



Investigating Trends, Causes, and Patterns of Idaho Wildfires

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Investigating Trends, Causes, and Patterns of Idaho Wildfires

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Abstract

Wildfires have become increasingly more common in much of the West, posing a large threat to both human and natural resources. This study uses a variety of spatial statistical methods to investigate the patterns, trends, and causes of wildfires across the state of Idaho. Leveraging tools such as the Global Moran's I and Hot Spot Analysis to identify significant clusters and emerging trends of fire patterns, Standard Deviational Ellipses were also employed to show the dispersion and orientation of wildfire occurrences. Regression analysis, including ordinary least squares (OLS) and geographically weighted regression (GWR), was used to examine how fire management practices influence the spatial patterns of wildfire incident sizes. The results indicate that human and natural-caused fires exhibit reverse patterns: human-caused fires tend to be smaller but more costly, whereas natural-caused fires tend to be larger but less costly. Unsurprisingly, human fires tend to be concentrated around higher population densities, while natural fires tend to occur in more remote areas. These findings highlight the importance of more localized and data-driven approaches to wildfire management and policy decision-making.

Keywords: fire ecology, regression, hot spots, climate, spatial statistics

Introduction

Wildfires have become an increasingly prevalent and complex issue, driven by a combination of environmental and human factors. While often perceived as purely destructive, they play a crucial role in maintaining the health and biodiversity of many ecosystems as they help clear dense underbrush, promote new growth, and control pests, thereby rejuvenating forests and rangelands. However, the increasing frequency and intensity of wildfires poses a significant challenge to both natural and human systems. America has a long and storied history of wildfires. For thousands of years, Native Americans across North America have used controlled burns for ecological purposes and to clear areas for crops and hunting (Adlam and Berger, 2022). However, following the largest wildfire in American history, known as “The Big Burn” in 1910—which burned around 3 million acres in Northern Idaho and Western Montana—federal policy has been guided by a strategy of fire suppression. This policy aimed to protect properties, timber supplies, and watersheds, leading to the creation of Smokey Bear and his infamous slogan, “Only you can prevent wildfires.”

Indeed, human activities are a major factor in wildfire ignitions, with many fires resulting from fireworks, campfires, and other preventable behaviors. Additionally, decades of fire suppression have led to the accumulation of dense fuels, creating conditions for more severe fires when they do occur (Balch et al., 2017). Understanding these dynamics is crucial for developing effective wildfire management strategies that balance ecological benefits with the need to protect human life and property.

In recent years, wildfires have become a contentious political issue. Some argue that mismanagement is the main culprit, while others point to climate change. Regardless, most acknowledge the growing risk. Research has consistently found that large wildfires have become the new normal across the Pacific Northwest (Halofsky, 2019). This increase in larger fires has been linked to climate changes such as decreased fuel moisture and higher temperatures (Abatzoglou and Williams, 2016). Additionally, research has found that fires are becoming more common in higher elevations once thought to be more fire-resistant because of cooler temperatures and greater precipitation. However, many of these higher elevations are seeing drier conditions, mainly driven by earlier snowmelt (Balzer, 2021). This earlier snowmelt has extended the fire season as vegetation loses its primary source of seasonal moisture, increasing its flammability.

In the last few years, fire size and frequency have drastically increased in Idaho. In 2024, a large fire burned over 120,000 acres near the Sawtooth National Recreation Area, destroying multiple summer cabins and sparking national coverage. Other notable fires have included the Moose Fire (2022), which consumed over 150,000 acres near the confluence of the Main and Middle Forks of the Salmon River—an area renowned as one of the nation’s premier whitewater rafting destinations and the Beaver Creek Fire (2013), which gained national coverage for how close it burned to the homes of numerous Hollywood stars. Fire suppression costs continue to climb, costing taxpayers millions of dollars, worsening air quality, and thousands of acres of public lands a blaze, all with no end in sight (Phillips, 2024).

This study is designed to build off the work of (Zerbe et al. 2023), where researchers used multivariate spatial regressions to explain fire hot spots across Washington. Specifically, these researchers used the variables of weather, landcover, population, and ignition type to investigate how natural and human ignitions vary across the state. They found a clear pattern of human ignitions concentrated around higher populated areas such as Spokane and more remote ignitions around the Cascade Range. However, this research will employ a more customized approach, maintaining regression analysis but with different variables and a wider set of geospatial tools. The goal of this research is to better understand the spatial patterns of human and natural-caused ignitions, incident sizes, and how fire management decisions contribute to the spatial patterns of ignitions across Idaho.

Study Area

The state of Idaho (Figure 1-1) was chosen as the study area due to its diverse terrain and climatic variability. The state is characterized by extensive forests, grasslands, and mountainous regions, each presenting unique wildfire dynamics. These ecosystems are sensitive to changing weather patterns, such as prolonged droughts and increased temperatures, which contribute to the frequency and intensity of wildfires. Idaho's large areas of public lands, including national forests and wilderness areas, provide ample research opportunities.

Moreover, Idaho's historical wildfire data and active fire management strategies make it an ideal location for spatial analysis. The state has experienced significant

wildfire events over the years, providing a wealth of data on fire frequency, severity, and recovery. This data can be leveraged to analyze trends and develop working models. Additionally, the involvement of local communities and agencies in wildfire management offers valuable insights into the socio-economic and policy dimensions of fire. Studying wildfires in Idaho thus provides a comprehensive understanding of both the ecological and human factors influencing wildfire patterns.

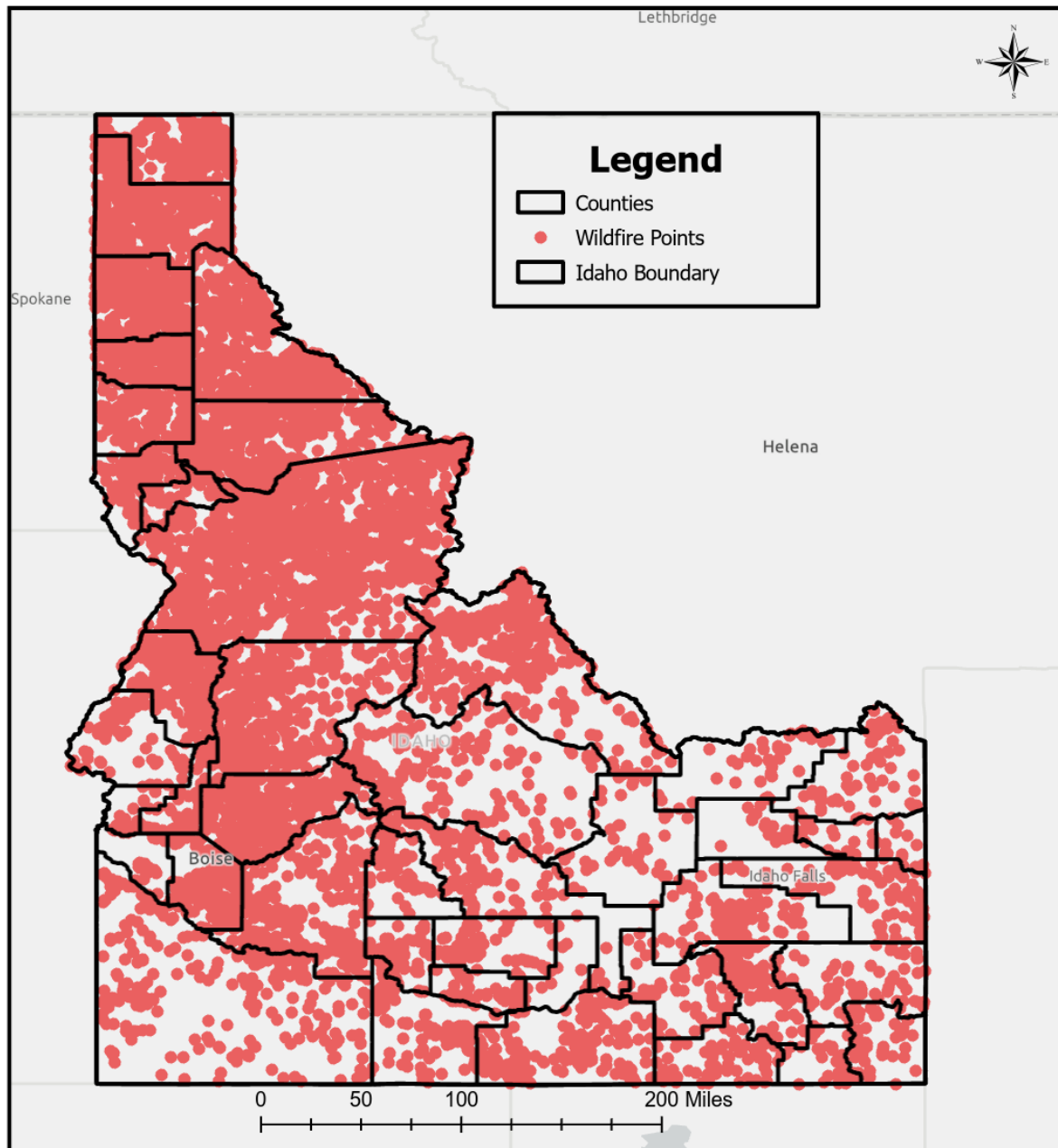


Figure 1: Study Area map of Idaho

Data

The primary dataset used for this analysis comes from the National Interagency of Fire. The data consists of all wildfire points, reported to the Integrated Reporting of Wildland Fire Information (IWRIN) system (Table 1-1). Some of the data attributes

include incident size, fire cause, coordinates, and fire management decisions. These points were then filtered to Idaho's boundary and counties, which were retrieved from the Idaho Geospatial Portal. Census data was downloaded from Idaho State University, which provides a wealth of geospatial data from raster to vector features across the state. Census data serves as a proxy for human behaviors. A polygon boundary of the Frank Church River of No Return was downloaded from ArcGIS Online. Lastly, Climate Engine, a cloud-based solution for downloading and visualizing satellite earth observation and climate data, was used to map the trend of maximum Vapor Pressure Deficit (VPD) from PRISM climate data. This data was downloaded as a csv along with a filtered dataset of the average burning index.

Data Table:

Name	Publication Year	URL	Description	Coordinate System	Geometry Type
Wildfire Incident Locations	Continuous	Wildland Fire Incident Locations National Interagency Fire Center	Point Locations for all wildland fires in the United States reported to the IRWIN system	NAD 1983	Points
Idaho Boundary	2024	GIS Data Idaho State University	Idaho state boundary	NAD 1983	Polygon
Idaho Counties	2024	Idaho Counties ITS GIS Hub	Idaho Counties	NAD 1983	Polygon
Frank Church River of No Return	2022	ArcGIS Online	Wilderness boundary	NAD 1983	Polygons

Maximum Vapor Pressure Deficit (VPD)	Continuous	PRISM Climate Group at Oregon State University	Maximum VPD from 2014-2024, recorded from PRISM climate monthly-4km data	EPSG:4326	Raster
Idaho Census Data	2010	GIS Data Idaho State University	Census data for Idaho includes features such as population, racial/age demographics, and socioeconomics	NAD 1983	Polygon
Burning Index	Continuous	ClimateEngine.org Web Application	Mean Burning Index, filtered to Idaho boundary	EPSG:4326	Raster

Table 1: Data sources and information

Methods

The initial analysis used a point density heat technique to map the distribution of human and natural-caused fires, based on a definition query which specified each ignition cause, split by the incident size. The next step was to use the Standard Deviational Ellipse and Mean Centers tools to show the orientation and dispersion of fires. This could help answer questions such as the average location of each ignition type and the spatial patterns over time. Hot Spot Analysis (Getis-Ord GI*) was employed using the incident size as the input field for each ignition type. This tool uses a set of weighted features to identify statistically significant hot and cold spots. An important parameter is the “conceptualization of spatial relationships,” this parameter has a significant influence on the output feature. Since the study area is an entire state boundary “fixed distance band,” was selected as its more suitable for larger study areas, ensures consistency, and accounts for a sphere or moving window, around each ignition point.

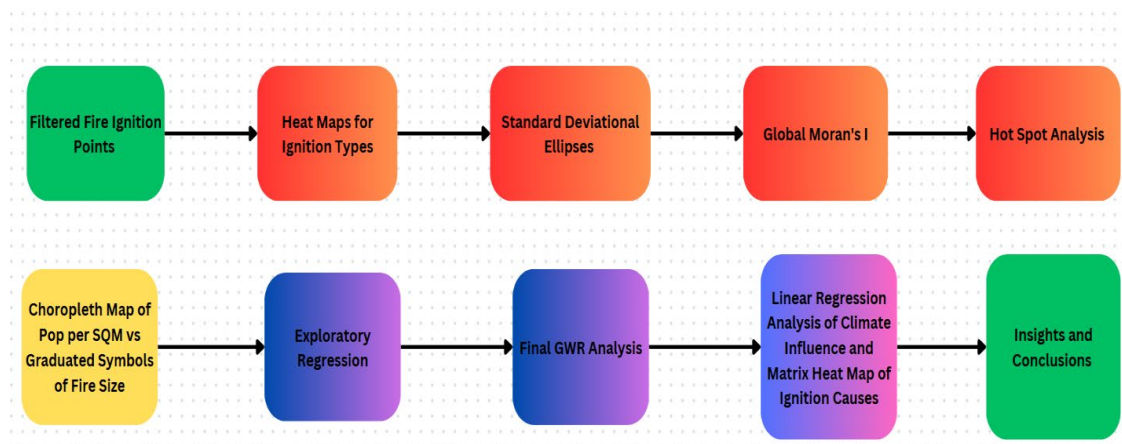


Figure 2: Box and Arrow Chart of Project Steps

Next, the Spatial Autocorrelation (Global Moran's) tool was used to determine whether each ignition type and its associated incident sizes exhibit a random, dispersed, or clustered spatial pattern. The "Create Space Time Cubes" tool was used to create a NETCDF file to run the "Emerging Hot Spot Tools," to provide a more enhanced view of the trends in each ignition type. This tool creates a three-dimensional representation of spatial and temporal data. Knowing these spatial patterns, it was important to explore the temporal trends in the incident sizes over time. A stacked bar graph was used to show the mean incident size for both human and natural ignitions, from the years 2015-2024.

Exploratory Regression

With the spatial and temporal patterns of each ignition type and its associated incident sizes established, the next objective was to explore how fire management affects each incident size. Exploratory regression is a useful feature engineering tool as it runs every possible combination of variables to see which best meets all the necessary requirements and assumptions of OLS. By running this tool, you increase the odds of finding the best combination of variables that explain whatever phenomena you're attempting to model. Six different explanatory variables were used including: initial response acres, discovery acres, estimated final cost, fire suppression percentage, latitude and longitude. Estimated final cost is a measure of the money and resources required for fire suppression, initial response acres refer to the current situation on the ground and plan of attack, and discovery acres refers to the burned acres at the time of reporting. Default values were used for the search criteria:

- Maximum number of explanatory variables: 6
- Minimum number of explanatory variables: 3
- Minimum acceptable adjusted R²: 0.5
- Maximum coefficient p-value cutoff: 0.05
- Maximum VIF value cutoff: 7.5
- Minimum accepted Jarque Bera p-value: 0.1
- Minimum accepted spatial autocorrelation p-value: 0.1

Ordinary Least Squares (OLS)

OLS is a linear regression technique used for choosing unknown parameters in a model, it relies on minimizing the sum of the squared residuals between the observed and predicted values. This method also relies on three key assumptions: the residuals follow a normal distribution, the variance is consistent, and the observations are independent. For this model, incident sizes were used as the explanatory variable and the dependent variables were estimated final cost, initial response acres, and discovery acres.

Geographically Weighted Regression (GWR)

Geographically Weighted Regression (GWR) is a spatial analysis technique that allows for local rather than global analysis by fitting a regression equation to every feature in the dataset. One of the main advantages of this technique is that it can account for spatial heterogeneity where spatial relationships aren't uniform across spacetime and are strongly influenced by local factors. Knowing the most significant fire management variables that influence the size of each ignition, it was necessary to understand the

variation in these spatial patterns, enabling a more localized insight into wildfire geography. The (GWR) tool was run using the explanatory variables: initial response acres, discovery acres, and estimated final cost. The golden search method was used as it helps find an optimal bandwidth or neighborhood size and narrows down the search space, making it easier to find the best value. The same explanatory and dependent variables as OLS were used to ensure an apples-to-apples comparison.

Other Influences

Knowing the spatial patterns of fire sizes and the role of management on these sizes, it was important to see their relationship with population density and the role climate has played in influencing these incident sizes. Population data was symbolized using a choropleth technique and was overlaid with a graduated symbols map of the average incident size. For climate data, Climate Engine was used to create a trend map for the max Vapor Pressure Deficit (VPD) from 2014-2024 and then these values were downloaded as a csv along with the average values for Burning Index and a simple linear regression analysis was run using Jupiter Notebooks. A matrix heat map showing the average incident size in relation to a binary of human vs natural causes and specific causes for each of these was also plotted using Jupiter Notebooks. VPD is a crucial variable as it essentially measures the atmosphere's drying power by taking the difference between the amount of moisture in the air and the maximum amount it can hold, which directly affects fuel moisture. The Burning Index is an index that rates fire danger based on fire behavior and is derived from the combination of the spread and ignition components, making it a useful predictor of burn size.

Results

The results of this study reveal distinct spatial and temporal patterns in wildfire ignitions across Idaho. Human-caused fires exhibit random spatial distribution, with smaller incident sizes often concentrated around urban centers like Boise. In contrast, natural ignitions show clustered patterns in more remote regions of central Idaho, where larger fires dominate. Trend analyses highlight how natural ignitions consistently result in bigger incident sizes compared to human ignitions over the last decade. Hot Spot and Emerging Hot Spot analyses confirm these patterns, identifying persistent fire-prone regions and areas of consistent cold spots.

The point density heat maps (Figure 3) show a spatial pattern where natural ignitions tend to occur in the remote parts of central Idaho and human ignitions in more southern and western parts of the state, which are more urbanized.

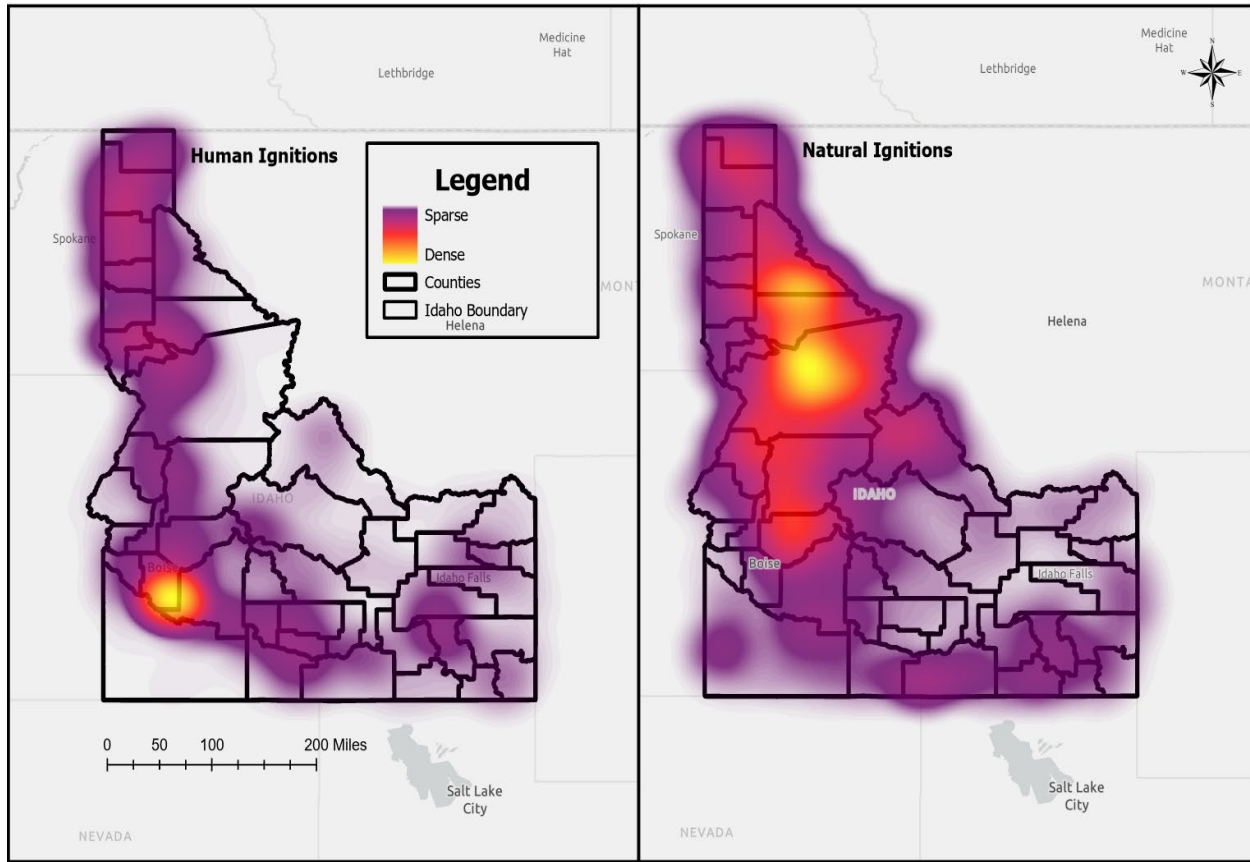


Figure 3: Point Density Heat maps of ignition densities, purple shows more sparsely distributed occurrences and orange and yellow the densest.

The directional ellipses (Figure 4) show a similar spatial pattern where natural ignitions tend to have a smaller ellipse, and the average ignition occurs within the Frank Church Wilderness. In contrast, human ignitions have a much larger ellipse and occur just this wilderness boundary to the southwest.

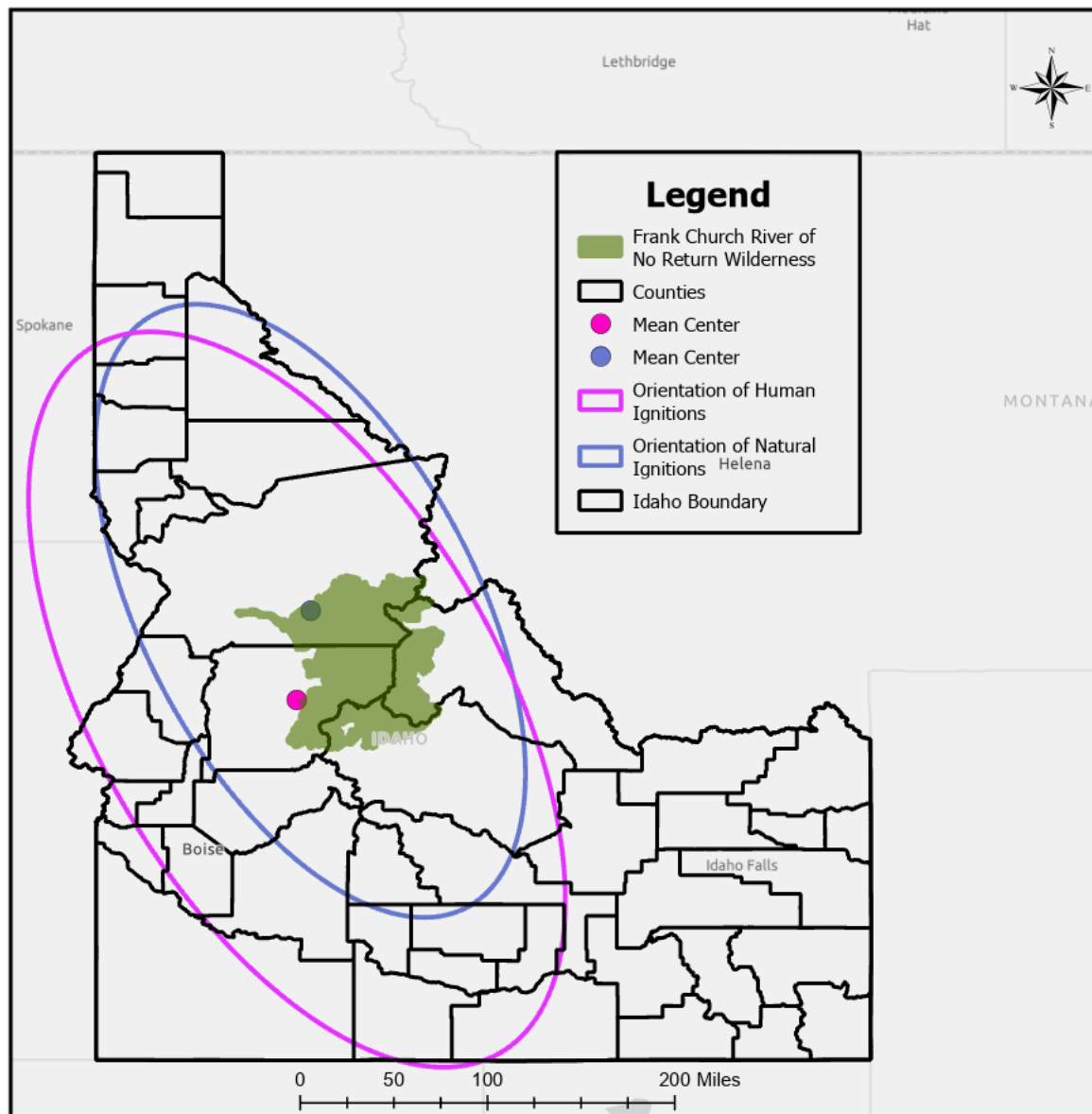


Figure 4: Dispersion, orientation, and average location for each ignition type. Pink features show human ignitions and blue shows natural ignitions.

Trend analysis (Figure 5) shows from 2015-2024 natural ignitions were on average much larger than human ignitions. Natural ignitions have more inter-annual variability.

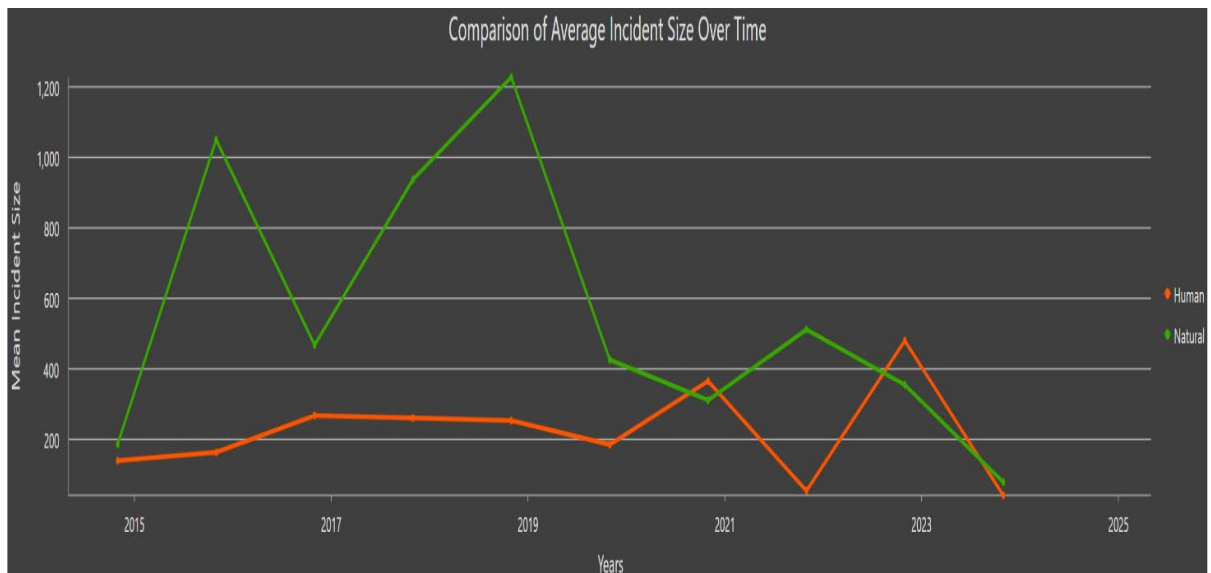


Figure 5: Line graph of average incident sizes in relation to ignition cause. Orange shows human fires and green shows natural-caused fires.

With a negative Moran's index, below expected index, negative z-score, and high p-value, human ignitions exhibit a random spatial pattern i.e. the size of each ignition is not consistent. In contrast, with a positive Moran's Index, above expected index, positive z-score, and low p-value, natural ignitions exhibit a clear clustered spatial pattern i.e. larger fires tend to occur in similar places.

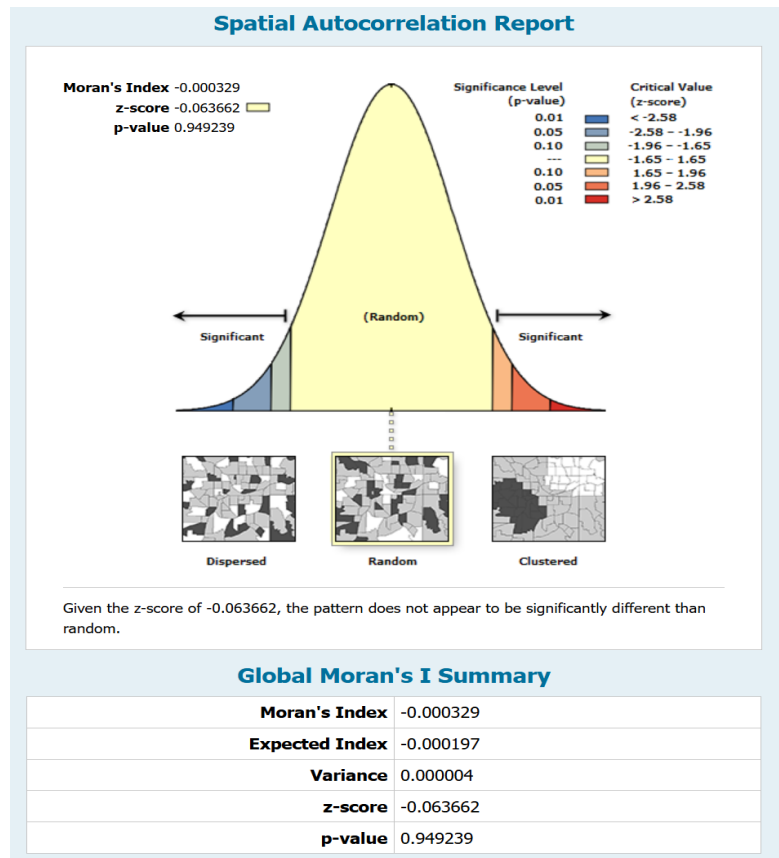


Figure 6: Spatial autocorrelation report of human ignitions

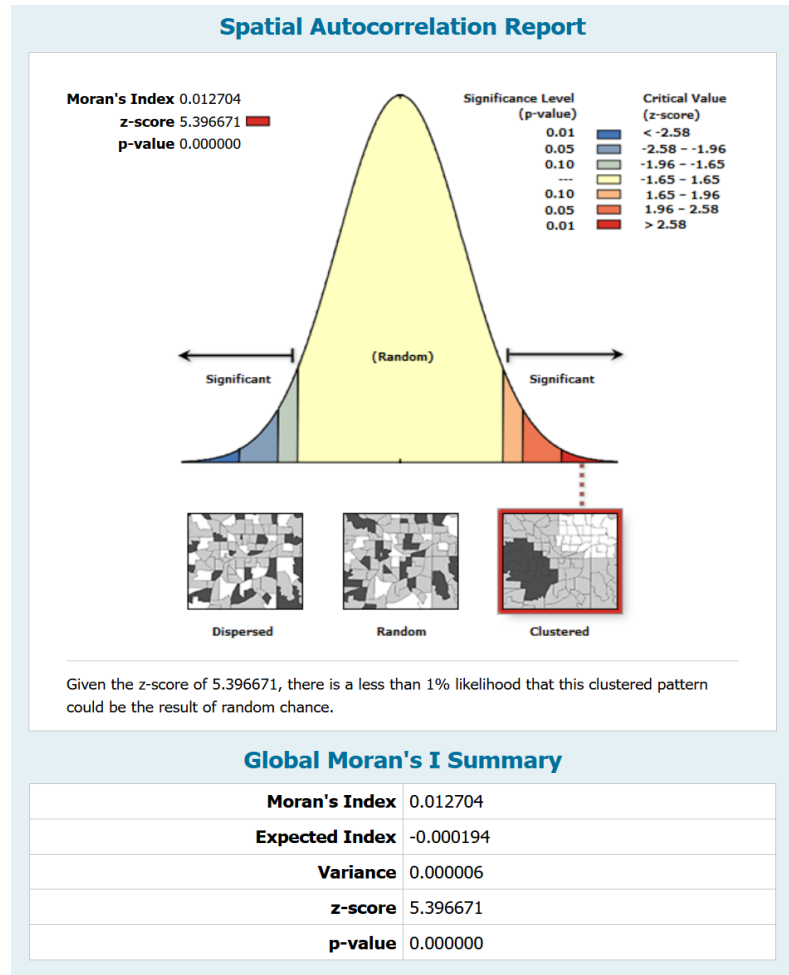
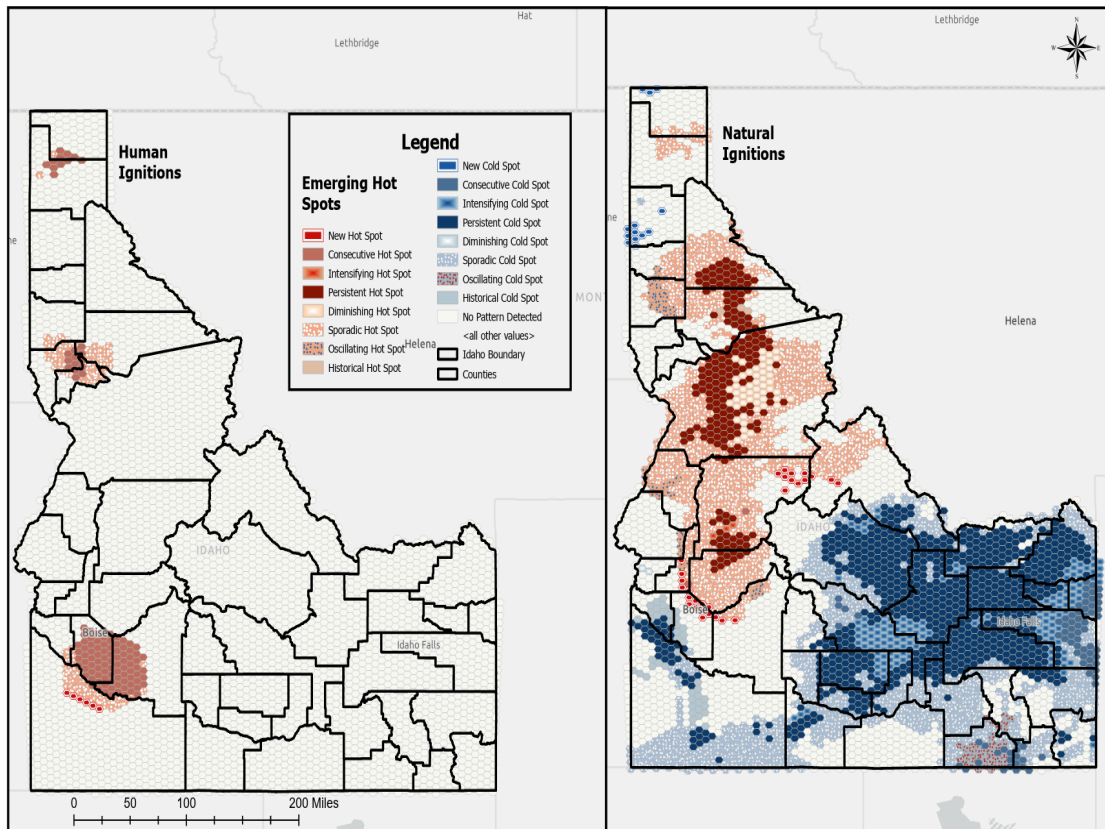


Figure 7: Spatial autocorrelation report of natural ignitions

From the Emerging Hot Spot Analysis (Figure 8), we can see areas that are consecutive or persistent hot spots whereas the eastern and southern parts are consistent cold spots. Human ignitions are somewhat clustered around Boise and other larger cities, but otherwise no clear pattern can be detected. However, it's important to note (incident size) was not included in the Emerging Hot Spot Analysis but its results still largely align with other findings that did include this.



Hot Spot Analysis validated these results as shown above larger fires exhibit high clustering in similar regions; human ignitions exhibit a weaker pattern. As seen in (Figure 9), larger natural fires tend to be highly concentrated in central Idaho as demonstrated by the clustering of higher z-scores. Human ignitions have a few clusters of higher z-scores, but the pattern is not as defined or widespread as it is for natural ignitions. There is also a high cluster of lower z-scores just south of Boise meaning there is a higher concentration of fires, but smaller incident sizes.

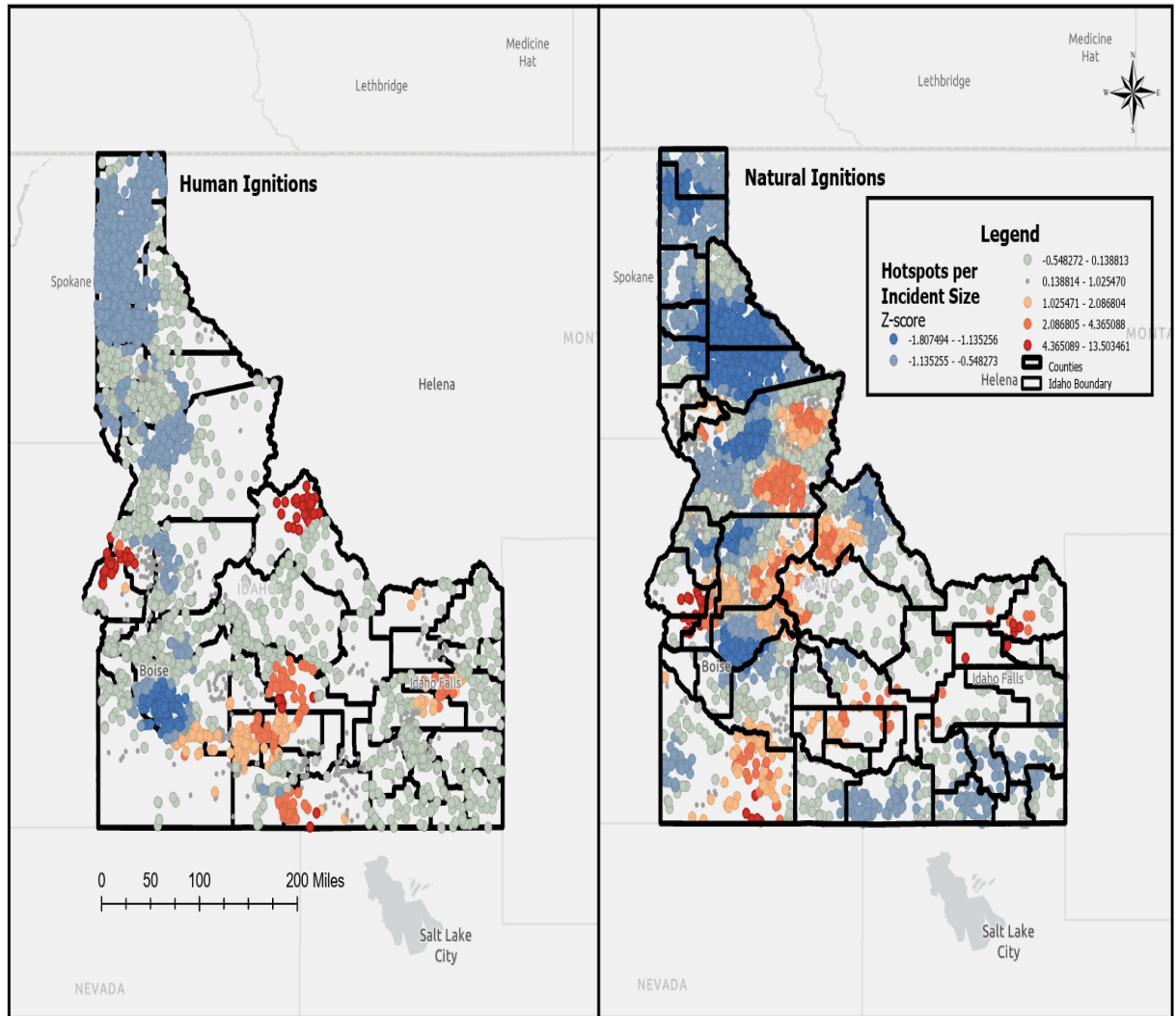


Figure 9: Results of the Hot Spot Analysis but using incident sizes.

In (Figure 10), a clear pattern can be seen where natural-caused fires are clustered around lower populations and smaller fires are clustered near higher populations with a few outliers. Large ignitions also occur at a much higher frequency than human ignitions.

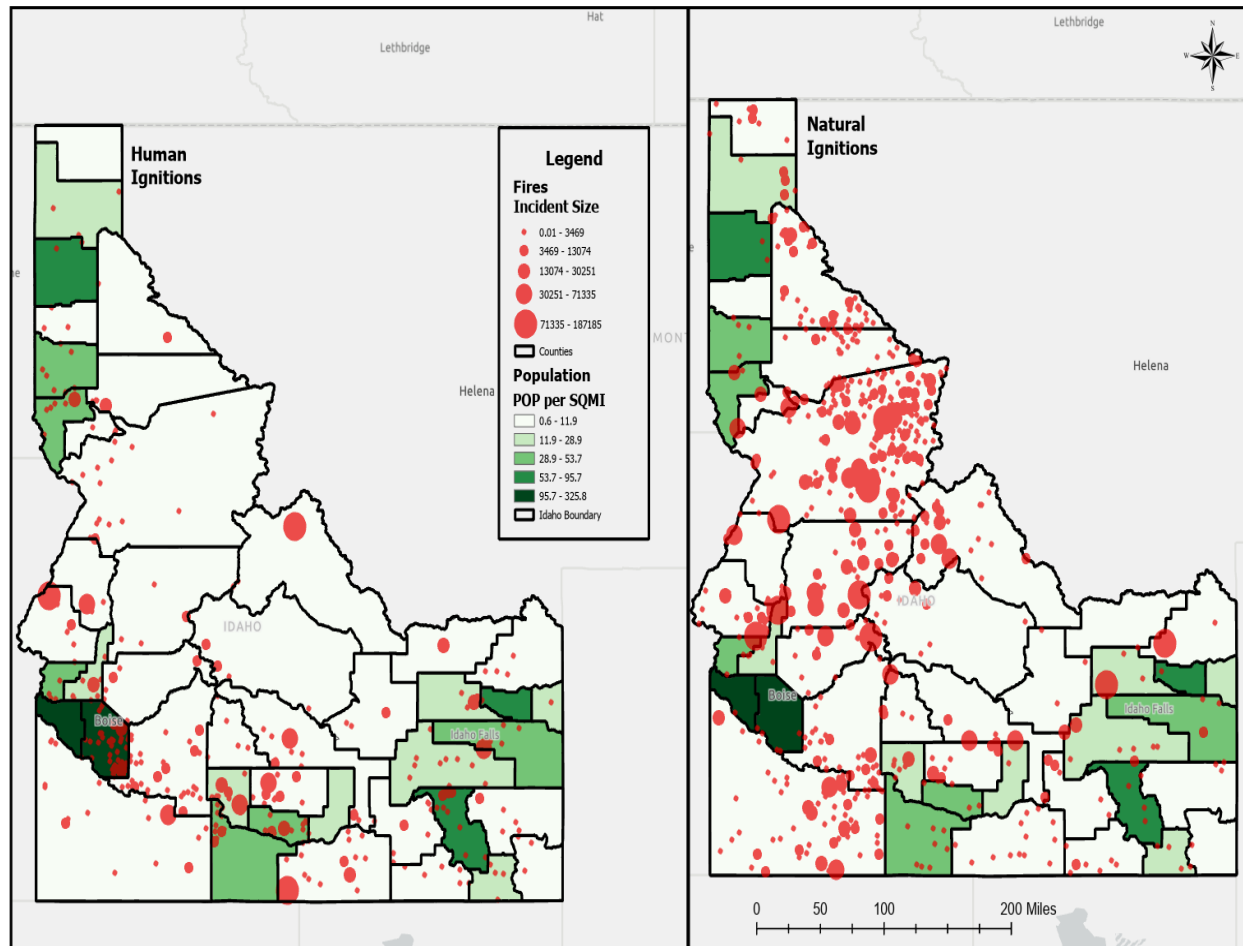


Figure 10: Population density per square mile in relation to the incident size of human and natural ignitions. Larger natural ignitions can be seen around more rural populations whereas smaller human ignitions are concentrated around higher populations.

The tables below (Table 2) and (Table 3) show the results from the exploratory regression after a second run and the GWR model. The first run included latitude, longitude, and fire suppression percentage but these were removed because of high

multicollinearity and an adjusted R^2 near zero. The top model consisting of estimated final cost, initial response acres, and discovery acres was selected to run OLS and GWR because it had the highest adjusted R^2 , lowest AICc, and a Variance Inflation Factor (VIF) score well below the threshold of 7.5. The top performing variable was the estimated cost of suppression with an R^2 of 0.41 and when combined with initial response acres, and discovery acres achieved an adjusted R^2 of 0.57.

Highest Adjusted R-Squared Results

AdjR2	AICc	JB	K(BP)	VIF	SA	Model
0.57	2224.33	0.00	0.00	5.41	0.67	+INCIDENTS.DISCOVERYACRES - INCIDENTS.INITIALRESPONSEACRES +INCIDENTS.ESTIMATEDFINALCOST***
0.55	2227.80	0.00	0.08	1.08	0.81	+INCIDENTS.DISCOVERYACRES +INCIDENTS.FIRESTRATEGYFULLSUPPPERCENT +INCIDENTS.ESTIMATEDFINALCOST***
0.53	2232.18	0.00	0.00	4.40	0.95	+INCIDENTS.FIRESTRATEGYFULLSUPPPERCENT - INCIDENTS.INITIALRESPONSEACRES +INCIDENTS.ESTIMATEDFINALCOST***

Table 2: Model results of the exploratory regression

Model Diagnostics

R2	0.7356
AdjR2	0.7102
AICc	2695.2332
Sigma-Squared	88463743.5784
Sigma-Squared MLE	80779409.5651
Effective Degrees of Freedom	115.9682
Adjusted Critical Value of Pseudo-t Statistics	2.3261

Table 3: Model results of the GWR model

OLS values with the lowest extreme deviations are clustered in the central parts of the state. These areas represent where the models perform the best. Likewise, extreme positive deviations primarily occur in the south, suggesting a poor model fit.

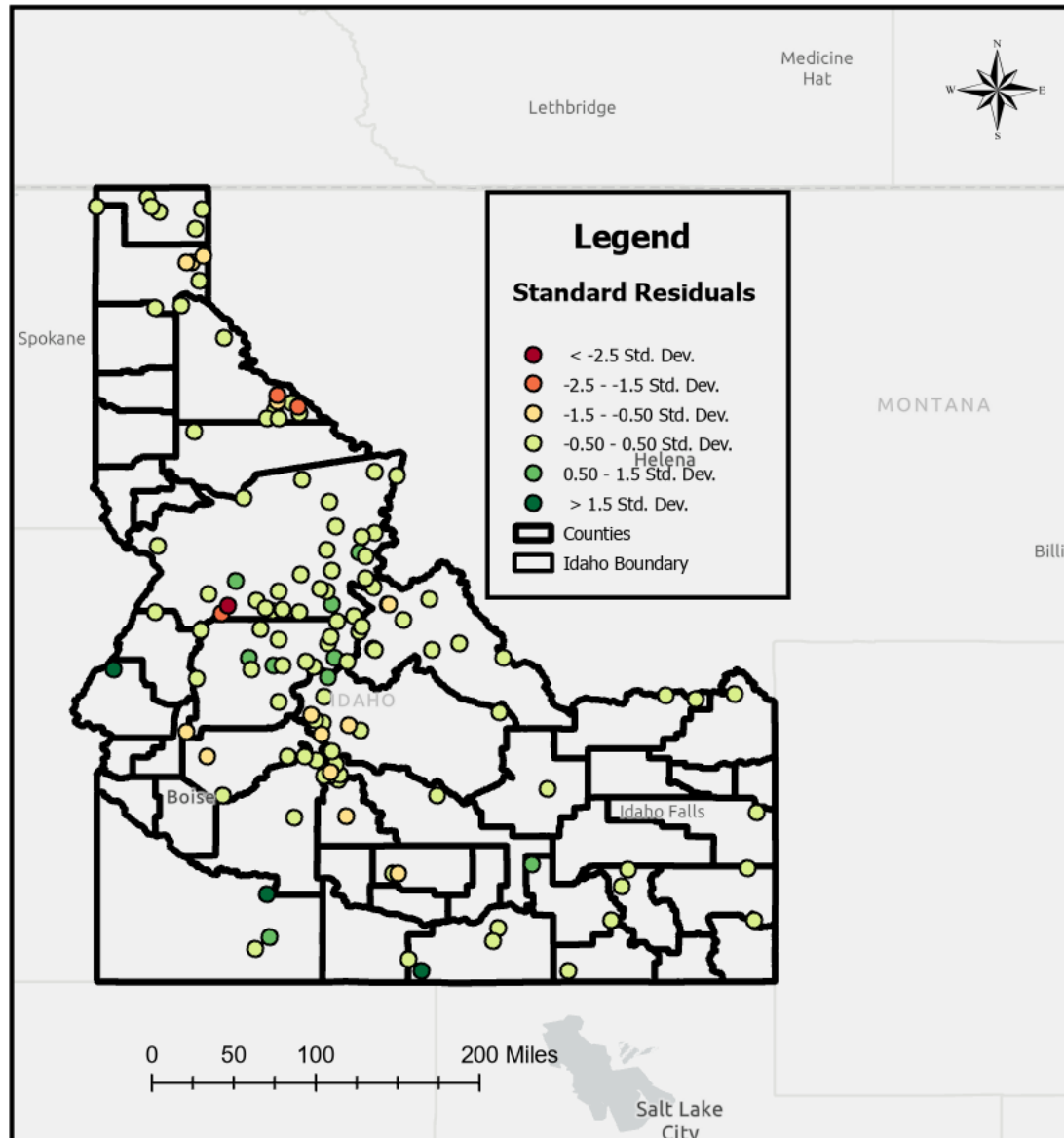


Figure 11: Results of the standardized residuals from the OLS model. Standardized residuals measure how far an observed value is from a predicted one. Values between +2 and -2 standard deviations are considered the sweet spot for a good model agreement.

Maps of the highest GWR coefficients show an intriguing spatial pattern. The coefficient for the estimated final cost shows a gradual pattern of the highest values in the south, moderate values in the south-central areas, and the lowest values in the northern panhandle. The initial response acres, shows a nearly identical pattern.

Coefficients in the northern panhandle are much lower while areas to the southcentral are much higher.

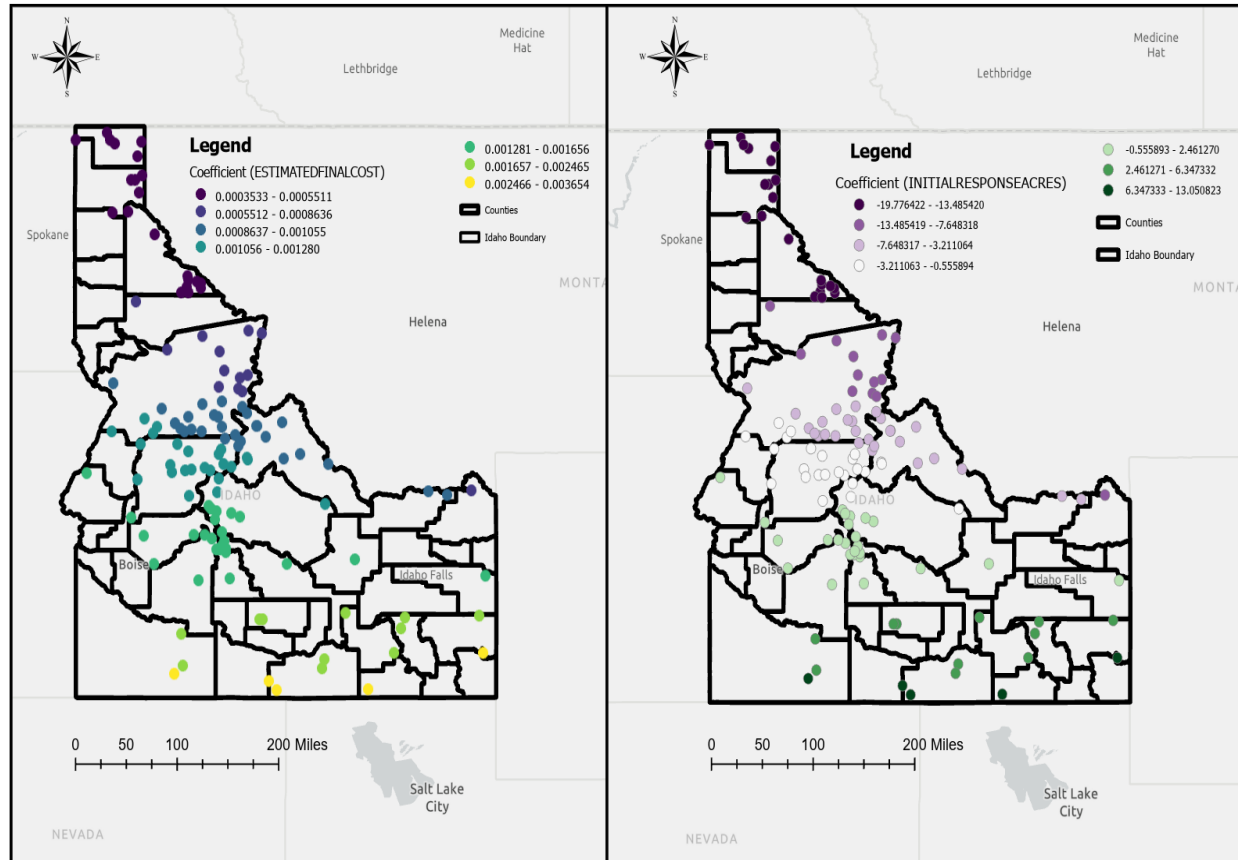


Figure 12: Results for the coefficients of the estimated final cost and initial response acres from the GWR model.

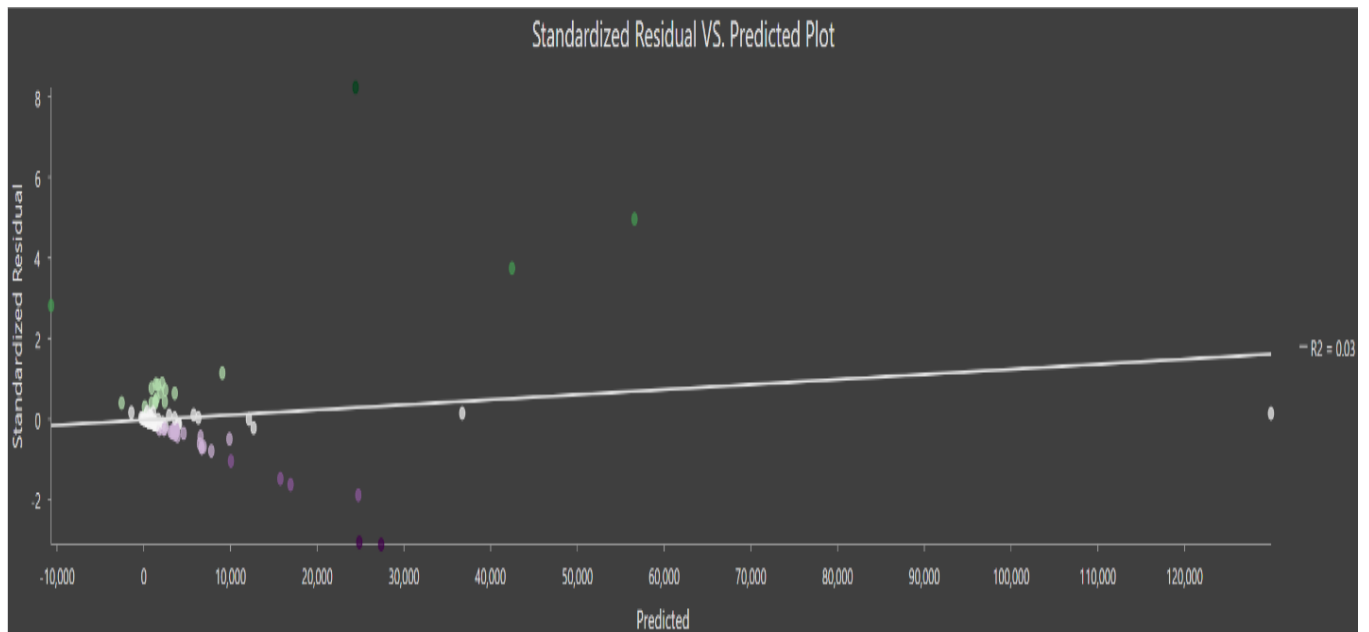


Figure 13: scatter plot of the standardized residuals vs the predicted incident size from the GWR model

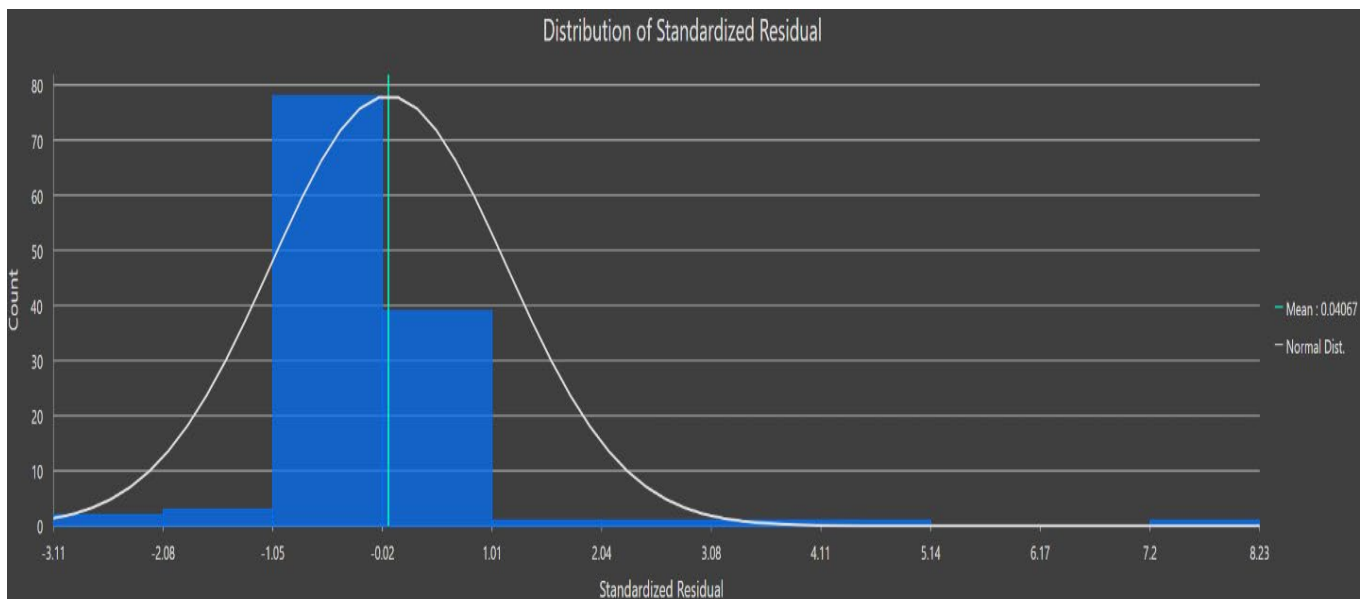


Figure 14: histogram of the standardized residuals distribution from the GWR model

The standardized residuals exhibit a random distribution in relation to the predicted incident size (Figure 13) and follow a normal distribution with a mean of 0.046

(Figure 14). This indicates that the model doesn't contain any major systemic biases and largely accounts for the necessary variables.

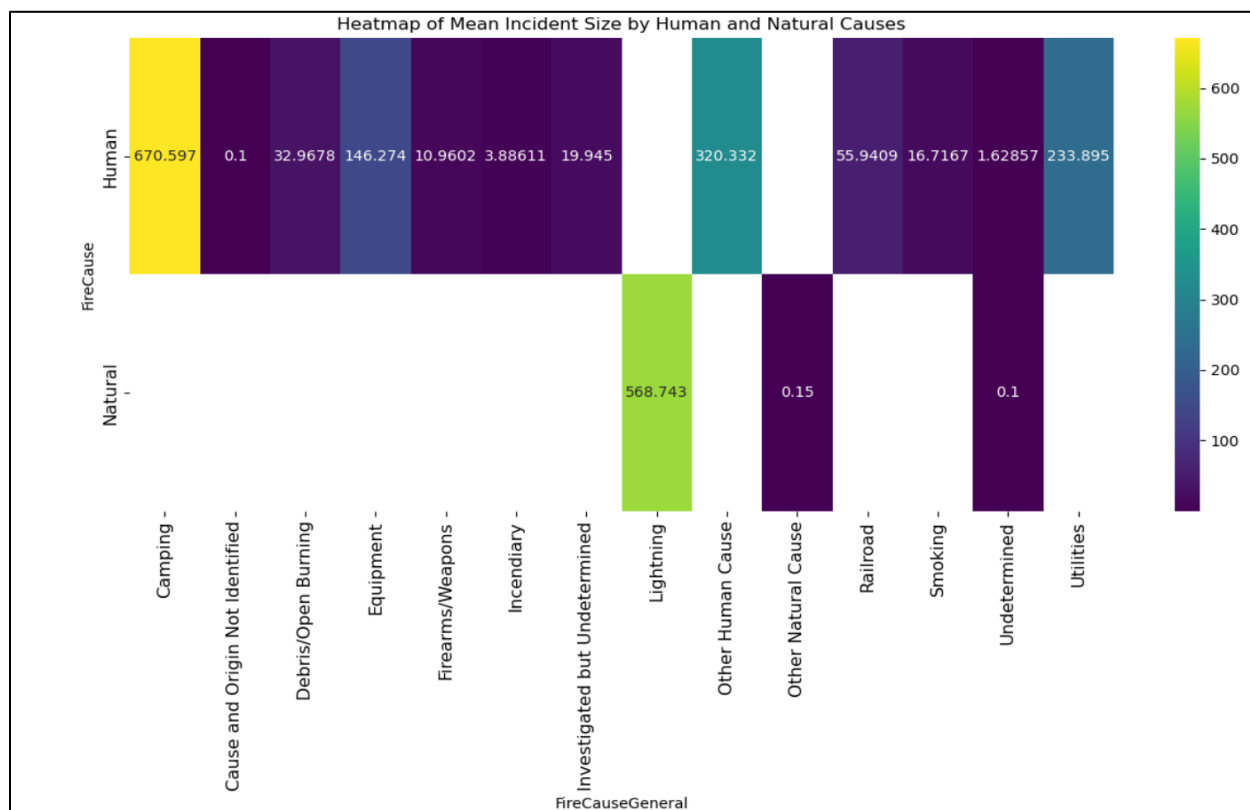


Figure 15: Matrix heatmap of mean incident size in relation to ignition cause. Smaller fires shown in darker colors and larger in lighter ones.

On average, lightning, camping, and other human causes account for the largest incident sizes. While, railroads, firearms/incendiary, and smoking result in much smaller incident sizes. These results largely validate the results above as summer lightning strikes tend to occur in the more rugged wilderness areas and dry deserts across Idaho. Idaho campgrounds are often located on the cusp or in the middle of wilderness areas,

often hotspots for outdoor recreation and risky behaviors like having non-approved campfires. Human ignitions from human behaviors are more predictable whereas natural ignitions are almost entirely the result of lightning, which is far less predictable.

Linear regression analysis shows a moderate-strong correlation, with an R-value of 0.61, between Vapor Pressure Deficit (VPD) and the burning index. This means as conditions become drier, fire activity intensifies. When lightning strikes in a dry, dense forest or grassland, or when embers from a campfire land in such areas, the dry vegetation acts as a tinderbox, significantly increasing the potential for large-scale fires

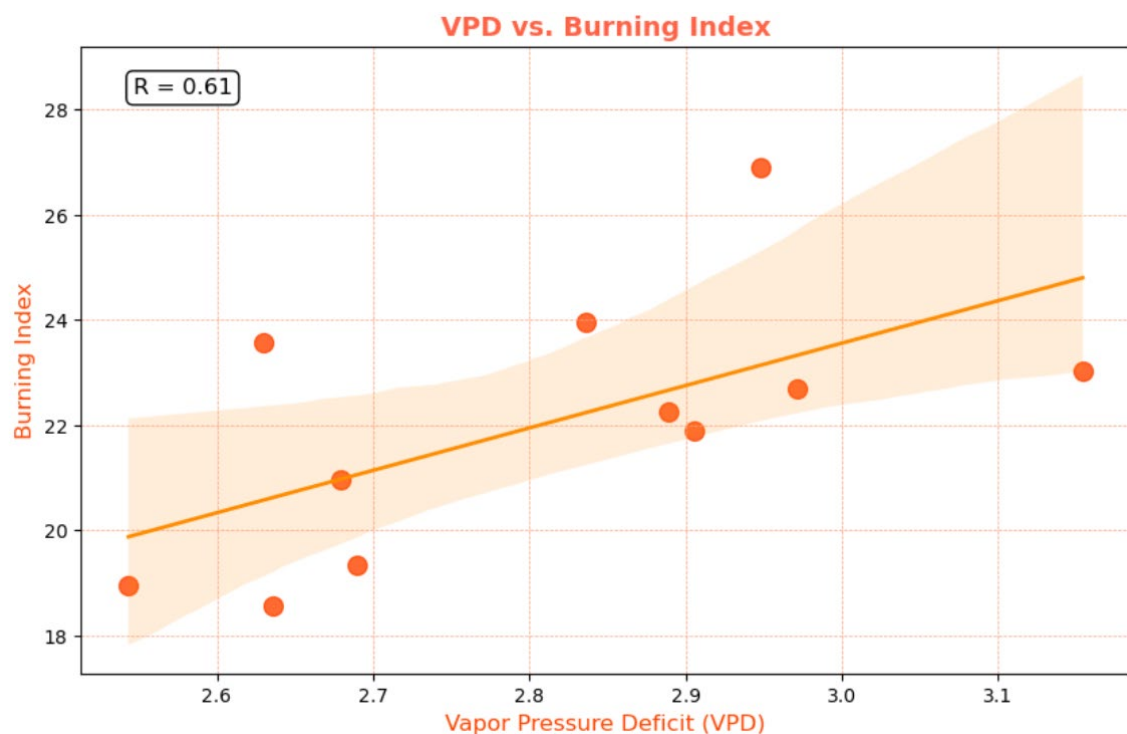


Figure 16: Scatter plot of VPD in relation to the Burning Index

Conclusions

The goal of this research was to analyze the spatial patterns of human and natural wildfire ignitions, incident sizes, and how management decisions influence these patterns across Idaho. Using advanced geospatial tools like Hot Spot Analysis, OLS, and GWR, I identified trends, assessed influencing factors, and demonstrated the importance of localized fire management decisions. This approach provided valuable insights into wildfire ecology and management strategies tailored to Idaho's unique geography. Spatial statistical techniques including OLS and GWR prove highly valuable for modeling the spatial patterns of wildfire ignitions across Idaho. However, these results confirm GWR is preferable over global models in capturing how localized management decisions affect incident sizes. For example, the estimated cost of suppression and the initial response acres are important factors in predicting how large a fire might become. In more remote areas, fires can often grow larger due to a lag in early detection, an abundance of fuel, and steeper terrain. Around more populated areas, fires can vary greatly in sizes because of the wider variation in ignition sources and less fuel. However, the cost of these fires can be much higher because of the resources required to protect lives, property, and critical infrastructure. This pattern aligns with an idea known as the “fire paradox” where the more effort you put into suppressing fire, the worse it becomes when it does occur. Early detection and location intelligence are crucial for making better management decisions, especially in the wildland urban interface (WUI) where human development meets wilderness areas. This analysis also confirms drier conditions have resulted in more extreme fire behavior across Idaho, but doesn't conclusively prove that these conditions are the main driver of larger burned areas. Overall, this paper demonstrates the importance of nuance in both general discussions and policy regarding wildfires. It

also shows the limitations of our knowledge and serves as a reminder to avoid jumping to conclusions as the best fire management decisions are rooted in embracing these nuances and localized decisions. Moving forward, the integration of geospatial tools in wildfire management not only enhances our understanding of their trends, patterns, and causes but also paves the way for more innovative and data-driven solutions to meet the growing challenges posed by wildfires in a changing world.

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