Lighting a Fire Under California Legislators:

An Analysis of Climate Change, California Wildfires, and Legislative Action

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Abstract

In this research paper, I ask if California legislators are more likely to vote in favor of either wildfire mitigation policy or pro-climate policy the year after their district experiences wildfires, compared to legislators in districts without wildfires. I ask this question to determine if our policymakers view wildfires as a current impact of climate change, and to see if they take more action against climate change when their constituents are already experiencing the effects of it as measured by wildfires. My hypothesis was that the legislators would be more likely to vote in favor of the wildfire policy, not the climate policy, because I believed that they would not attribute the wildfire activity to climate change. In contrast, legislators in wildfire districts would be more likely to vote for the wildfire policy because it would positively benefit their constituents that were affected by a heavy wildfire season.

I found that the wildfire activity in a district did not have a statistically significant impact on the legislator's vote for either the wildfire or the climate change policies. The only factor that did have a significant impact was the legislator's party affiliation: Republicans were less likely than Democrats to vote in favor of either bill, and the correlation was stronger for the climate bill. However, since I did not compare wildfire data and legislator votes across years with differing wildfire levels, I could not determine if these voting patterns would change compared to a year with a normal fire season that was not as impacted by climate change.

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Introduction

With current events taking over our news feeds and the struggles of day-to-day life at the forefront of our minds, it is easy to forget about the less salient, yet ominous, issue of climate change. Atmospheric carbon dioxide levels have increased from 313 ppm in 1958 to 417 ppm as of March 9, 2022.[1] Global average temperatures have risen about 1.53℉ from the average temperatures between 1951-1980,[2] and the effects from this temperature increase have already started, and will only be exacerbated over time. Sea levels are rising[3] and natural disasters, such as wildfires, are increasing both in intensity and in frequency. We have statistical evidence that climate change is real. We are already experiencing the widespread effects of rising temperature levels, and they reach over nearly every aspect of our current environment. But are our legislators recognizing the current impacts of this impending dilemma, or do they simply believe it to be a future problem?

In my senior thesis, I aim to explore if California legislators are taking action against the current effects of climate change, not just preparing for the potential future effects. I want to discover if legislators are more likely to take pro-climate political action if their district has been recently affected by the effects of climate change, specifically measured by California wildfire data. In this thesis, I ask the following two questions:

1. Are California legislators more likely to vote in favor of a wildfire policy the year after their district experiences wildfires, compared to legislators in districts without wildfires?

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[1] Monroe
[2] Nasa Global Climate Change
[3] Church and White

2. Are California legislators more likely to vote in favor of a climate change policy the year after their district experiences wildfires, compared to legislators in districts without wildfires?

My goal with these two questions was to determine if the current effects of climate change, specifically wildfires, have any impact on California legislators' actions on current climate change and wildfire policies. I chose to focus on wildfires because they are a salient marker of climate change in California. In California, the average summer temperature has increased by 3 degrees Fahrenheit in the past 100 years, and from 1972 to 2018 the California wildfire burn area has increased fivefold.[4] 2017 was the second-hottest year in California history, and at the time it was the most destructive wildfire year in California in terms of property damage.[5]

While destructive wildfires take over the California news cycle every season, the general public has trouble connecting these wildfires to climate change. The general science is as follows: rising carbon dioxide levels create the greenhouse effect and traps heat in the atmosphere. This in turn causes average global temperatures to rise, which leads to a myriad of consequences such as more frequent droughts. Higher average temperatures lead to drier climates so once fires start, they have more fuel to burn through and they end up being bigger fires and they burn for longer. While most wildfires are caused by humans, climate change exacerbates the dry conditions and makes the fires more destructive and intense.[6]

With this background on the effects of climate change, I wanted to look at it from a more political viewpoint. I don't believe that there is currently enough political focus on climate change and wildfires. In general, climate change is seen as a "far away" issue- as of 2021, 25%

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[4] Scripps Institute of Oceanography
[5] CAL FIRE
[6] Center for Climate and Energy Solutions

of Americans fall under the "Concerned" category of the famous Yale Six Americas study.[7] This study polls American citizens about their beliefs on climate change and divides them into six different categories: Alarmed, Concerned, Cautious, Disengaged, Doubtful, and Dismissive. The spectrum ranges from believing that global warming is an urgent threat that needs action now to believing that it is not real and not human caused. The Concerned category includes people who believe that global warming is happening now, but think the impacts of climate change are going to happen more in the future than now so they are not a high priority at the moment. So, to many people, climate change is not viewed as being as crucial as other problems that are more immediate, like the coronavirus pandemic or ongoing wars.

With the understanding that climate change is viewed as less salient than other important problems, and that people are less likely to think of wildfires as an effect of climate change, I want to see if California legislators are taking action on climate change and wildfires. My hypothesis is that if there have recently been more wildfires in a representative's district, they will be more likely to vote in favor of wildfire policies, but it will not affect their votes on climate change policy. I believe that legislators in fire-having districts will be more likely to vote for wildfire policies because if there were more fires in the district they represent, the fires will have directly impacted their constituents. Thus, wildfires will be a salient issue in their constituents' minds and they will support their representative if they vote in favor of the wildfire bill. Legislators want to act in the best interest of their constituents so that they will retain their vote and get re-elected, so if their constituents have been affected by wildfires they should in theory vote favorably on wildfire policies.

However, I hypothesize that the wildfires will not have an impact on climate policy votes because the representatives, and the constituents, do not actively consider that climate change

[7] Yale Program on Climate Change Communication

had an effect on the frequency and intensity of the wildfires. That is to say, people in the area surrounding a wildfire will not have stronger feelings about climate change after experiencing more wildfires because they will be thinking about wildfires, not climate change.

Additionally, politician's votes on climate policy may not be affected by wildfires because climate change has highly partisan connotations. Democrats are more likely to say that the effects of global warming have already begun, and more likely to say that global warming is caused by human activities.[8] Additionally, 78% of Democrat-leaning voters believe that climate change should be a top policy priority for the President and Congress compared to only 21% of Republican-leaning voters.[9] So, it is possible that the representative party will have a strong effect on the likelihood of that legislator voting for a climate policy. I will be including the representative's parties as a covariate in my analysis because I believe that the representative's party will have an impact on their vote on the climate bill- that is to say, Democrats will be more likely to vote in favor of climate policy, while Republicans will be less likely.

To review the goal for this thesis, I want to determine if the current impacts of climate change are being adequately addressed by policy decision makers in California. Wildfires will only continue to become more frequent and more intense as the years go on and temperatures continue to rise, so I wanted to ask if action is already being taken now. Before I can dive into my research process, I need to do background research on the current knowledge of wildfires, the connection to climate change, and if legislators are already taking policy action after their constituents experience the effects of climate change.

[8] Dunlap et al.
[9] Pew Research Center

Literature Review

My next step for my thesis was to examine the past research that has been done on this subject. First, I wanted to research if firsthand experience with wildfires had an impact on voters' behavior. Shifting to the political effects of climate change, I also wondered if voters were more likely to support their representatives if they voted on natural disaster policies. I researched if more natural disasters lead to more policy action relating to managing the disasters. Lastly, I reviewed the current research on whether politicians take more action on climate policy if their constituents have been affected by the impacts of climate change.

First, I researched how wildfires impacted voters and their voting patterns on wildfire policies. I asked this question because I want to determine what effect, if any, the direct experience of a wildfire has on a person's policy views. My hypothesis is that legislators in wildfire districts will vote for wildfire mitigation policies because it affects the people in their district and their constituents will want action to be taken against wildfires, so it is relevant to see if the voters will actually have stronger feelings about wildfire policies after personal experience. "Baptism by Wildfire?" by Hui et al. examined how Californians' experiences with wildfires impacted their support for wildfire policies.[10] Their "experience" with wildfires was measured by geographic proximity to wildfires, and their support for policies was measured with a survey asking the voters if various wildfire policies should be just allowed or fully required.

The paper found that in general, Californians valued personal choice and the ability to rebuild in wildfire-prone areas, while being less in favor of policies that forced individuals to move away. There wasn't much of an impact of proximity to wildfires on voters' policy

[10] Hui et al.

preferences, but some Republicans had lower opposition towards using public money for relocating homeowners when they were closer to wildfires. So far, this research is showing that wildfire proximity is not a strong indicator of voter preference on wildfire policy, while voter party may be more of an indicator than wildfire exposure.

Another paper on voting behavior was "Wildfire Exposure Increases Pro-Climate Political Behaviors" by Hazlett and Mildenberger.[11] In contrast to the previous paper, this paper focused on climate policy rather than wildfire policy. This is relevant to my research because it asks if wildfire exposure changes people's votes for climate action. Researchers measured how wildfire exposure (measured via proximity data) impacted the voting outcomes of environmental ballot initiatives in California from 2006-2010. The study found that Californians in a census block group that was 5-15 kilometers away from a wildfire were 4 to 6 percentage points more likely to vote for the pro-environment ballot initiative than Californians who were farther away from a wildfire. Census blocks that had a wildfire within their boundaries had 3.6% more support for the pro-environmental policies relative to blocks that didn't have wildfires within their boundaries. However, this effect is highly partisan: Democratic block groups had a 7-9 percentage point increase at the 5-15 kilometer range, while Republican census block groups had a very small effect, no matter how far away they were from a wildfire.

So, these past two studies show that proximity to wildfires has a very slight impact on constituent voting patterns for wildfire policy and a slight impact on climate policy votes. In my study, this result could point to the wildfire data having a minimal impact on legislator votes as well. However, both studies showed that the voter's party did have an impact on their support for wildfire and climate policy. In my research, I will make sure to include analysis with

[11] Hazlett and Mildenberger

representative parties as a covariate because these studies showed a difference in behavior between parties.

The next paper measured how voters hold elected officials accountable for their natural disaster policy decisions. I wanted to research voter accountability because my hypothesis was that politicians would vote for wildfire policies because they would want to keep their voters happy after they experienced a wildfire. If voters do not change their vote due to political action after a natural disaster such as a wildfire, then the politicians do not have that incentive to vote in favor for the wildfire policies. "Myopic Voters and Natural Disaster Policy" by Healy and Malhotra measured presidential election data and compared that with presidential spending data of federal funding for natural disasters.[12]

The study found that voters rewarded an incumbent presidential party with their vote if they paid disaster relief funds, but they did not reward incumbents who invested in disaster preparedness. The authors argue this could be because voters remember what an elected official has done to mitigate the effects of a disaster, and they don't remember a less-newsworthy prevention policy. I believe this also could be because if the disasters happened, they had a personal impact on the voters and they will remember what the president did to mitigate the disaster. A natural disaster is much more salient than a news article about a policy being passed because people can actually see the effects that happened from the disaster.

Relating this issue back to my thesis, this could be an incentive for California policymakers to vote for wildfire policy if their constituents personally experienced fires in their district. Voters in wildfire-having districts may be more likely to support their representative if they vote for the wildfire policy because the legislators took memorable action against the

[12] Healy and Malhotra

wildfire after the disaster occurred, and this could mean that the legislators will be more likely to vote for the wildfire policy if their constituents experienced wildfires.

Then, I examined climate change impacts on policy change. I have researched the changes in voter behavior after wildfires and climate change impacts, and now I want to shift to policymaker behavior. “Local Adaptation Policy Responses to Extreme Weather Events” by Giordono et. al. measured how extreme weather events in communities impact policy change, and what conditions after an extreme weather event lead to “adaptation-oriented policy adoption”.[13] They found 15 cases of extreme weather that could act as “focusing events”, meaning they were sudden, rare, harmful, and the public and policymakers both knew about the event (aka, the events were salient in the public eye). These extreme weather cases ranged from flooding to wildfires to hurricanes and they were measured by newspaper articles about the events.

The study found a “moderate level” of policy change after these events, mostly in the form of anticipating and responding to future risk, but there was not much evidence of mitigation policies after an event. They found that Democratic communities with a lot of media coverage on the weather event had more policy adoption, and Republican communities with other weather events that had recently occurred would also have more policy adoption. This paper also showed a partisan divide between the reaction to extreme weather events. More salient events led to more policy adaptation, so this could potentially correlate with my thesis. Maybe larger wildfires will lead to more legislator action (measured by their wildfire and climate policy votes) compared to smaller wildfires that burned fewer acres and damaged fewer structures.

To be more relevant to my research, I looked for literature on how the effects of climate change impacted legislative action via representative’s votes. Representative voting patterns are

[13] Giordono et al.

more relevant to my thesis than general policy changes because it connects to the representative's home district and their constituents. Herrnstadt and Muehlegger looked at the effects of climate change salience and extreme weather on Congressional voting patterns in the US.[14] They found that when a Congressional member's home state experienced unusual weather, that member was more likely to vote in favor of an environmental bill.

This was a country-wide study that focused on unusual snowfall and temperature patterns, not specifically wildfires. However, the same partisan divide with pro-environmental action was found in this study because the relationship between unusual weather patterns and pro-environmental voting was strongest in moderate Democrats. This may be because stronger Democrats are likely to vote pro-environment regardless of the weather in their home state, and Republicans are less likely to vote pro-environment regardless of weather as well. However, this paper does not look at wildfires specifically, so it will be interesting to see how wildfire conditions affect legislators' votes, not just heat waves. Additionally, this was a country-wide study, and it will differ from my California-based study due to the state's unique climate and political nature.

To summarize my literature, many of the papers I reviewed noticed a partisan divide between Republicans and Democrats and their opinions on and actions taken towards climate change. My research fills a gap in the current literature, because while some research has been done on wildfire proximity and constituent votes, and there is research on weather patterns and legislator votes, there is not specific research about wildfire proximity (measured by the occurrence of wildfires in a legislative district) and the effects it has on legislator votes about climate policy.

[14] Herrnstadt and Muehlegger

I am excited to add to the current literature on California wildfires, climate policy, and legislative action. However, I must be careful to consider the party of the representatives in my study because it seems to have a significant impact in the policy outcomes studied in the relevant research. After my literature review, I believe the representative's party will have a stronger impact on their votes on the climate bill than I initially anticipated, but I am not sure if the party variable will have an impact on the votes for the wildfire bill.

Research Design

The first step of my research design is to determine how I will measure my independent and dependent variables. My independent variable is wildfire data in each California State and Assembly district in 2017, and my dependent variable is the voting record of California State Legislators on two separate bills from 2018. The two bills that I will be collecting data on are SB-901: Wildfires and SB-100: California Renewables Portfolio Standard Program: Emissions of Greenhouse Gases. I will measure my independent variable of the 2017 California wildfires using data from the California Department of Forestry and Fire Protection.

Independent Variable: California Wildfires

First, I will discuss how I will measure my independent variable which is the wildfire data. I chose to look at the wildfire data from 2017 because it was one of the most intense wildfire years on record. 2017 was the second-hottest year in California history, and at the time it was the most destructive wildfire year in California in terms of property damage.[15] I am going to use several different measures for the "effects" of a wildfire on each district, because there are different ways to measure the magnitude of a fire. For each district, my dataset lists how many wildfires occured, how many acres were burned, how many fatalities occurred (for firefighters and civilians), and how many buildings were damaged and destroyed, among other measures.

The simplest measure of my wildfire data is the number of wildfires per district, as it simply asks if there was a fire in that district that year. It does not consider how impactful the fires were on human life because it does not factor in if any property was damaged or how big

[15] CAL FIRE

(in area) the fires were. If there are a lot of small wildfires in less populated areas, there will be a high number for the amount of wildfires, but there will not be very many acres burned or many buildings damaged, so there will be less of an impact on the constituents and the wildfires won't be as salient as wildfires with higher burn areas in more populated locations.

So, I am also going to use the number of acres burned as one of my independent variables. This variable measures more of the impact on human life than simply the number of fires because larger wildfires burn more land and cause more widespread damage than smaller fires. However, this variable does not distinguish between damage done to wild land versus damage done to populated areas and structures. So, I will also be using the data on building damage and fatalities caused by each fire to show which districts had wildfires with the most impact on human life.

The building damage variable will simply measure how many buildings were either damaged or destroyed by wildfires in each district. However, it will not include the dollar damage figure. That is to say, my building damage variable does not differentiate between inexpensive structures versus buildings that are crucial to the community. If a district had more dollar damage from a fire, that would be a better proxy for human impact than simply the building damage. If I was able to find the data on the dollar damage caused by each wildfire, I would include it in my research so that it could better account for constituent experience.

The different measures of "wildfires" will show if merely having a wildfire nearby is enough to be correlated with more legislator action, or if the human impact of wildfires is what spurs action for policymakers. I hypothesize that the fatalities, building damage, and acre burnage will show more of an impact on their votes than the measure of the amount of wildfires, because these variables are a better proxy for how their constituents experience wildfires. In turn, legislators will be more likely to vote for wildfire policy when those variables have a stronger impact because the wildfires will be more salient in legislators' minds since they can easily see how their constituents were impacted. However, it could also be the case that these alternative wildfire variables do not have more of an impact compared to the simple wildfire variable because legislators could be more aware of how many fires occurred in their district versus how much damage was caused (measured by acres burned, buildings, and fatalities).

Dependent Variables: Legislator Votes

My dependent variable is the voting record of California legislators on a wildfire bill and a climate change bill in 2018. I can access the data on representative votes on specific bills from the California Legislative Information website. For each bill that goes through the state Congress, the Bill Search website shows how each Senator and Assembly Member voted on said bill: either for, against, or no vote recorded.

The first bill I will study in my dependent variable is SB 901: Wildfires, which was passed in 2018[16]. SB-901 passed with 49 out of 80 votes in the State Assembly and 29 out of 40 votes in the Senate. SB-901 includes provisions such as allocating $165 million per year from the Greenhouse Gas Reduction Fund to the Department of Forestry and Fire Protection for healthy forest and fire prevention programs, new regulations on the timber industry, and the creation of a Wildfire Resilience Program to educate timberland owners about wildfire resilience. I chose this bill because it was the most significant wildfire bill in 2018, the year after my wildfire data. State Senator Bill Dodd, a co-author of the bill, stated that SB-901 was "the most comprehensive wildfire-prevention and safety package the state has passed in decades"[17]. After a severe wildfire

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[16] SB-901 Wildfires
[17] Los Angeles Times

season, legislators knew that wildfire prevention would be a salient topic for voters and they created this far-reaching bill.

For climate change policy, I chose to analyze the votes on SB-100: California Renewables Portfolio Standard Program: Emissions of Greenhouse Gases[18]. SB-100 passed with 25 out of 40 Senate votes and 44 out of 80 votes in the Assembly, which was a slightly lower majority than SB-901. SB 100 asserted that the state of California should aim for 100% renewable and zero-carbon energy by 2045. The overall goals of the bill was to reduce fossil fuels consumption and reduce greenhouse gas emissions in order to combat the climate crisis. This bill, also known as the California 100% Clean Energy Act, was one of the most landmark climate bills in recent years. It was relevant to my research because I needed a climate bill from 2018 and this was the most impactful bill in that year.

Analytical Design

I will be using the voting records on the bills from 2018 and the wildfire data from 2017. This is because the bills were passed in September 2018. If I used the wildfire data from 2018, it would include fires that happened later in 2018 after the bills were passed. So, the 2017 wildfire data will be more relevant and accurate than the 2018 wildfire data in terms of its impact on the legislators' votes.

My research plan is to analyze legislators' votes for one wildfire policy and one climate policy in the same year. This does not examine how different wildfire data over the years in one district may affect the votes of that district's representative. I will be able to see the difference between the votes of a representative in a district with low wildfire activity versus a

[18] SB-100 California Renewables Portfolio Standard Program: Emissions of Greenhouse Gases.

representative in a heavy wildfire district, but there could be other confounding variables between the districts that could account for the different voting patterns of representatives.

For example, some districts are in more urban areas while other districts are in more rural, fire-prone areas. Assembly District 1 in Northern California is larger than Assembly District 79 in central San Diego, and District 1 is in a rural area with a drier climate compared to the urban coastal region in District 79. So, District 79 would be less likely to have any wildfires compared to District 1, because there is not nearly as much "room" for a wildfire to occur in San Diego. I understand this could be a significant drawback to my research, but with the time and resource constraints of an undergraduate thesis I only had the means to study one year's worth of wildfire and policy data.

While 2017 was a heavier wildfire year than usual, I will not be able to determine if the districts had more wildfires than normal or not. If it is normal for a specific district to have more wildfires, then that will not cause a legislator to change their voting patterns on either a wildfire or climate policy bill. With factors such as local climate and size of the district, some districts are going to have more wildfires than others, but that could be just a normal part of that environment. California has many different regions with different climates, and those different climates will have different wildfire patterns, and may not be conducive to wildfires at all. So, the district's climate will have an impact on its wildfire data, and I do not have a way to control for that in my data. If I had data on the average wildfire data for each district, I would include it as a control variable and find districts that had more wildfires than usual in 2017. Since I do not have access to that information, I will simply account for which districts had fires and the intensity of the fires (measured by acres burned, damage caused to buildings, and fatalities).

Another potential confounding variable is going to be the representatives' political party. As I have mentioned before, I believe that may have a significant effect on the way a representative votes due to the partisan nature of climate change. So, in addition to my regressions with the wildfire activity as the single dependent variable, I will run the same regressions as multivariate regressions with party as a covariate.

My research plan is to create a dataset in R with all of my wildfire data and legislator data combined. I will create a dataset with the legislators in the Assembly and Senate as the unit of analysis, so I will have 120 rows total (80 assembly members and 40 state senators). For each representative, I will measure their vote SB-901 and SB-100 (in favor, against, or no vote recorded), their political party, their district, and the wildfire data for their district. The wildfire data will include variables such as how many wildfires there were in that district in 2017, the amount of acres burned in that district, the number of buildings damaged and destroyed, and the number of fatalities, along with other relevant data points from CalFire. I will then run regression analyses with the wildfire data as the independent variables and the representatives' votes on the two bills as the dependent variables.

Then, I will run the same regressions and include the representatives' political parties as a covariate to see if that has any impact on their votes. I will also run regressions with the party as the sole independent variable and the voting record as the dependent variable. I am doing this because I want to see how strong of an impact the legislator's party has on their voting patterns. Once I have run all of my regressions, I will be able to see which, if any, of my regressions resulted in a statistically significant relationship between my independent and dependent variables.

Methods

The first step in my statistical analysis was to create my dataset. First, I cleaned up the CalFire 2017 wildfire dataset to make it more applicable to my analysis. The CalFire data included the geographic information of where each fire occurred, but the data was county-based, not district-based. California districts do not align with the counties, so I had to change the geographic data to map it into which district the fires occurred in. So, I used GIS mapping to change the wildfire location data from county-based to district-based. Another point of notice is that the Senate and Assembly districts overlap, so each fire is in one Senate district and one Assembly district. However, this will not lead to a duplication of the data because my unit of analysis is by district. If both a Senate and Assembly district have the same wildfire in their area, the wildfire would have a potential impact on both districts.

After changing the geographical data, it was time to further clean the data. I created a subset that removed some unnecessary variables to make the dataset more easily readable. My next step was to change my unit of analysis. The CalFire dataset had 540 observations of each wildfire that occurred in 2017. I needed to change my unit of analysis from wildfire-based to district-based so that I could align it with the representative for each district. I used the group_by function to change the unit of analysis so that I had 120 total variables (one for each of the 40 Senate districts and 80 Assembly districts), and I combined the wildfire data so that it aggregated to each district.

Then, I had to add in the variables for the district representative, their votes on SB-901 and SB-100, and their political party. Using the voting records from the California Legislative Information website, I hand coded a dataset with the Senate and Assembly districts as the unit of analysis, and I added each representative, their votes, and their party. I coded Democratic representatives with a value of 0 and Republican candidates with a value of 1. For the votes on the bills, I gave each representative a value of 1 if they voted yes on a bill, and a value of 0 if they voted no or if they did not have a vote recorded. I chose to code an NVR as a 0 because it was not a vote in support of the bill, so functionally it is the same as a no vote. I do not believe my data will be impacted by combining the NVR and no votes into one variable because legislators who chose not to vote made the choice not to vote in support of the bill. I merged my hand-coded voting dataset with the subsetted wildfire data by matching up the districts to create my final dataset. I cleaned up some errors and created some new variables to help supplement my analysis.

From the wildfire data, I knew how many fires occurred in each district in 2017, but I also wanted a binary fire variable. I created a variable called firesyn that measured if a fire took place in a district or not. If a district had 0 fires, I set firesyn equal to 0, and if it had 1 or more fires I gave firesyn a value of 1. I wanted to have a binary variable because I wanted to see if simply having at least one fire would have an impact on the legislator's vote, regardless of how many fires there were.

I had a variable for how many total acres were burned per district, but I also wanted another variable for acres burned as a proportion of the district's total area. I did this to account for the districts' varying sizes. Some districts are much larger than others and have more open land to burn. If a large district had fires burn a large area, that will have a smaller impact on that district than a fire of the same size in a smaller district. So, creating the acres_burn_by_area variable accounts for that discrepancy. I also created a fatalities variable that combined the data from how many civilians died and how many firefighters died so I had one variable for the total deaths that each district had from wildfires. Lastly, I created a variable called buildings_total that combined how many buildings were damaged and how many buildings were completely destroyed, because both of those variables measured the damage caused to man made structures and the combination of those two variables would be more efficient. Below I have included a partial screenshot of my dataset that includes the district as the unit of analysis and the relevant variables.

district_votes

	NAMELSAD	buildings_destroyed	buildings_damaged	total_acres_burned	fatalities_fire	fatalities_civilian	num_fires	ALAND	REP	PARTY	SB100	SB901	firesyn
1	Assembly District 1	216	17	235180	0	0	89	64121394641	DAHLE	1	0	1	1
2	Assembly District 10	0	0	0	0	0	0	0	LEVINE	0	1	0	0
3	Assembly District 11	783	120	51624	6	0	1	1832135982	FRAZIER	0	0	1	1
4	Assembly District 12	0	0	0	0	0	0	0	FLORA	1	0	1	0
5	Assembly District 13	0	0	0	0	0	0	0	EGGMAN	0	1	1	0
6	Assembly District 14	0	0	0	0	0	0	0	GRAYSON	0	1	0	0
7	Assembly District 15	0	0	0	0	0	0	0	THURMOND	0	1	1	0
8	Assembly District 16	0	0	0	0	0	0	0	BAKER	1	1	0	0
9	Assembly District 17	0	0	0	0	0	0	0	CHIU	0	1	1	0
10	Assembly District 18	0	0	0	0	0	0	0	BONTA	0	1	0	0
11	Assembly District 19	0	0	0	0	0	0	0	TING	0	1	1	0
12	Assembly District 2	137	319	110424	1	21	18	32090482906	WOOD	0	1	1	1
13	Assembly District 20	0	0	0	0	0	0	0	QUIRK	0	1	1	0
14	Assembly District 21	0	0	0	0	0	0	0	GRAY	0	0	0	0
15	Assembly District 22	0	0	0	0	0	0	0	MULLIN	0	1	0	0
16	Assembly District 23	0	0	0	0	0	0	10470478478	PATTERSON	1	0	0	0
17	Assembly District 24	0	0	0	0	0	0	0	BERMAN	0	1	1	0
18	Assembly District 25	0	0	0	0	0	0	0	CHU	0	1	1	0
19	Assembly District 26	2	0	76938	0	0	14	38850291141	MATHIS	1	0	0	1
20	Assembly District 27	0	0	0	0	0	0	0	KALRA	0	1	0	0
21	Assembly District 28	0	0	0	0	0	0	0	LOW	0	1	1	0
22	Assembly District 29	6	0	391	0	0	1	2235460677	M STONE	0	1	1	1
23	Assembly District 3	361	21	37956	4	0	6	18059608990	GALLAGHER	1	0	0	1
24	Assembly District 30	1	0	50309	0	0	2	12278279150	CABALLERO	0	0	0	1
25	Assembly District 31	1	0	51871	0	0	7	7753095258	ARAMBULA	0	0	0	1
26	Assembly District 32	1	0	48660	0	0	2	8440233491	SALAS	0	0	0	1
27	Assembly District 33	1	0	2958	0	0	8	47198056497	OBERNOLTE	1	0	0	1
28	Assembly District 34	0	0	1083	0	0	2	10750872169	FONG	1	0	0	1
29	Assembly District 35	24	1	32186	0	0	8	10946013703	CUNNINGHAM	1	0	0	1
30	Assembly District 36	0	0	0	0	0	0	7179536855	LACKEY	1	0	0	0
31	Assembly District 37	6	3	6049	0	0	5	8556644822	LIMON	0	1	0	1
32	Assembly District 38	7	4	6809	0	0	3	1036589091	ACOSTA	1	0	0	1
33	Assembly District 39	129	82	23573	0	0	3	395298215	RIVAS	0	1	1	1

Figure 1: Final dataset (partial image)

After my dataset was all cleaned up, it was time to run my statistical analysis. I used logistic regression, as opposed to linear regression, for my analysis because logistic regression is used for classification of binary variables. My dependent variables (the votes on the SB901 and

SB100 bills) are both binary variables: either a 0 for voting no/no vote recorded or 1 for a yes vote.

Results

Before I started on my regressions, I gathered some simple data on the representatives who voted for SB-100 and SB-901. First, I looked at the data for SB-100: Greenhouse Gasses. In districts that did not have a fire, 16 representatives either did not vote or voted against SB-100, while 53 representatives voted in favor of the bill. In districts that had one or more fires, 35 representatives either did not vote or voted against the bill, while 16 representatives voted in favor.

SB-100	**No/DNV**	**Yes**
No Fires	**16**	**53**
1 or More Fires	**35**	**16**

Figure 2: Table of SB-100 votes and wildfire data

Then, I looked at the party data for SB-100. Out of the Democratic representatives, 14 legislators either did not vote or voted against the bill while 68 voted in favor of the bill. Out of the Republicans, 37 representatives voted no or did not vote (DNV) while only 1 representative voted in favor of the pro-climate bill. In this preliminary analysis, there seems to be more of a correlation between a representative's party rather than if they had a fire in their district or not. Out of all of the votes in favor for SB-100, only one of them was from a Republican representative. However, this table data is preliminary and further analysis is necessary.

SB-100	No/DNV	Yes
Democrat	14	68
Republican	37	1

Figure 3: Table of SB-100 votes and party

Next, I looked at the vote breakdown for SB-901: Wildfires. In non-fire districts, 18 representatives either voted against the bill or did not vote, while 51 representatives voted in favor. In districts with at least one fire, 24 representatives voted no or DNV and 27 representatives voted in favor.

SB-901	No/DNV	Yes
No Fires	18	51
1 or More Fires	24	27

Figure 4: Table of SB-901 votes and wildfire data

As for the party breakdown, 19 Democratic legislators voted no/DNV while 63 voted in favor. For Republicans, 23 representatives voted against/DNV the wildfire bill and 15 representatives voted for SB-901. As with the previous bill, there also seems to be more of a correlation between representative party and their votes rather than the wildfire data and votes. However, the correlation between party and the wildfire bill seems slightly smaller than the correlation between party and the climate bill. Again, this is only a preliminary analysis to help me make better sense of the data I have to work with. Next, I will dive further into my analysis by running my regressions, and I will include party as a covariate.

SB-901	**No/DNV**	**Yes**
Democrat	**19**	**63**
Republican	**23**	**15**

Figure 5: Table of SB-901 votes and party

<u>SB-100 Data</u>

To start my analysis, I focused on the regressions for SB-100: Greenhouse Gasses. First, I used the binary firesyn variable. If there was at least one fire in a representative's district in 2017, the log odds of that representative voting yes on the climate policy decreased by -0.454, and these results were statistically significant with a p-value of less than 0.001.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$firesyn)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7681  -0.3137   0.2319   0.2319   0.6863

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.76812    0.05346  14.368  < 2e-16 ***
district_votes$firesyn -0.45439    0.08201  -5.541 1.86e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 6: Regression with SB-100 and firesyn

Then, I used my numfires variable that accounted for how many fires occurred in each district. For each fire that occurred in a representative's district, the representative's log odds of voting in favor of SB-100 decreased by 0.01. While this relationship was statistically significant, the effect that each fire had on a representative's vote is so low that it is functionally insignificant. Such a small effect may be due to the fact that there were outliers in the amount of fires: many districts had only 1 or a few fires, while a couple had up to 89 or 93.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$num_fires)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6141  -0.5763   0.3859   0.3859   0.5871

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.614059   0.046157  13.304  < 2e-16 ***
district_votes$num_fires -0.010058   0.003558  -2.827  0.00552 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 7: Regression with SB-100 and num_fires

Continuing with SB-100, I ran a regression using my variables for how many total acres were burned in each district and how many acres were burned as a proportion of the district’s size. Using the total_acres_burned variable, I found that for each acre burned in a district, the representative’s log odds of voting in favor of SB-100 decreased by -3.223e^-06, or -0.008. This slight result was statistically significant, but when I controlled for the acres burned as a proportion of the district’s size the result was not statistically significant.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$total_acres_burned)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6297  -0.6012   0.3703   0.3703   0.7334

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                        6.297e-01  4.756e-02  13.241  < 2e-16 ***
district_votes$total_acres_burned -3.223e-06  1.080e-06  -2.984  0.00345 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 8: Regression with SB-100 and total_acres_burned

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$acres_burn_by_area)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5791  -0.5763   0.4209   0.4209   0.4957

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                        5.791e-01  4.807e-02  12.046   <2e-16 ***
district_votes$acres_burn_by_area -5.075e+06  1.932e+07  -0.263    0.793
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 9: Regression with SB-100 and acres_burn_by_area

Next, I ran a regression using buildings_total. For every building that was destroyed or damaged by a wildfire, the representative’s log odds of voting for SB-100 decreased by 0.0003, but these results were not statistically significant.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$buildings_total)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5975  -0.5969   0.4026   0.4026   0.7892

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                     0.5974474  0.0476757  12.531   <2e-16 ***
district_votes$buildings_total -0.0003169  0.0002180  -1.454    0.149
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 10: Regression with SB-100 and buildings_total

Lastly, I ran a regression with my total_fatalaties variable. For every fatality in a representative's district (civilian or firefighter), their log odds of voting in favor of SB-100 increased by 0.002, and these results were not statistically significant either.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$fatalities)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6324  -0.5729   0.4270   0.4270   0.4270

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.572946   0.046511  12.319   <2e-16 ***
district_votes$fatalities 0.002125   0.009981   0.213    0.832
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 11: Regression with SB-100 and fatalities

To summarize, when I am not controlling for the representative's party, the only statistically significant variable on a representative's likelihood for voting in favor of SB-100 was my binary fires variable. If a district had one or more wildfires in 2017, the log odds of their representative voting for the climate bill decreased by 0.454. I did not expect a negative correlation here, and I will explore possible reasons for this in my Discussion section. Next, I am going to examine the effects of my independent variables on SB-100 when I control for party.

SB-100 and Party Data

First, I ran the same regression with firesyn as my independent variable and the SB-100 vote as my dependent variable, but I added the representative's party as a covariate. With the added party covariate, the binary fire variable ended up not being statistically significant. However, when a representative was Republican, the log odds of them voting in favor of the climate bill decreased by -0.749 , and this was statistically significant.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$firesyn +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.85500  -0.00516   0.14500   0.14500   0.89436

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.85500    0.04005  21.346   <2e-16 ***
district_votes$firesyn -0.10047    0.06940  -1.448     0.15
district_votes$PARTY   -0.74936    0.07375 -10.161   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 12: Multivariate regression with SB-100 and party and firesyn

Next, I ran a multivariate regression with the party and the total number of fires on the SB-100 vote. This also showed that the total number of fires did not have a statistically significant impact on the representative's vote, but as with the previous analysis, Republicans were less likely to vote for the climate bill than Democrats: the log odds of Republicans voting for SB-100 decreased by .798 points.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$num_fires +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.82997  -0.03029   0.17003   0.17003   0.96812

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.8299726  0.0363412  22.838   <2e-16 ***
district_votes$num_fires -0.0005775  0.0025486  -0.227    0.821
district_votes$PARTY     -0.7980944  0.0678210 -11.768   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 13: Multivariate regression with SB-100 and party and num_fires

For either measure of the amount of acres burned in each district (either divided by district area or not), the amount of acres burned did not have a statistically significant impact on legislator vote, but Republicans were more likely to vote against the bill. I had the same results for the number of fatalities and the number of buildings damaged. I have included the regression outputs for those four regressions below.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$total_acres_burned +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.83933  -0.05398   0.16067   0.16067   0.94194

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)
(Intercept)                       8.393e-01  3.675e-02  22.841   <2e-16 ***
district_votes$total_acres_burned -9.978e-07  7.552e-07  -1.321    0.189
district_votes$PARTY             -7.813e-01  6.596e-02 -11.845   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 14: Multivariate regression with SB-100 and party and total_acres_burned

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$acres_burn_by_area +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.83276  -0.02825   0.16724   0.16724   0.97010

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)
(Intercept)                       8.328e-01  3.759e-02  22.155   <2e-16 ***
district_votes$acres_burn_by_area -4.380e+06  1.271e+07  -0.345    0.731
district_votes$PARTY             -8.029e-01  6.433e-02 -12.481   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 15: Multivariate regression with SB-100 and party and acres_burn_by_area

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$buildings_total +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.84807  -0.04754   0.15193   0.15193   0.95218

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                     0.8480725  0.0369254  22.967   <2e-16 ***
district_votes$buildings_total -0.0002776  0.0001424  -1.949   0.0537 .
district_votes$PARTY           -0.8002517  0.0633530 -12.632   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 16: Multivariate regression with SB-100 and party and buildings_total

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$fatalities +
    district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.83774  -0.02804   0.16226   0.16226   0.97196

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.837741   0.037051  22.610   <2e-16 ***
district_votes$fatalities -0.006554   0.006576  -0.997    0.321
district_votes$PARTY      -0.809701   0.064442 -12.565   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 17: Multivariate regression with SB-100 and party and fatalities

To summarize, when I controlled for party, none of my wildfire independent variables had a statistically significant impact on the legislators’ votes on SB-100. So, I ran a simple regression with party as my dependent variable and SB-100 votes as my independent variable to determine the effect of the representative party on their climate vote while controlling for all other variables. When a representative was Republican, the log odds of them voting in favor of SB-100 decreased by 0.80 compared to their Democrat counterparts, and again this was statistically significant. This is a strong negative correlation, which I expected due to the partisan divide on climate policy.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$PARTY)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.82927  -0.02632   0.17073   0.17073   0.97368

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.82927    0.03606   23.00   <2e-16 ***
district_votes$PARTY -0.80295    0.06408  -12.53   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 18: Regression with SB-100 and party

SB-901 Data

Next, I looked at the effects of the wildfire data on the representatives' votes on the wildfire bill SB-901. First, I ran regressions with the different wildfire measures as a single independent variable, then I added party as a covariate, then I looked at party as a singular independent variable on the representative vote. For my binary fire variable, if a representative had at least one fire in their district, the log odds of them voting to support the wildfire bill decreased by -0.210. This statistically significant negative correlation surprised me, and I will delve further into possible explanations for this in the Discussion section.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$firesyn)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7391  -0.5294   0.2609   0.2609   0.4706

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.73913    0.05652  13.077   <2e-16 ***
district_votes$firesyn -0.20972    0.08670  -2.419   0.0171 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 19: Regression with SB-901 and firesyn

When I looked at my regression with the number of fires, I found that the number of wildfires in a district did not have a statistically significant impact on a representative's vote for the wildfire bill.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$num_fires)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6648  -0.6458   0.3352   0.3352   0.6736

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.664762   0.045794  14.516   <2e-16 ***
district_votes$num_fires -0.003801   0.003530  -1.077    0.284
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 20: Regression with SB-901 and num_fires

I also ran the regressions with my independent variable set as total acres burned, acres divided by district area, total number of fatalities, and total number of buildings that were damaged or destroyed. None of these independent variables had a statistically significant impact on the representatives' votes on SB-901, so it seems these measures of wildfires have no impact on a representative's vote for the wildfire bill. I have included the outputs for those regressions below.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$total_acres_burned)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6636  -0.6565   0.3363   0.3363   0.5256

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                        6.637e-01  4.747e-02  13.980   <2e-16 ***
district_votes$total_acres_burned -8.047e-07  1.078e-06  -0.746    0.457
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 21: Regression with SB-901 and total_acres_burned

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$acres_burn_by_area)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7259  -0.6315   0.3553   0.3685   0.3685

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)
(Intercept)                       6.315e-01  4.610e-02  13.699   <2e-16 ***
district_votes$acres_burn_by_area 2.300e+07  1.853e+07   1.241    0.217
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 22: Regression with SB-901 and acres_burn_by_area

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$buildings_total)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7424  -0.6290   0.3627   0.3710   0.3710

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    0.6289629  0.0460234  13.666   <2e-16 ***
district_votes$buildings_total 0.0002970  0.0002105   1.411    0.161
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 23: Regression with SB-901 and buildings_total

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$fatalities)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.6933  -0.6362   0.3638   0.3638   0.3638

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.636201   0.044465  14.308   <2e-16 ***
district_votes$fatalities 0.014275   0.009542   1.496    0.137
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 24: Regression with SB-901 and fatalities

SB-901 and Party Data

Next, I ran the same regressions but with the legislators' party as a covariate. As was the case with the data from SB-100, once I added in the covariate of the party data, the binary fires variable ended up not being statistically significant and the party variable was statistically significant. When accounting for the fires and the party, the log odds of a representative voting in favor of SB-901 decreased by -0.350 when the representative was Republican.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$firesyn +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7797  -0.3854   0.2203   0.2648   0.6146

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.77969    0.05538  14.078  < 2e-16 ***
district_votes$firesyn -0.04450    0.09596  -0.464 0.643677
district_votes$PARTY   -0.34982    0.10197  -3.431 0.000833 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 25: Multivariate regression with SB-901 and party and firesyn

I ran all of the other regressions with the number of fires and the other wildfire variables combined with the party covariate. As expected, none of the other wildfire variables had statistically significant effects in the multivariate regressions, and the party variable did have a statistically significant impact. In all regressions, Republicans were less likely to vote in favor of the wildfire bill than Democrats. Below are the outputs of the multivariate regressions for SB-901 with the number of fires, total acres burned, acres by area, total buildings damaged, and total fatalities.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$num_fires +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7724  -0.3909   0.2326   0.2326   0.6121

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.7674308  0.0498514  15.394  < 2e-16 ***
district_votes$num_fires  0.0007067  0.0034961   0.202     0.84
district_votes$PARTY     -0.3795009  0.0930342  -4.079 8.29e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 26: Multivariate regression with SB-901 and party and num_fires

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$total_acres_burned +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7799  -0.3873   0.2345   0.2345   0.6141

Coefficients:
                                   Estimate Std. Error t value Pr(>|t|)
(Intercept)                       7.655e-01  5.077e-02  15.079  < 2e-16 ***
district_votes$total_acres_burned  2.766e-07  1.043e-06   0.265    0.791
district_votes$PARTY              -3.796e-01  9.112e-02  -4.166 5.97e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 27: Multivariate regression with SB-901 and party and total_acres_burned

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$acres_burn_by_area +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7883  -0.3868   0.2503   0.2503   0.6244

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                        7.497e-01  5.119e-02  14.646  < 2e-16 ***
district_votes$acres_burn_by_area  2.332e+07  1.731e+07   1.347     0.18
district_votes$PARTY              -3.741e-01  8.760e-02  -4.270 3.99e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 28: Multivariate regression with SB-901 and party and acres_burn_by_area

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$buildings_total +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7539  -0.3707   0.2531   0.2531   0.6297

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    0.7469157  0.0509073  14.672  < 2e-16 ***
district_votes$buildings_total  0.0003156  0.0001964   1.607    0.111
district_votes$PARTY          -0.3766261  0.0873417  -4.312 3.39e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 29: Multivariate regression with SB-901 and party and buildings_total

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$fatalities +
    district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7549  -0.3920   0.2451   0.2451   0.6080

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                0.754868   0.050751  14.874  < 2e-16 ***
district_votes$fatalities  0.010385   0.009007   1.153    0.251
district_votes$PARTY      -0.362864   0.088270  -4.111 7.35e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 30: Multivariate regression with SB-901 and party and fatalities

To get a more clear picture of party impact on the wildfire bill votes, I ran a simple logistic regression with party as the only independent variable and the SB-901 votes as the dependent variable. I found that the log odds of a Republican representative voting in favor of the wildfire bill decreased by -0.374 points, and this was statistically significant.

```
Call:
glm(formula = district_votes$SB901 ~ district_votes$PARTY)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7683  -0.3947   0.2317   0.2317   0.6053

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.76829    0.04947   15.53  < 2e-16 ***
district_votes$PARTY -0.37356    0.08790   -4.25  4.3e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 31: Regression with SB-901 and party

Additional Analysis

After running all of these regressions, a couple questions arose during the research progress. First, I wanted to know the correlation between a representative voting in favor of SB-901 and them voting in favor of SB-100. Basically, are representatives who voted in support of the wildfire bill more likely to have voted in support of the climate bill? This correlation was interesting to me because I wanted to see if the same representatives were voting in favor of both bills. I ran a regression with the representatives’ votes on the wildfire bill as the independent variable and the votes on the climate bill as the dependent variable. I found that representatives who voted in favor of the wildfire bill had a 0.408 increase in the log odds of them voting in favor of the climate bill, and this was statistically significant.

```
Call:
glm(formula = district_votes$SB100 ~ district_votes$SB901)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.7179  -0.3095   0.2821   0.2821   0.6905

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.30952    0.07070   4.378 2.60e-05 ***
district_votes$SB901  0.40842    0.08769   4.658 8.46e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 32: Regression with SB-100 and SB-901

I also wanted to examine if there was a correlation between whether a district had a fire or not and the party of their representative. I wanted to examine this because I know that rural districts are more likely to have Republican representatives compared to coastal, urban areas where the population is more Democratic, and rural districts have more land that is susceptible to wildfires. So, I anticipated there being a correlation between districts with wildfires and having Republican representatives. I ran a logistic regression with my binary fires variable as the independent variable and the representative party as the dependent variable. I found that in districts that had at least one fire in 2017, the likelihood of the representative for that district being a Republican increased 0.472. This was statistically significant as well.

```
Call:
glm(formula = district_votes$PARTY ~ district_votes$firesyn)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5882  -0.1159  -0.1159   0.4118   0.8841

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.11594    0.04884   2.374   0.0192 *
district_votes$firesyn  0.47229    0.07492   6.304 5.22e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 33: Regression with party and firesyn

This was a very interesting result. I believe it may have something to do with the urban/rural divide of California. Democrats usually concentrate in urban or suburban areas of California, like the Bay Area or around Los Angeles, while the inland rural areas of California tend to have more Republicans. Rural districts have more open land than urban districts and thus have more wildfire-prone areas than urban, Democratic leaning districts. So, the representative party may be acting as a confounding variable in my data since it has a stronger impact on the votes for either bill than any of my wildfire variables.

Discussion

In this section, I will discuss the results of my analysis and possible reasons for those results. I will first focus on the data from the climate policy bill, then the wildfire bill, then my overall results from my analysis.

SB-100 Discussion

When I ran the regression analysis of the effects of wildfires on the representatives' votes on the climate policy without party as a covariate, the only statistically significant result was with my binary fire variable as the independent variable. Meaning, if a district had one or more fires in 2017, in 2018 the log odds of the representative voting for the climate policy bill decreased by 0.454 (aka, they were less likely to vote for said bill). I did not anticipate a negative correlation here, because I anticipated there not being a correlation between wildfires and climate votes. I did anticipate that the other wildfire measures (number of fires, acres burned, buildings damaged, and fatalities) would not impact the climate policy votes.

But when I added in the representative party as a covariate for this regression, the binary fires variable ended up not being statistically significant. This means that the representative party was the confounding variable here: representatives in districts with wildfires were less likely to to vote for the climate bill because they were more likely to be Republican, not because the wildfires made them less likely to vote for the climate bill.

The representative party was my only statistically significant indicator of representative vote: when I did a regression with party as the only variable, the results showed that the log odds of Republican representatives voting for SB-100 was 0.803 lower compared to their Democrat counterparts, and again this was statistically significant.

So, the negative correlation from my initial binary fires regression may be due to the fact that districts with fires were more likely to have Republican representatives. I believe this is because districts with more fires are likely to be in areas where wildfires are more likely to occur, which are rural areas away from the coastal cities dominated by Democrats. So, rural districts are more likely to have more fires and are more likely to have Republican representatives, which affects how the representatives voted on the climate bill.

I anticipated that legislators would not change their votes on the climate policy bill due to the wildfires because my initial hypothesis was that legislators do not believe that more frequent wildfires are due to the effects of climate change. It turns out that wildfires did not impact climate policy votes because the legislators in fire districts represented areas that are more rural, more likely to have fires, and more Republican-leaning, and these legislators voted mostly along party lines.

<u>SB-901 Discussion</u>

As with the climate policy data, when I ran my initial single variable regressions, the only statistically significant relationship was with the binary fire variable. It was a slightly smaller correlation than with SB-100. If a representative had at least one fire in their district, the log odds of them voting to support the wildfire bill decreased by -0.210. This negative correlation initially surprised me, because I anticipated that legislators in fire districts would have been more likely to vote in favor of the wildfire bill because it would benefit their constituents who experienced the fires. I was also surprised that the only wildfire measure that impacted the representative's vote was the binary fire variable, and none of the other fire measures were statistically significant. This goes against my hypothesis that the other measures of wildfires would show a higher impact on human life that the representatives would care more about.

But once I added in the party covariate, the binary fire variable was not statistically significant either, and only the party was. And when I did the single regression with party as the only independent variable, I found that the log odds of a Republican representative voting in favor of the wildfire bill decreased by -0.374 points, and this was statistically significant.

I believe that the same thing happened with this data that happened with the climate policy bill: the initial regression with the binary fire variable as the only dependent variable had a negative correlation because districts with fires were more likely to have Republican representatives. Wildfire districts were less likely to have a representative who voted for the wildfire bill because Republicans were less likely to vote for the wildfire policy than Democrats.

However, the correlation between party and the wildfire vote was significantly less strong than the correlation between party and the climate policy vote (-0.374 versus -0.803). So, a representative's party had a stronger effect on their likelihood of voting on the climate policy bill than the wildfire bill. This aligns with my expectations because climate policy is a more divisive partisan issue than wildfires. Wildfires are a natural disaster, while climate change has strong partisan ties.

Discussion Summary

To summarize, the only statistically significant variable in my data that impacted a representative's vote on either bill was their party. Republicans were less likely to vote for both the climate bill and the wildfire bill than Democratic representatives, although that negative relationship was stronger for the climate policy bill than the wildfire bill. My initial hypothesis that wildfires would lead to more votes in favor of the wildfire bill was incorrect: legislators within wildfire districts were not more likely to vote in favor of the wildfire bill compared to non-wildfire districts. My hypothesis that wildfires would not lead to a difference in votes on the climate policy bill was correct, although I think that was for different reasons than I initially hypothesized.

I originally thought that legislators would not change their votes on climate policy if their districts had wildfires because people in general do not connect wildfires to climate change, and they would not take wildfires as an indicator that climate change is happening and needs more action. After reviewing my data and viewing the correlation between a district having fires and that representative's party, I believe that legislators in fire districts were less likely to vote for the climate policy simply because they are more likely to be Republican, and Republicans are less likely to vote in favor of a partisan climate policy bill.

It seems that overall, the number of wildfires in 2017 had very little impact on legislators' votes in 2018. I think there are a few possible reasons why I got this result. First of all, I believe a legislator's party has a stronger influence on their vote on the climate and wildfire bills than I initially anticipated, and it acted as a strong confounding variable in my data.

Additionally, I think that my measure of wildfires could have been improved if I was able to gather wildfire data from more than one year. I was not able to factor in how a more heavy wildfire season than usual would change a legislator's voting behavior compared to a normal wildfire season. Wildfires happen every year and they are not an unusual weather event in California. Many districts have wildfires every year, so the fact that a particular district had wildfires in 2017 would not necessarily be an unusual event in the eyes of the representative. Climate change affects the frequency of wildfires and their size.

So, if I compared across two or more years, I would be able to see how legislators' voting behaviors changed (or did not change) in a normal year compared to a heavy wildfire year. Adding the comparison across years would more accurately ask how the effects of climate change impacted political action, because climate change makes wildfires more frequent and more intense, and it is not the sole cause of every wildfire that happens each year. If I were to redo this study, I would want to account for different years, although that does bring up problems about different wildfire bills and climate bills each year, legislators terming out, and districts switching parties. I would also want to account for the climate of each district, and if they were urban or rural, to account for which districts are more wildfire-prone regardless of climate change.

Conclusion

To summarize, my initial hypothesis was incorrect. If a district had one or more wildfires in 2017, their representative was not more likely to vote in favor of either the wildfire bill or the climate bill in 2018 compared to representatives in districts that did not have a fire. A representative's party was the only statistically significant indicator of their voting pattern on either bill: Republicans were less likely to vote in favor of either bill compared to Democrats, and this correlation was stronger for the climate bill than the wildfire bill.

My wildfire indicators that measured human impact (acres burned, building damage, and fatalities) did not have a statistically significant impact on a representative's vote on either bill. I originally hypothesized that these wildfire measures would show more of an impact on the constituents of the district and the representative would want to take more policy action on wildfires because the fires were more salient on their voter's minds. In contrast, I believe these indicators did not appear to change legislator behavior because they are, unfortunately, a standard component of wildfires that happen every year. Wildfires are a normal part of the California climate, and they cause damage to land area, buildings, and human life. However, it is when they have a disproportionate impact on human life that policymakers take more notice and take more action.

If I were to compare wildfire data and legislator behavior across years with different wildfire activity levels, I would have a better understanding of how the current effects of climate change impact legislator voting patterns. It seems my analysis was only a snapshot of one heavy year, and I could not compare the statistics of the intense 2017 wildfire season to a more moderate season that was less impacted by climate change.

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