out of school by 5. The coefficient is significant at 5% level. Finally, the third hypothesis aims to test if the number of people receiving a welfare income within a PUMA will increase the days out of school. The regression indicates that the hypothesis is validated. As we increase the percentage of people receiving a welfare income within a PUMA by one unit (one percent), we would expect the number of days out of school to increase by 3.48 days. The coefficient is strongly significant at 1% level.

The results also indicate that various control variables are statistically significant. If the percent of individuals enrolled in Public schools in a PUMA increases by one percent, the number of days out of school increases by 1.36 at 1% significance level. If we increase the percent of individuals receiving retirement income in a PUMA by one percent, we expect the number of days out of school to increase by 2.38 at 1% significance level. Furthermore, it shows that an increase in the teacher student ratio by one unit, which means one more student per teacher, increases the number of days out of school by 0.32 at 10% significance level.

We can now look into the results taking into account all the disasters of our database but with a PUMA fixed effect. The variable that measures the severity of a disaster has a significant positive impact on the number of days out of school. If the number of days the disaster strikes increases by one day, we would expect the number of days out of school to increase by 0.08 days. . So, every 100 days of a disaster strike it increases the number of days out of school by 8. The coefficient is strongly significant at 1% level. For the second hypothesis, related to the poverty level of the school, if the percent of students eligible for Free-Reduced Price Meals increases by one percent, we expect the number of days out of school to increase by 0.02 days ($P < 0.05$). Similarly, the percentage of individuals receiving welfare income within a PUMA has a positive impact on the dependent variable. So, coefficients behave similarly which validates the results. Accordingly, an increase by one percent of the individuals receiving a welfare income within a PUMA will increase the number of days out of school by 3.07, and the result is strongly significant at 1% level. This table also indicates that various control variables are statistically significant for the regression that includes PUMA fixed effect. If the percent of Hispanics within a school increases by one percent, we expect the number of days out of school to decrease by 0.03 at 1% significance level. Furthermore, the results show that a one unit increase of the percent of individuals enrolled in private schools in a PUMA, decreases the number of days out of school to decrease by 18.51 at 1% significance level.

On average, the number of days out of school in PUMA 11101, keeping everything else constant, is 11.94 days more than PUMA 11103 at a high significance level of 1%. The number of days out of school in PUMA 11102, keeping everything else constant, is on average 57.02 days more than PUMA 11103 at a 1% significance level. On average, the number of days out of school in PUMA 11105 and 11106 is 27.58 and 24.38 days more than PUMA 11103 respectively, keeping everything constant at a high significance level of 1% for both. PUMA 11104 is the only PUMA that bore an insignificant result and PUMAs 600701, 600702, 608900 and 3701500 have been omitted because of collinearity.

For both version 1 and 2 of the model, we can notice that the coefficients of most of the variables related to the characteristics of the students in the school are not significant. In other words, not only race, gender, but also age measured via the type of school show no obvious relationship with close closure. However, for all the variables related to the neighborhood, either at PUMA or school district level, we can observe that the coefficients have the same signs between the two versions with and without PUMA fixed effect but the significance change. A mentioned in the previous section we also looked at the model that would only take into account the schools that were affected by a fire disaster. Those results are shown in the appendix 2. The regression with PUMA fixed effect is likely to give more robust results than the regression with county fixed effect. Hence, we will discuss the results with PUMA fixed effect for all the disasters included in our discussion section.

CHAPTER 4: DISCUSSION, IMPLICATIONS AND LIMITATIONS

4.1 Discussion

This study sought to examine the impact of disasters on social institutions, specifically schools, in the context of climate change. Climate change can increases the number of natural disasters, which have severely affected the US. The purpose of this study was threefold: to study the relationship between the number of days out of school and (1) the length of the disaster (2) the economical status of the students within a school and (3) the vulnerability of the population in the area. These variables were hypothesized to affect the exposure of the community to natural disasters and hence were expected to have a negative impact on education.

Disasters impact communities in a variety of ways. In addition to the death toll that may be incurred, people may also be injured physically and emotionally (psychological shock), and subject to trauma, illness, or homelessness either due to their houses being completely destroyed or severely damaged. There can also be economic loss with effects on the local community and the nation. The amount of damages a community suffers gives indication on not only the severity of the disaster but also on the preparedness of the community for a disaster. The preparedness of an individual for a disaster is often related to their resources, since insurance and robust and resilient houses are expensive. Two of our hypotheses test whether the severity of the disaster, via the length the disaster strikes, and the preparedness of a community via the poverty level of the schools, have a positive impact on school closure. The third hypothesis tests the impact of school vulnerability via the percentage of individuals receiving a welfare income, on school closure. Additional variables were added to the model to control other community differences that could affect school closure.

4.1.1. Testing the hypotheses in light of previous literature

4.1.1.1. Hypothesis 1: the length of the disaster will increase the number school closure days

The amount of damages and destruction a community suffers from determines the amount of aid a community receives from FEMA after a disaster. Since we were not able to gather the amount of public assistance attributed per disaster, we used the length of the disaster (the number of days a disaster struck) as an alternative to measure the severity of the disaster. As every disaster of this database rises to the level of FEMA disaster declaration we are looking into large disasters where the damages are important(FEMA, 2019). Hence, we assumed that the longer the disaster is, the more severe the disaster is and its impact too. The hypothesis related to the severity of a disaster is supported. The results indicate that the longer a disaster lasts, the more severe is the impact on school closure. There are no official studies that measure the relationship between the length of the disaster and their impact of school closure. From this paper we can imply that the length of the disaster has a positive impact on schools. So, we can assert that the longer a disaster strikes, the more damages the community encounters. This evidently will force schools to close down more days, and thus negatively impact education. It should be stated that the number of days a disaster strikes is a proxy for the severity of the disaster. In an earlier study, Gad-El-Hak (2009) created a scale where the number of injured and the area the disaster strikes are the only two components to measure the severity of a disaster. We must note that a disaster that strikes only in a short period of time can also inflict severe destruction depending on the number of individuals and the area affected.

4.1.1.2. Hypothesis 2: the economic status of the children within the school will impact the number of days out of school

The amount of damages a community suffers from is also related to, as the literature review indicates (Palm & Carroll, 1998 as cited in Fothergill et Peek, 2004), the lack of preparedness of a community or an individual for a disaster. Preparedness is often linked to economic status. A wealthy individual has the resources to purchase insurance in anticipation of damages from natural disasters or to have disaster resistant buildings or houses. It can cost a large sum of money, and this renders these resources inaccessible for many. Thus, investing in preparation is not a priority for individuals or communities with less resources. For this analysis, data on socioeconomic status were collected at the school level via the percentage of students eligible for Free-Reduced Price Meals. This was done to test how socioeconomic vulnerability may differentially influence the patterns of school closures. In the results, the percent of students eligible for FRPM showed a positive impact on school closure. From this paper we can imply that the economic status of the children within a school has a positive impact on schools. It supports our hypothesis, which states that the higher the poverty level of a school, the more days a school will be closed after a disaster. This suggests that poorer areas are less prepared to cope with a disaster and hence are more severely affected if a disaster strikes. These results fall squarely with the articles cited in Disaster Technical

Assistance Center (U.S.), issuing body. (2017) and those cited in Fothergill et Peek (2004). The preparedness of a community for natural disasters is an important factor to reduce the impact disasters can have on education. Hence, increasing resiliency through building structure resistance and the level of preparedness is highly important in the task of recovering.

Fothergill and Peek (2004) suggest that some schools close in anticipation of a disaster, so that they can return to normal activities quickly, especially with abundant access to disaster aid and minimal damage. On the other hand, schools that receive more serious damages have to close for a longer period of time, for the apparent reason that they have to undertake repairs for the structure and facilities. Thus, we can speculate that the duration of school closure depends a lot on access to disaster aid and the extent of school damage.

4.1.1.3. Hypothesis 3: the vulnerability of the population in the area will impact the number of days out of school

The vulnerability of a community can be measured by its preparedness for a disaster, but also via its population. As the literature review indicates, there exists some groups of population classified as at-risks groups, including elderly persons, individuals with disabilities, pregnant women, minorities, children, prisoners, undocumented workers, and individuals with language barriers(Hoffman, 2009). Those groups may not cope with natural disasters the same way. For example, according to the study conducted via Kilijanek et Drabek (1979), in the short-term, the elderly are more vulnerable than younger victims. In addition to having special needs during and after the disaster and needing special assistances to deal with the situation, these at-risks groups also often face discrimination from shelters. In this article, we define a shelter as a safe place that provides basic needs and medical care whenever a disaster strikes. It was reported to The National Spinal Cord Injury Association that American Red Cross shelters discriminate against people with disabilities and later it was confirmed that American Red Cross implemented a policy to refuse shelter access to people with obvious disabilities(National Council on Disability (U.S.), 2006).

For this analysis, data on the vulnerable population was collected at the PUMA level, as measured by the percentage of individuals receiving welfare income in 2017 in an area. This was done to study how demographic vulnerability may differentially influence the pattern of school closures. This variable considers the welfare provided to the elderly (age 65+), blind or disabled persons with low income, families with dependent children and General Assistance aids given to other members of the community. Therefore, it provides us an understanding of the composition of the at-risks groups within an area identified in the literature review. In the results, the percent of individuals receiving welfare income showed a positive impact school closure. These results support our hypothesis, which states that a higher number of vulnerable people in a community will increase the number of days a school serving that community closes. Previous studies focused on the vulnerability of certain groups of people with regard to disasters, but not how those at-risks groups have an impact on the area, and subsequently the educational system. From this paper we can imply that the proportion of at-risks groups there are in an area has a positive impact on schools. Given the results, we can assert that the more at-risks groups there are in an area, the longer it takes for the community to recover. This variable considers the welfare provided to the elderly (age 65+), blind or disabled persons with low income, families with dependent children and General Assistance aids given to other members of the community. It is a proxy for the composition of the vulnerable population in an area. It does not include, for example, prisoners, undocumented workers, and individuals with language barriers. A better understanding of those excluded at-risks groups can assist the government in allocating resources and aid in a situation of an emergency.

4.1.2. Understanding Our Control Variables in Light of Previous Literature

For this analysis, data on demographics characteristics were captured at the school level, such as percentage of children who are males or females, the range of ages, and the percentage of minority students, in order to examine if the variation in the demographics of a school may influence the pattern of school closures. The results showed that the coefficient of the percentage of Hispanic students was the only demographic characteristic that had a significant relationship with the number of days a school closes. An increase in the percentage of Hispanics students in a school is associated with a decrease in the number of days a school closes. This finding is not in line with previous studies about disasters that include social vulnerability as a variable. In those studies, Hispanics are often included in the vulnerable population. This supposedly put them more at risks of a disaster, and hence a school with a higher percentage of Hispanics is more likely to close for a longer period. But, this result reinforces the finding of(Esnard et al., 2018), where their research focused on the features of schools affected by a disaster, and found that the percentage of Hispanics has a positive relationship with school closure.

Interestingly, the percent of individuals enrolling in private schools within a PUMA play a significant role in the number of days out of school. The literature review indicates that there are two difference forces that may influence school closure. Public schools receive more governmental aid than private schools after a natural disaster. Thus, we would expect that a higher number of individuals enrolling in public schools decreases the number of days a school closes, since they have more aid to assist them with the recovery process. On the other hand, private schools often enjoy a better financial status, thanks to greater amounts of endowment, higher tuition and private funds. With that in mind, they are more capable of coping with the aftermath of a disaster than a public school. While public schools are accessible to the general population, private schools cost on average $10,740 per year, ranging anywhere from $5,330 to more than $25,000, according to a report from the National Center for Education Statistics (NCES)(Lindenberger, 2019). Our results indicate that if the percentage of individuals enrolled in private schools within a PUMA increases, the number of days out of school decreases. From this paper we can imply that the economic status of the children within a school has a negative impact on schools Since the individuals enrolling in private schools come from families with more resources and may also receive some aid after a disaster, these results confirm findings of studies in our literature review. Moreover, normally, private schools do not have to follow as many procedures as public schools do and thus may be more likely be able to reopen sooner.

4.2. Implications

In order to limit the impacts of natural disasters, public perception of natural disasters will have to change. Furthermore, in addition to this necessary shift in the public perception around disasters, policies and practices run by local governments need to be integrated to empower small communities around the nation to build their resilience to natural disasters.

This section aims to provide insights and suggestions for the variables this study examined in order to eventually assist policy makers in making decisions. In order to consider increasing the quality of crisis management for education after a disaster we cannot limit ourselves to study only the schools. We need to look at a larger system. We cannot only focus on schools to find policies. The recovery process have to focus on the entire population all together. Hence, we will examine how implementing research, building successful programs or even encouraging government cooperation can be the key factors in diminishing natural disasters impacts.

4.2.1. The importance of understanding the severity of a disaster

As the results of this study showed, the severity of a disaster has an influence on school closure. Regardless of the availability of human and financial resources, the severity of a natural disaster is independent from the resources allocated to a community and cannot be controlled by humans. Also, a disaster announced by an “emergency declaration” is associated with a large number of affected people and geographic areas, and requires considerable resources from the local and federal government for the recovery process. Since the severity of a disaster is independent from human efforts, it is a difficult variable to study. Hence, in order to reduce the amount of damages a disaster can inflict, the solutions would be to intervene before the disaster strikes. Policy makers should look into what can be done to prevent damage and to anticipate disasters. Reducing the severity of a disaster, via the number of people affected, is possible before one strikes, unlike many of the other solutions developed later on.

For example, seismologists have the knowledge and the technology, and also records, that provide patterns of certain types of disasters. For example for certain earthquake zones, to anticipate and predict the disaster’s occurrence, location, and severity(British Geological Survey, 2019). The National Hurricane Center (NHC) uses different tools, such as satellites, reconnaissance aircraft, radars and other tools to track and predict the intensity, size, and location of the center of a hurricane, and the characteristics of a storm for all tropical cyclones(Hurricanes: Science and Society, 2015).

The first solution to mitigating the severity of disasters before they strike is to use the predictions of the forecaster as a warning and evacuate or prepare shelters for several medium or large cities in the path of the extreme event. If the government manages to be successful in the evacuation of the at risks areas, it could minimize human impact but also the economical impact since less medical care will be needed. However, for certain disasters such as tornadoes, the forecast cannot be made more than fifteen minutes ahead of the event, hence the window for action is quite small. This leads to the second solution that propose pay a particular attention on disaster prediction using judiciously the finite resources available. Indeed, weather conditions favoring the formation of a tornado can be predicted a few hours ahead. This is a far more reasonable time frame in which to evacuate an area than the fifteen minutes(Gad-El-Hak, 2009). By reducing the human impacts of a disaster, the recovery process can rapidly focus on reconstructions in order for people to rapidly go back to their daily routine.

4.2.2. Importance of an appropriate allocation of resources

The economic situation of a school can vary between schools located in the same geographic areas. Some school districts have more resources than others due to higher property taxes in their areas, thereby enabling their preparedness. However, it should also be noted that there are other barriers to the way resources are not spent efficiently, leading to a disaster response that is, therefore, also not efficient. Some problems that cause this inefficiency are: the need to clear the idea of the problem that needs to be solved rather than a goal that must be worked towards, a need for improved communication to share crucial information, and a need for the reduction of bureaucratic and regulatory barriers in order to move faster in a situation that needs immediate attention(Teutsch, 2010). Governments can exert two different actions. By understanding the real reason of a slow recovery, the governments can either identify which schools might need more support, depending on their poverty level, for a better allocation of the resources or they can create support systems through comprehensive, universal programs utilized across school districts.

As mentioned before, the preparedness of a community for natural disasters is an important factor to reduce the impact disasters can have on education. Hence, increasing resiliency through building structural resistance and the level of preparedness is highly important to creating community resiliency that will mitigate the amount of damage a community has to recover from. However, not everyone can afford such preparedness since some individuals have other priorities such as their basic needs(Disaster Technical Assistance Center (U.S.), issuing body., 2017). Therefore, instead of releasing large amounts of aid after a disaster, it could be useful and more practical for the government to assist communities beforehand so that they can invest in preparing for a disaster. In the long term, this would reduce the damages of the disasters, thereby benefitting underserved public schools and reducing the duration of school closures.

4.2.3. The importance of understanding the population characteristics in an area

As mentioned before, a natural disaster does not discriminate at any level. Hence it can strike anyone at anyplace. Although it is devastating for everyone, at-risks groups experience it at disproportional levels(Hoffman, 2009). For example, individuals with disabilities or those with access and functional needs represent a particular challenge in a disaster. They need additional resources particular to their disability. For example, one out of five individuals, counting adults and children, had a mental illness in the United-States. This is why a sufficient understanding of this population and other at-risk populations within an area is critical for local, state, and federal governments invested in building resilient communities. In the past, members with disabilities have been discriminated from shelters(Hoffman, 2009; National Council on Disability (U.S.), 2006). Hence one of the priorities for the government is to make sure that shelters, initially created to provide support, medical care and any other basic needs, are free from discrimination. They can also create campaigns to educate or inform individuals about to access to shelters. They can also instore organizations where people can address their complains to or seek for help whenever they suffer from discrimination. As mentioned before, the recovery process have to focus on the entire population all together. Hence, a thorough understanding of the population characteristics in an area helps local government in making decisions after a natural disaster and moving forward in the recovery process. A reinforcement of leadership management within the communities is also a solution to consider. This way the individuals can collaborate on how to prepare, to achieve common objectives, to adapt strategies on distributing resources before and after a disaster, and others. Hence at every geographical levels, people are taking action in preparing for a disaster and alleviating the consequences.

4.3. Limits and further research

This section highlights the limitations of the research study that can have an influence on the results and the interpretation of the results in some way. We will also provide advice to other researchers on where further studies might build on our findings.

4.3.1. The limits of the model

It should be emphasized that the study is only a one-year cross-sectional analysis. A stronger case would require a multi-year panel study to validate findings in this study.

Further studies should also look into the relationship with the number of days out of school and some independent variables. In this model we assumed there was a linear relationship for every variables of the model. This may bias the coefficients. Therefore, using a model that takes into account non-linear relationship could be a good contribution. For example, the number of days the disaster strikes and the number of days the school close they don’t have an obvious linear trend. It may be the case that the number of days the disaster strike impact school closure in a non-linear manner.

This study is primarily limited by the data collected. Concerning the disasters being studied in this paper, the dataset contains only six disasters, where five of them are fires that struck California and three of the five fires stuck Ventura county. Hence, the results showed that Ventura county and fire related disasters are the main factors that drive the results. Also, even when our dataset contains 387 observations, the variability was limited, since those schools were located in only four different counties. Shasta county contains only two schools. Future research could build on our findings by looking at a larger number of counties, and specifically tailoring their research around finding different types of disasters in a larger selection of counties. This would increase the variability of the dataset. A larger variation in the dataset would allow the study area to be more complete.

4.3.2. The limit of the variable used to measure the severity of a disaster

4.3.2.1. The length of the disaster, a proxy variable

Another limitation is the proxy variable used to estimate the severity of the disaster. As mentioned before, since the amount of public assistance and individual assistance grants provided by FEMA are unavailable, the severity of the disaster could only be estimated by the number of days a disaster affected a given area. Returning to normalcy is typically a slow process that depends on the severity, as well as the resources that local governments can get access to and the efficiency of the recovery process. In our consideration of the duration of the disaster, we were particularly interested in how the longer a disaster lasts, the more damage it can evoke and the longer it will take for a community to recover. However, by considering the severity of a disaster apart from duration, future studies might better understand the importance of the severity of a disaster.

4.3.2.2. The data this study was able to collect

Severity is a difficult variable to measure, since if an individual is seriously injured or has all of their assets destroyed by the disaster, it can be catastrophic for their family. However, as disastrous as that may seem, the consequences may well be on a small, individual scale rather than community or county scale. As mentioned in the literature review, only the disasters that are declared emergencies receive aid from the government. Due to their severity, those disasters attract the resources from both local communities and central governments. FEMA, for example, provides the public assistance and individual assistance grants, but these are only awarded for a specific group of incidents. In the records that FEMA provides, one can see only a single dollar amount dedicated to more than one disaster. That amount is not specified by the community or by the disaster. Records of grants given cover incidents in one area of the same type, from the same period, and in close proximity to one another.

A disaster's severity will be classified depending on the number of people it affects, and/or the extent of the geographic area involved as seen in Figure 20. Thus, further research can focus on exploring new proxies to represent the severity of a disaster either via the damages the disaster in question inflicts, the size of the areas affected, and/or the amount of aid provided for it.

A future study might specifically focus on the amount of aid provided per incident, however that data is not readily available. While we considered the length of the disaster to measure severity, we believe it would have been more effective to measure severity through the amount of aid provided per disaster. Below, we have also provided data we collected through the study that we were not able to use because it did not specify how much money went to each disaster. In other words, it did not offer a value that could be entered because several disasters were classified under a single code.

Disaster incidents classified by FEMA under Code DR-4353: Thomas Fire. The incident period was between December 04, 2017 and January 31, 2018 while the major disaster declaration took place on January 02, 2018. The entire disaster incidents included:

- ◊ Thomas Fire (Ventura and Santa Barbara Counties)
- ◊ Creek Fire (LA County)
- ◊ Rye Fire (LA County)
- ◊ Skirball Fire (LA County)
- ◊ Lilac 5 Fire (San Diego County)

Therefore, for the entire disaster, which contained these 5 different incidents:

- ◊ Total PA Approved: $163,158,018.92
- ◊ Total IA Approved: $5,083,103.10
- ◊ Total IA Applications Approved: 737

Disaster incidents classified under code DR-4407: California Wildfires. The incident took place between November 08, 2018 and November 25, 2018; while the major disaster declaration was on November 12, 2018.

The entire disaster included the incidents:

- ◊ Camp Fire
- ◊ Woolsey Fire
- ◊ Hill Fire

Therefore, for the entire disaster, which contained these three different incidents:

- ◊ Total PA Approved: $87,237,995.83
- ◊ Total IA Approved: $87,773,139.24
- ◊ Total IA Applications Approved: 8,028

DR-4407 is still an open disaster and is still actively recovering. Hence, IA and PA numbers will change.

4.3.2.3. Generating estimates for the magnitude of the cost per disaster

Gad-El-Hak (2009) created a universal metric (Figure 20) which classifies the severity of a disaster based on the number of displaced/tormented/injured/killed, and/or the size of the geographic areas affected. The system is able to estimate the scale of the disaster if the information of at least one those two criteria can be gathered. This scale can be used for all types of disasters. According to Gad-El-Hak (2009), some other scales that might be used to analyze specific disasters include the following: Saffir-Simpson scale for hurricanes, the Fujita scale for tornadoes, the Richter scale for earthquakes, and the recently introduced Northeast Snowfall Impact Scale for the winter storms that occasionally strike the United States. Those scales might be more precise since they target a particular type of disaster. Hence, using FEMA information and, for example, the disaster scope scale by Gad-El-Hak (2009), it would be possible to generate estimates for the magnitude of the cost per disaster.

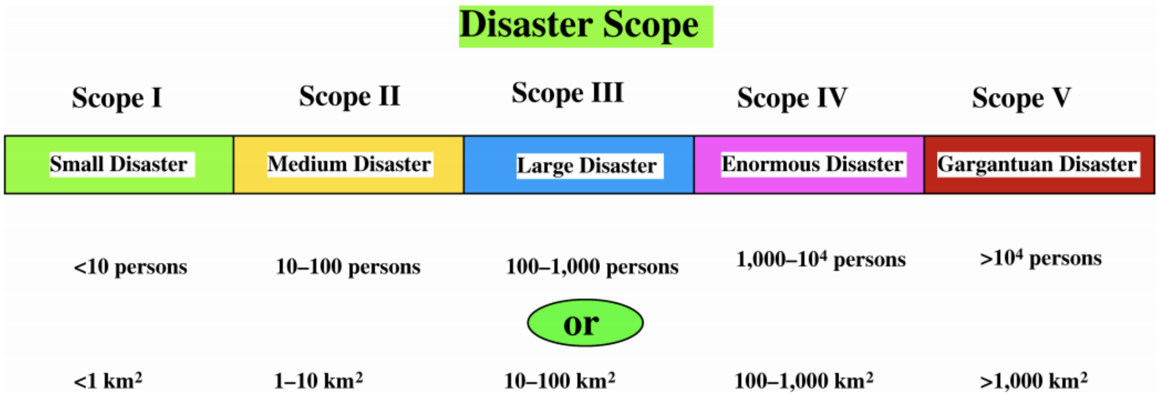

Figure 19: Classification of disaster severity (source: Gad-El-Hak, 2009)

4.3.3. Future research on economic vulnerability

Further research might consider other variables to measure the economic poverty or wealth of a school. The Free or Reduced-Price Meals is the proxy variable used to estimate the poverty level of the schools. Given that American schools are funded by property taxes, examining a school's tax revenue and the amount of money spent on each pupil might provide a better income control and a more accurate indicator of school level spending and poverty than a consideration of the number of students receiving Free or Reduced-Price Meals. Using variables like tax revenue, a county's property tax, or the dollars spent per pupil could further nuance one's understanding of the risk factors affecting schools.

Future studies can focus more on understanding how state governments distribute grants and resources within their state. This can help researchers and law makers to determine the level of access to resources of disadvantaged school districts. Areas that receive more federal and state resources and grant funding, are more resilient to damage from disasters. Determining where funding comes from could help future researchers determine the resiliency of a particular PUMA or district. Furthermore, our results indicate that the resources an area receives can greatly impact, the number of days out of school, hence its recovery process. Further research might explore the importance of an area's economic ability to recover from a disaster.

CONCLUSION

As the effects of climate change continue to reveal themselves, the number of natural disasters across the world has been increasing and will continue to increase. The United States is among the many countries that suffers from and will continue to suffer from the effects of climate change and the natural disasters it exacerbates. In 2018, the U.S. was the country with the third most natural disasters in the world. In 2018, it was also the country with the most economic losses due to natural disasters, specifically from the California wildfires, Hurricane Michael, and Hurricane Florence. In that same year, the U.S. also suffered from one of the deadliest disasters of the United States since 1940s, the Campfire. As these natural disasters continue to impact the country, it is crucial that we understand how to make communities more resilient to their effects.

The purpose of this study was to consider the impact of natural disasters by identifying factors that contribute to school closures after a natural disaster. A cross sectional OLS was used to analyze our data in order to respond to three hypotheses: the relationship between the number of days out of school and (1) the length of the disaster, (2) the economic status of the students within a school and (3) the vulnerability of the population in the area. Those variables are hypothesized to affect the exposure of the community to natural disasters and hence are expected to have a negative impact on the educational experiences of children in those schools. Our data was collected exclusively from disasters that rise to the level of a FEMA disaster declaration.

The first hypothesis considered the issue from the level of the disaster to understand how a disaster can affect school closure. The results indicated that the length of the disaster, used to measure the severity of the disaster, had a positive impact on school closure. So, the disaster's severity increased the days a school closed. With the knowledge and technology available currently, especially in the U.S., we could prevent some damages by anticipating future disasters.

The second hypothesis considered data captured at the school level in order to study how the economic vulnerability of the schools could have differentially influenced the pattern of school closures. Results indicate that if the poverty level of the school increases, the number of days out of school also increased. With a better understanding of which schools need the most support, the community, the government or other organizations would be able to better allocate resources to mitigate those risks.

The third hypothesis is analyzed at the PUMA level in order to study if the composition of an area affects school closure. The results indicate that if the number of individuals receiving welfare income increases, the number of days out of school also increases. Hence, the demographic makeup of a community where the schools are located indeed impacts school closure. The results suggest that by understanding the composition of the population, the government might take steps to increase community awareness and take adequate measures with respect to at-risks groups in a case of an emergency.

This study provides critical insights into a growing problem the U.S. faces due to climate change and worsening natural disasters via their number and their severity. By understanding the factors that influence school closure, policy makers can make decisions more easily. As the hypothesis suggest, the impact on school closure is related to features of the school at different levels. Hence, through interventions in local communities throughout the whole nation, it is possible to minimize the damages that can occur after a disaster and therefore limit the impact on education. Beyond this study, the key to minimizing the damage of more numerous and severe disasters that may affect the U.S., could be a deeper understanding of all the features that makes an area vulnerable.

APPENDIX

Appendix 1: General regression for all the disasters and county fixed effect

VARIABLES	(3) with county fixed effect
Days_disaster_strike	0.122***
	(0.0162)
P_FRPM	0.0365**
	(0.0169)
P_welfare_2017	-24.22***
	(8.231)
P_Oth_School	-0.0545
	(0.0558)
P_His_School	-0.000957
	(0.0157)
P_B_School	-0.00189
	(0.0189)
P_F_School	-0.00954
	(0.0572)
P_Public_2017	-2.839**
	(1.187)
P_Private_2017	-5.713***
	(1.702)
P_retirement_2017	-7.942***
	(3.050)
Student_Teacher_Ratio	0.838*
	(0.464)
Middle schools	0.152
	(0.605)
High schools	0.457
	(0.520)
Butte	60.52***
	(17.15)
Shasta	46.47**
	(18.74)
Chatham	3.022
	(3.645)
Constant	148.5**
	(58.33)
Observations	351
R-squared	0.714

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2: General regression for fire related disasters

VARIABLES	(1) without fixed effect	(2) with PUMA fixed effect	(3) with county fixed effect
Days_disaster_strike	0.101***	0.0795***	0.122***
	(0.0213)	(0.0140)	(0.0162)
P_FRPM	0.0556***	0.0193*	0.0400**
	(0.0211)	(0.0112)	(0.0178)
P_welfare_2017	3.525***	141.0***	-23.99***
	(1.051)	(10.32)	(8.235)
P_Oth_School	-0.0734	-0.0113	-0.0542
	(0.0621)	(0.0212)	(0.0555)
P_His_School	-0.00945	-0.0286***	-0.00184
	(0.0186)	(0.0106)	(0.0161)
P_B_School	0.0454*	0.0116	0.00489
	(0.0252)	(0.0217)	(0.0214)
P_F_School	0.0326	-0.0264	-0.00174
	(0.0626)	(0.0393)	(0.0591)
P_Public_2017	1.373***	16.11***	-2.794**
	(0.0810)	(1.111)	(1.188)
P_Private_2017	-0.109	123.1***	-5.641***
	(0.441)	(9.344)	(1.704)
P_retirement_2017	2.387***	-2.212***	-7.829**
	(0.372)	(0.266)	(3.052)
Student_Teacher_Ratio	0.368	0.278	0.822*
	(0.393)	(0.424)	(0.464)
Middle schools	0.464	-0.136	0.191
	(0.642)	(0.413)	(0.628)
High schools	0.730	-0.254	0.508
	(0.583)	(0.378)	(0.543)
PUMA 11101		75.94***	
		(5.736)	
PUMA 11102		-131.2***	
		(10.42)	
PUMA11104		217.3***	
		(15.48)	
PUMA 11105		18.10***	
		(0.955)	
PUMA 11106		-	
PUMA 600701		-	
PUMA 600702		-	
PUMA 3701500		-	

Appendix 2 continued

Butte			59.88***
			(17.16)
Shasta			45.91**
			(18.75)
Constant	-56.49***	-637.7***	146.1**
	(12.57)	(47.70)	(58.39)
Observations	337	337	337
R-squared	0.663	0.867	0.712

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: CalOES email to get the amount of PA and IA

GAVIN NEWSOM
GOVERNOR

MARK S. GHILARDUCCI
DIRECTOR

Cal OES
GOVERNOR'S OFFICE
OF EMERGENCY SERVICES

October 3, 2019

VIA EMAIL: cpoujaud@purdue.edu

Camille Poujaud
Graduate Student/Research Assistant
Agricultural Economics
Purdue University

Subject: September 24, 2019 Public Records Act Request

Dear Ms. Poujaud:

This letter responds to your California Public Records Act request, dated September 24, 2019, and clarified on September 26, 2019. In brief, you requested records pertaining to the total amount of Public Assistance and Individual Assistance that was provided for each of the Camp, Woolsey, Hill, and Thomas Fires.

Cal OES understands you have already received these costs per federally declared disaster, which is the same information Cal OES has and would provide. However, Cal OES does not maintain this data in the format you requested.

Should you have any questions, please contact me at (916) 845-8971, or at pra@caloes.ca.gov.

Sincerely,

Joy Peng
Attorney, Office of Legal Affairs

cc: Jennifer L. Bollinger, Assistant Chief Counsel

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