Network Analysis of Alberta Wildfires: Understanding Clustering and Root Causes

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Abstract

Background: Wildfires in Alberta are a major ecological and economic concern, with increasing frequency and intensity due to climate change, human activities, and environmental factors. Existing wildfire models often fail to capture spatial clustering and the combined effects of critical predictors such as temperature, humidity, and wind speed. This gap in research hampers effective wildfire prevention and mitigation strategies.

Objective: This study investigates how environmental and geographical factors influence wildfire clustering and dominant causes in Alberta. Specifically, it aims to analyze wildfire clusters, identify key contributing factors, and evaluate the role of large fires in connecting wildfire clusters.

Methods: Wildfire data, including latitude, longitude, temperature, humidity, and wind speed, were analyzed using density-based (`DBSCAN`) and partition-based (`K-Means`) clustering techniques. Wildfires were modeled as nodes in a network, with edges representing shared causes and geographic proximity. Key network metrics, such as degree and eigenvector centrality, were calculated to assess the influence of specific regions and fire events.

Results: Human activities, including "Cooking and Warming" and "Debris Disposal," emerged as the leading causes of wildfires. High temperatures and low humidity were significantly correlated with larger fires. The Banff–Jasper region had the highest eigenvector centrality, indicating its prominence in wildfire activity. Large wildfires exhibited high degree and betweenness centrality, acting as critical connectors in the network.

Conclusions: This study provides valuable insights into wildfire clustering and causes, emphasizing the importance of targeted interventions to mitigate risks. Findings highlight the need for enhanced monitoring and resource allocation in regions with high temperatures and low humidity. Future research should

incorporate additional predictors, such as vegetation and topography, to refine wildfire management strategies.

Keywords: Wildfires, Network Analysis, Data Visualization, Alberta Wildfires

Introduction

Wildfires are among the most devastating natural disasters, with far-reaching consequences for ecosystems, human settlements, and economies. Alberta, one of Canada's most wildfire-prone provinces, experiences hundreds of wildfires annually. The increasing intensity and frequency of these events can be attributed to factors such as climate change, human activity, and natural causes. The growing threat posed by wildfires in Alberta highlights the urgent need for effective prevention, mitigation, and response strategies.

Existing wildfire models often fail to fully capture the interplay of critical environmental factors such as wind speed, temperature, vegetation, and topography. These models also lack the ability to analyze the spatial and temporal clustering of wildfires, which can provide crucial insights into underlying causes and fire propagation patterns. This gap in current research limits our understanding of wildfire dynamics and hampers the development of data-driven decision-making frameworks for wildfire management.

This project addresses these gaps by leveraging **network analysis** techniques to investigate wildfire behavior in Alberta. By treating wildfires as nodes in a network and connecting them based on factors such as geographic proximity, common causes, and environmental conditions, we aim to uncover patterns of wildfire clustering and propagation. This innovative approach allows for a deeper exploration of the relationships between wildfire events and the factors driving them.

The research is guided by the following key questions:

1. What are the most common causes of wildfires in Alberta, and how do these causes influence clustering and spread patterns?
2. Which year experienced the largest wildfires in Alberta, and what were their defining characteristics?
3. Are larger wildfires more likely to have multiple causes, and do they play a critical role in connecting fire clusters?
4. How do environmental and geographical factors influence wildfire clustering and dominant causes in Alberta?

This research makes a significant contribution to the field by applying advanced network analysis methods to a real-world problem. The findings from this study will provide a framework for better understanding wildfire dynamics in Alberta and offer data-driven solutions to mitigate the increasing threat of wildfires in the province.

Related Works

This section reviews prior research and literature relevant to the project:

Relating pre-fire canopy species, fire season, and proximity to surface waters to burn severity of boreal wildfires in alberta, canada.[1]
Characterisation of initial fire weather conditions for large spring wildfires in alberta, canada.[2]
Alberta's 2023 wildfires: Context, factors, and futures.[3]

Recent studies have used tools like machine learning and remote sensing to predict where wildfires might happen and how severe they could be. However, these studies rarely explore the relationships between different fires, which is where network analysis can help. For example, while Rupasinghe and Chow-Fraser (2021) and Tymstra et al. (2021) have provided valuable insights into fire severity and spring fire conditions, they didn't focus on how fires are connected or spread in patterns. Similarly, Beverly and Schroeder (2024) looked at Alberta's 2023 wildfires in the context of climate and policy but didn't examine how fires cluster or spread based on environmental factors. Our study fills this gap by using network analysis, a method often used in areas like disease tracking and transportation systems, to uncover new patterns in wildfire clustering and how fires spread across regions.

Existing Wildfire Models

Wildfire models are essential tools for predicting fire behavior, assessing risks, and supporting wildfire management. The most commonly used wildfire models include:

- **Empirical Models:** These models are based on historical data and statistical relationships. They predict wildfire behavior under specific conditions but lack the flexibility to adapt to novel scenarios.
- **Deterministic Models:** These simulate fire spread using physical principles, such as heat transfer and combustion. While accurate, they require extensive computational resources and detailed input data.
- **Stochastic Models:** These use probability distributions to model uncertainties in wildfire behavior. They are valuable for risk assessment but often lack spatial and temporal precision.
- **Machine Learning Models:** These models use advanced algorithms to predict fire occurrence and spread based on large datasets. However, they are limited by the quality and availability of training data and are sometimes treated as "black boxes" with limited interpretability.

Limitations of Existing Models

While these models have proven useful in various applications, they face significant limitations:

- **Data Dependency:** Many models rely heavily on high-quality, extensive datasets, which may not be readily available for all regions.
- **Complexity and Computational Costs:** Deterministic and machine learning models require significant computational power, making them impractical for real-time applications in resource-constrained settings.
- **Static Assumptions:** Most models assume constant environmental and human factors, ignoring the dynamic and evolving nature of wildfires.
- **Limited Integration of Spatial and Network Effects:** Existing models often fail to account for the interconnected nature of wildfire spread across regions, which can be influenced by wind, vegetation, and other geographic factors.

Value of Network Analysis in Wildfire Research

Network analysis offers a novel approach to understanding and managing wildfires by focusing on relationships and interactions rather than isolated events. The key advantages include:

- **Cluster Detection:** Network analysis can identify clusters of wildfires based on spatial, temporal, and causal relationships, providing insights into high-risk regions.
- **Community Detection:** Methods such as the Louvain algorithm can reveal communities of wildfires with shared characteristics, aiding in targeted interventions and resource allocation.
- **Centrality Analysis:** Centrality measures (e.g., degree, betweenness) can identify critical fire events or regions that serve as connectors between disparate clusters, enabling better control strategies.
- **Integration of Environmental Factors:** Network models can incorporate geographical and environmental variables, such as wind direction and vegetation zones, to improve predictions and understanding of wildfire dynamics.
- **Policy Insights:** By mapping wildfire clusters to policy zones, network analysis can evaluate the effectiveness of existing regulations and identify gaps in wildfire management.

Our Contribution

While existing wildfire models provide valuable tools for prediction and management, their limitations highlight the need for complementary approaches. Network analysis offers a powerful framework to explore wildfire dynamics, uncover hidden patterns, and integrate spatial and temporal factors. By bridging the gaps in current methodologies, network analysis can enhance our ability to predict, prevent, and respond to wildfires effectively.

Methodology

Data Collection

The wildfire dataset was obtained from the Open Canada website, provided by the Government of Alberta. The dataset includes detailed records of wildfires in Alberta from 2006 to 2023. For each fire, the dataset tracks a range of attributes, including:

- **Cause:** Identified activity or event leading to the wildfire.
- **Size:** Current and total area burned (in hectares).
- **Location:** Geographic information, including latitude, longitude, legal land description, and forest area.
- **Time and Duration:** Date and length of time the fire was active.
- **Weather Conditions:** Data on temperature, relative humidity, wind speed, wind direction, and overall weather conditions during the fire.
- **Suppression Efforts:** Staffing, physical resources (e.g., firefighting equipment), and strategies used to control the wildfire.

The dataset is publicly accessible at: `https://open.canada.ca/data/en/dataset/a221e7a0-4f46-4be7-9c5a-e29de9a3447e`

Data Cleaning and Preprocessing

To ensure the accuracy and usability of the dataset, extensive data cleaning and preparation steps were performed. The primary focus was on handling missing, inconsistent, and erroneous data, as well as deriving additional variables to enhance the analysis. The cleaning and preparation process included the following steps:

- **Handling Missing Values:**
  - Records with critical missing fields such as fire size, latitude, and longitude were removed.
  - Non-critical fields, such as weather conditions, were imputed using mean, median, or mode, depending on the variable type.
- **Addressing Inconsistencies:**
  - Standardized categorical variables like *activity_class* and *cause* to ensure consistent naming conventions.
  - Verified location data (latitude and longitude) to ensure points fall within Alberta's boundaries.
- **Validation and Quality Checks:**
  - Ensured the dataset had no duplicate records based on unique fire identifiers.
  - Verified that derived variables, such as cluster labels, aligned with geographical and temporal patterns.

After cleaning, the dataset was fully prepared for analysis, with missing values minimized, outliers addressed, and all fields transformed to be analysis-ready.

Data Analysis

Edge Creation Based on Geographical Proximity

Edges in the wildfire network were formed by connecting fires within each activity class that were geographically close (within a 50 km radius). By grouping fires with similar causes (activity classes) and proximity, the network effectively highlights regional fire patterns and clusters, allowing for a more detailed understanding of wildfire dynamics.

To connect wildfires in our network, we set a 50 km radius based on studies showing that this distance matters for how fires spread due to environmental and human factors. We tested other distances, like 30 km and 100 km, but found that 50 km struck the right balance between making the network detailed and easy to interpret.

To study how wildfires group together in different areas, we tried out a few clustering methods. We chose DBSCAN because it's good at finding clusters of any shape and can handle scattered data points, like outliers. We also used K-Means to compare results, as it focuses on dividing data into clear groups.

Visualization and Clustering

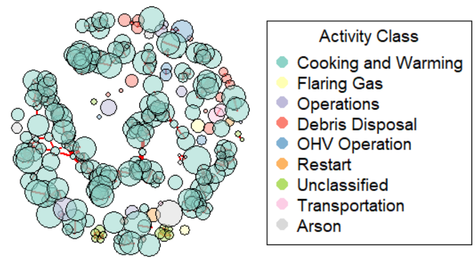
For analyzing the network, we measured things like how connected a wildfire is (degree), how often it acts as a bridge between others (betweenness), and how central it is to the overall network (closeness and eigenvector centrality). We used well-known methods like Brandes' algorithm for betweenness. To identify groups of related fires, we used the Louvain algorithm, which is fast and works well for uncovering nested structures in networks. All our work was done in Python, using tools like NetworkX for building and analyzing the network, and Geopandas for working with geographic data.

Two prominent layout algorithms were employed to visualise the network:

- **Kamada-Kawai Layout:** This algorithm minimizes the energy of the network to create an intuitive spatial arrangement, enabling the clear identification of clusters.
- **Fruchterman-Reingold Layout:** A force-directed approach that balances attractive and repulsive forces between nodes, providing a visually distinct view of network structures.

Nodes in the network visualization were:

- **Color-Coded by Activity Class:** Each activity class (e.g., lightning, human activity) was assigned a unique color for clear differentiation.
- **Scaled by Fire Size:** Node sizes were logarithmically scaled based on the fire size (current_size), emphasizing the relative impact of larger fires.
- **Clustered:** The visualizations revealed cohesive clusters of related wildfires, making patterns of related fire incidents identifiable.



Community Analysis: We identified 69 communities of wildfires via the Louvain algorithm, with the largest containing 25 fire events linked by both similar activity causes and geographic proximity. Notably, the Banff–Jasper cluster exhibited both high eigenvector centrality (1.0) and a diverse range of causes, indicating that it is not only a hotspot but also a structurally central node in the network. In contrast, Red Deer, though less central in eigenvector terms (0.57), displayed the highest closeness centrality, suggesting it serves as a critical bridge connecting multiple sub-networks. These distinctions highlight the complexity of wildfire networks, where the importance of each node or fire event can be captured by different dimensions of centrality.

Results

Question 1: What are the most common causes of wildfires in Alberta, and how do these causes influence clustering and spread patterns?

The analysis of wildfire activity classes revealed critical insights into the common causes of wildfires in Alberta. The data showed that human activities such as "Cooking and Warming," "Debris Disposal," and "OHV Operations" are among the leading causes of wildfires.

- **Cooking and Warming:** The most common cause of fires in Alberta, from the data we analyzed there were about 8320 fires due to Cooking and Warming about 7000 more than the next highest cause. However these fires are moderate in size about 400 hectares on average.
- **Debris Disposal:** A significant contributor with about 1,100 incidents, although the fires were smaller on average, with an average size of 2.56 hectares.
- **OHV Operations:** While less frequent (160 incidents), these fires had an average size of 223.1 hectares, reflecting a significant environmental impact.
- **Arson:** Deliberate acts of fire-setting accounted for 712 incidents, with huge fires spreading over an average size of 316.9 hectares.

Table 1: Key Statistics for Wildfire Causes

Activity Class	Frequency	Avg. Fire Size (ha)
Cooking and Warming	8,320	478.5
Debris Disposal	1,176	2.56
OHV Operations	1129	47.33
Unclassified	1109	3.15
Arson	712	316.9

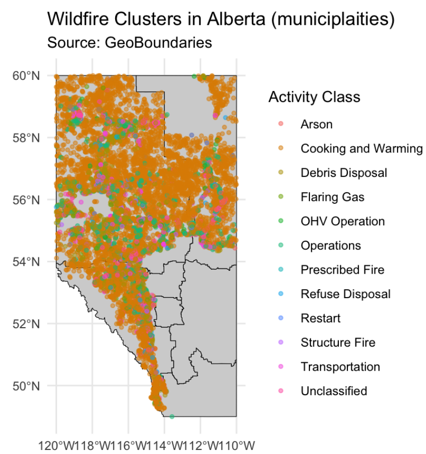


Fig. 1: Wildfire Clusters in Alberta

The data displays the importance of targeted interventions to reduce wildfire risks associated with avoidable human activities such as debris disposal, OHV operations, and recreational cooking and warming.

Table 2: Wildfire Network Centrality Metrics by Region

Region	Degree	Betweenness	Closeness	Eigenvector
Banff–Jasper–Rocky Mountain*	8	0	0.0182	1.0000
Calgary	8	0	0.0192	0.8922
Edmonton	8	0	0.0217	0.7532
Lethbridge–Medicine Hat	8	0	0.0238	0.6445
Red Deer	8	0	0.0270	0.5716
Wood Buffalo–Cold Lake	8	0	0.0196	0.7587
Athabasca–Grande Prairie–Pe*	8	0	0.0196	0.9486

– **Regions Experiencing the Most Fires:** The degree centrality of all the nodes is **8**, which suggests that all the regions are equally connected which suggests that the fire activity is equally distributed.
– **Eigenvector Centrality:** The **Banff–Jasper–Rocky Mountain** region has the highest eigenvector centrality of **1.0** while regions like **Athabasca–Grande Prairie–Pe** and **Calgary** have high eigenvector centralities of **0.95** and **0.89** respectively suggesting strong influence in the wildfire network and they likely experience the most significant wildfire events.
– **Closeness Centrality: Red Deer** followed by **Lethbridge–Medicine Hat** and **Edmonton** have the highest closeness centralities of **0.027, 0.023 and 0.021** respectively, suggesting they are geographically or environmentally well-positioned to influence or be influenced by fire activity in other regions.

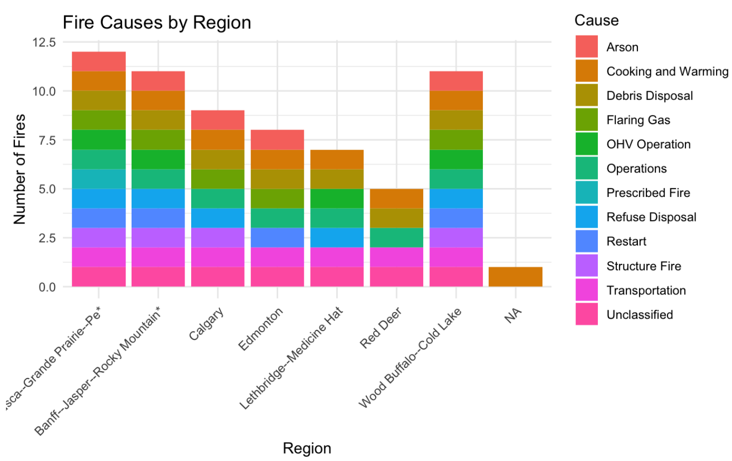


Fig. 2: Fire Cause by Region

Question 2: Which year experienced the largest wildfires in Alberta, and what were their defining characteristics?

The analysis revealed that 2023 had the largest total fire size among the years analyzed, with over 2 million hectares burned. This is a significant increase compared to other notable years, such as 2016 and 2019. While 2015 had the highest number of recorded fire events, the fires in 2023 were fewer but larger in scale. The key findings for 2023 include:

The bar chart in Figure 3 shows the total wildfire size by year, with 2023 clearly standing out. Additionally, the cumulative fire size chart (Figure 4) shows that the wildfire season in 2023 was heavily concentrated in May and June.

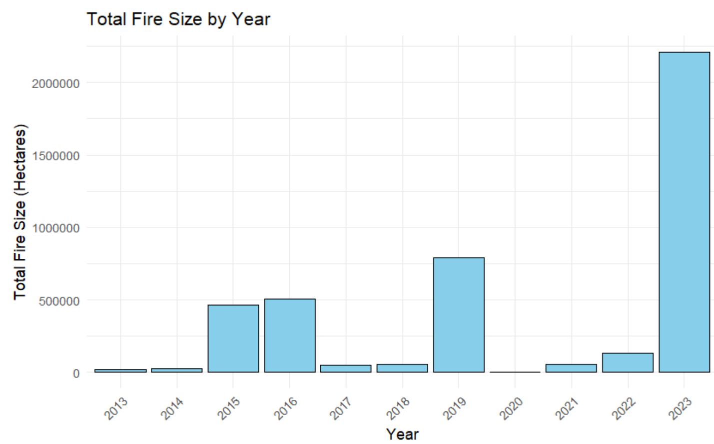


Fig. 3: Total Fire Size by Year. 2023 experienced the largest fire sizes, with over 2,000,000 hectares burned.

Table 3: Key Statistics for 2023 Wildfires.

Metric	Value	Description
Total Fire Size	2,000,000 ha	Largest fire year in the dataset.
Average Temperature	+20°C	Strongly correlated with large fires.
Peak Month	May	Most fires occurred during this period.

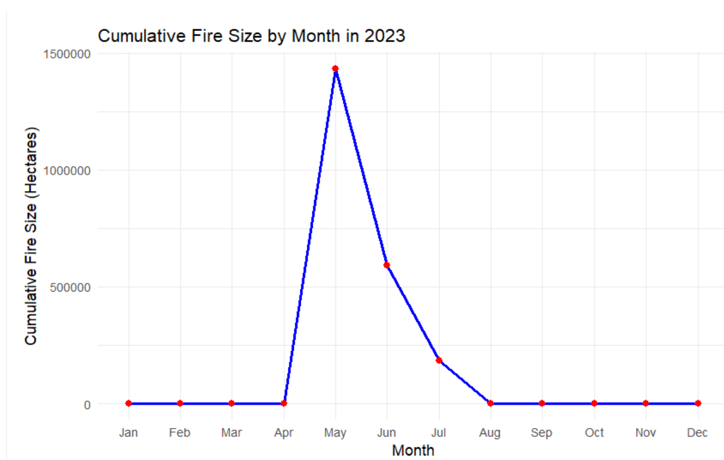


Fig. 4: Cumulative Fire Size by Month in 2023. The wildfire season peaked in May and June, with cumulative fire sizes exceeding 1.5 million hectares.

Question 3: Are larger wildfires more likely to have multiple causes, and do they play a critical role in connecting fire clusters?

Large Fires and Causal Diversity: The diversity of causes for large fires (such as "Cooking and Warming," "Debris Disposal," and "OHV Operations") suggests a multi-faceted origin for most of the fires in the network. This indicates that large fires often emerge from varied and overlapping human and environmental triggers, rather than a single isolated incidents. This finding supports the hypothesis that larger wildfires are more likely to have multiple causes due to the interplay of human activities, environmental factors, and their vast spatial extent.

The Role of Large Fires in the Network: Larger fires show higher Degree and Betweenness centrality metrics.

– **Degree Centrality:** Indicates these fires are highly connected within the wildfire network, with a higher number of direct links (edges) to other fires or clusters.

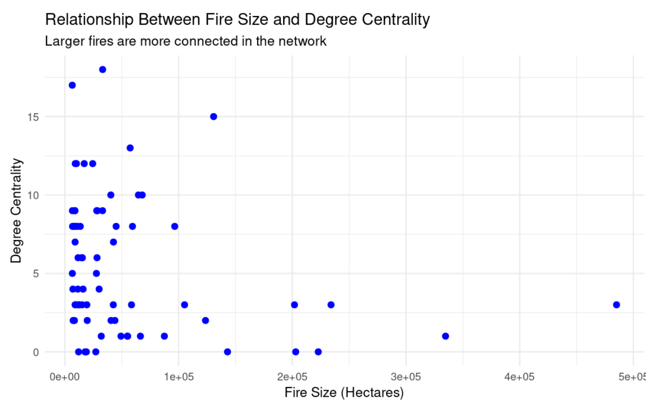


Fig. 5: Relationship Between Fire Size and Degree Centrality. Larger fires are more connected in the network.

The scatterplot shows that large fires (in hectares) tend to have higher degree centrality, indicating they are connected to more nodes in the wildfire network. Smaller fires cluster near the bottom of the degree axis, highlighting lower connectivity. Fires of larger sizes likely act as significant hubs within the network, impacting nearby clusters through shared causes or geographic proximity. The presence of larger fires in highly connected positions suggests their importance in overall fire cluster dynamics.

– **Betweenness Centrality:** Demonstrates that large fires serve as bridges connecting otherwise disconnected clusters of smaller fires, facilitating interaction or propagation.

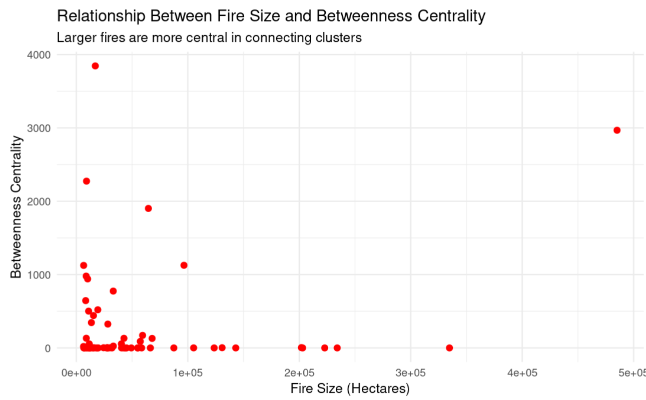


Fig. 6: Relationship Between Fire Size and Betweenness Centrality. Larger fires are more central in connecting clusters.

The scatterplot reveals a positive relationship for select larger fires, where fires with extreme sizes exhibit significantly higher betweenness centrality. These large fires appear crucial for connecting otherwise separate subclusters in the network. Smaller fires mostly exhibit minimal betweenness centrality. Large fires play a bridging role within the network, connecting distinct clusters of wildfires and facilitating interaction across fire groups. This implies their pivotal influence in the spread or co-occurrence of wildfires within Alberta.

These metrics highlight the strategic importance of large fires in the network. They act as connectors, influencing the spread of fire clusters and possibly playing a pivotal role in cascading wildfire effects.

Wildfire Network Visualization

The wildfire network visualization highlights the prominence of larger fires within the network structure. As shown in Figure 7, red nodes represent the largest fires (top 25% by size), emphasizing their central role in the network's connectivity. These fires are often at critical junctions, connecting dense sub-networks of smaller fires.

The strategic position of larger fires within the network indicates their role as focal points for wildfire management. Their connections suggest that managing large fires can disrupt or prevent cascading effects on smaller interconnected wildfires.

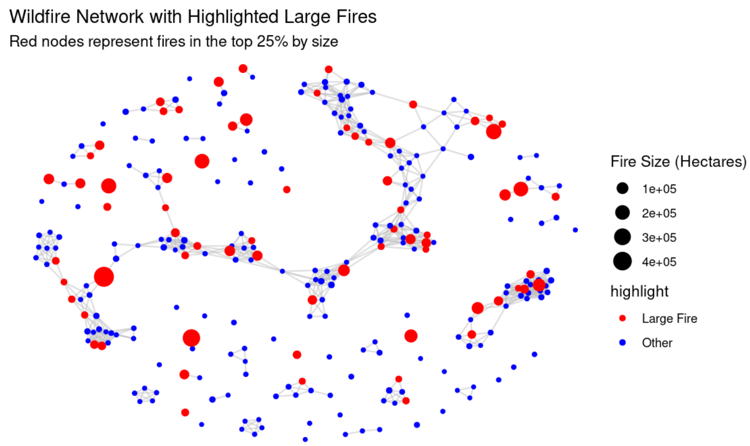


Fig. 7: Wildfire Network with Highlighted Large Fires. Red nodes represent fires in the top 25% by size.

Larger wildfires in Alberta demonstrate higher connectivity (degree centrality) and bridging (betweenness centrality) within the wildfire network. These fires play a significant role in connecting distinct clusters, underscoring their critical role in wildfire dynamics. Effective management strategies targeting these high-centrality wildfires could significantly mitigate wildfire spread and impact.

Question 4: How do environmental and geographical factors influence wildfire clustering and dominant causes in Alberta?

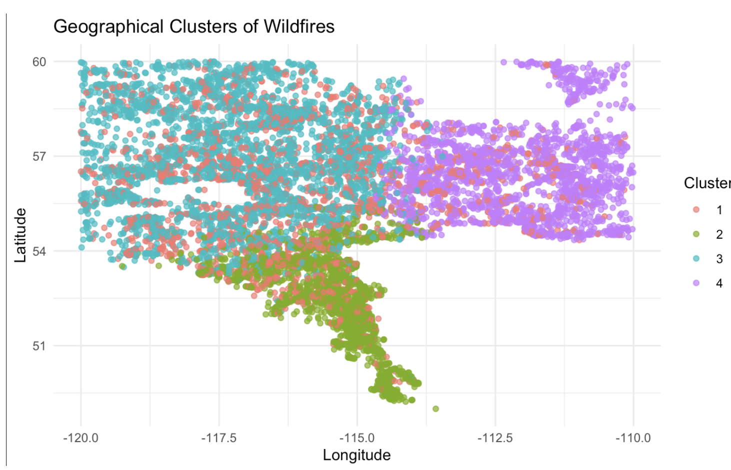
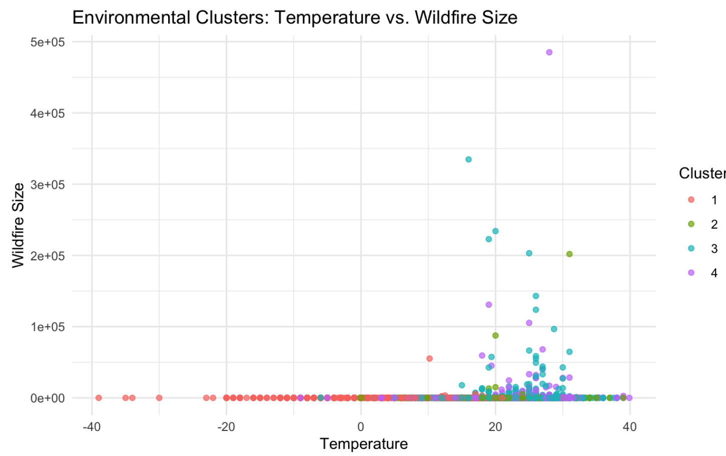


Fig. 8: Geographical Clustering of Wildfires

Wildfires were grouped into distinct spatial clusters based on their latitude and longitude. These clusters likely represent regions with shared environmental conditions or wildfire propagation patterns.



Clusters showed distinct relationships between temperature and wildfire size. Higher temperatures were often associated with larger wildfires.

Cluster Summary

Calculated average temperature, humidity, wind speed, wildfire size, and count of wildfires for each cluster.

cluster <int>	avg_temperature <dbl>	avg_humidity <dbl>	avg_wind_speed <dbl>	avg_size <dbl>	n_wildfires <int>
1	11.49364	68.99209	5.675773	26.46973	2782
2	18.81436	37.73879	6.876991	84.48062	4081
3	21.48840	37.64523	11.196847	617.58816	4059
4	19.55641	40.27747	9.316497	455.20165	3049

Fig. 9: Cluster Summary of Wildfires

- Average environmental conditions varied significantly across clusters:
  - **Cluster 1:** Higher temperature, lower humidity, moderate wind speed, and larger wildfire sizes.
  - **Cluster 2:** Moderate temperature, high humidity, and smaller wildfire sizes.
  - **Cluster 3:** Low temperature, moderate humidity, and minimal wildfire activity.
  - **Cluster 4:** Extreme wind speeds and scattered wildfire sizes.
- Each cluster differed in the number of wildfires it contained, indicating varying susceptibility across regions and environmental conditions.

Discussion

Overall Discussion

Human activities and climatic conditions are critical drivers of wildfire clustering and size. Larger fires act as key connectors in the wildfire network, amplifying their impact on surrounding areas. The findings emphasize the need for targeted interventions, such as focused fire prevention efforts in regions and months identified as high-risk, particularly during peak wildfire seasons. Addressing overlapping human and environmental triggers (cooking and warming, debris disposal, high temperatures, low humidity) can significantly reduce large-scale wildfire incidents. This study highlights the importance of integrating network analysis with environmental and geographical data to provide actionable insights for resource allocation, targeted monitoring, and policy-making.

Future research could further refine these models by incorporating additional predictors, such as vegetation types and topography, to enhance the accuracy and effectiveness of wildfire management strategies. Additionally, a comparison with existing literature highlights the study's unique contribution in bridging gaps through the integration of network analysis.

Our results confirm that human activities remain the primary driver of wildfires in Alberta, with "Cooking and Warming" fires outpacing other causes by a large margin. This dominance suggests a need for improved public education, especially in recreational zones where visitors may underestimate the consequences of unattended fires.

The presence of large, highly connected wildfires acting as central nodes within the network highlights the urgency to strategically allocate suppression resources to these hubs, potentially preventing cascades of smaller fires. Moreover, the strong correlation between higher temperatures and fires in 2023 aligns with broader climate change forecasts, reinforcing action on climate-adaptive strategies such as modified seasonal firefighting schedules and proactive vegetation management.

Limitations

While this study provides valuable insights into wildfire clustering and causes in Alberta, there are some limitations to consider:

- **Availability of Feasible Datasets:** The analysis was constrained by the availability of comprehensive and high-quality datasets. Some datasets lacked detailed temporal or spatial information, limiting the granularity of the analysis.
- **Unavailability of Certain Predictors:** Critical environmental and geographical predictors such as vegetation type, topography, and soil moisture were unavailable. Including these factors could have provided a more robust understanding of wildfire dynamics.

- **Generalization of Results:** The findings are specific to Alberta and may not be directly applicable to other regions with different environmental and geographical conditions. Further research is needed to validate the methods in diverse settings.
- **Simplified Modeling Assumptions:** Clustering algorithms like DBSCAN and K-Means rely on certain assumptions (e.g., fixed cluster shapes or densities) that may not fully capture the complexity of wildfire propagation patterns.

Addressing these limitations in future research could enhance the accuracy and applicability of wildfire clustering models and improve data-driven decision-making for wildfire management.

Challenges Faced and Overcoming Them

- **Data Quality and Preprocessing:** The dataset contained missing values and inconsistencies, particularly in geographical coordinates and activity classes. To address this, we applied rigorous data preprocessing techniques such as removing whitespace, filtering incomplete records, and validating coordinates. Additionally, the dataset gave an impression that all fire events had a unique number, but these numbers were only distinct by year instead of throughout the dataset. Hence, we had to create a unique identifier combining the fire name and fire number together, which took significant time due to the large data set and R's computational limitations.
- **Edge Construction and Computational Complexity:** Constructing edges based on geographical proximity (50 km threshold) was computationally intensive for our large dataset. To overcome this, we optimized the distance calculation process by filtering fires based on year and activity class before calculating distances. This reduced the computational burden while maintaining meaningful connections.
- **Tool Limitations and Compatibility Issues:** Some R packages (e.g., `rgeoboundaries`) were unavailable or incompatible with our system setup. We substituted these with alternative libraries (`rnaturalearth`, `sf`) to achieve similar functionality for mapping and spatial analysis.

Reflections and Improvements for Future Work

If we were to approach this topic again, we would consider the following improvements:

- **Expand Dataset Scope:** The analysis was limited to wildfires in Alberta. Including data from additional provinces or countries would provide a broader perspective and allow for cross-regional comparisons.
- **Advanced Machine Learning Models:** Machine learning algorithms could be employed to predict influential nodes or clusters based on historical data, enhancing the practical applications of the network analysis.

- **Stakeholder Collaboration:** Engaging with wildfire management authorities and domain experts would help refine research questions, validate findings, and tailor the analysis to real-world applications.

Conclusion

The wildfire network analysis has produced several findings and patterns. Using these findings, patterns, and other several metrics, a few conclusions can be drawn.

- **Key Regional Insights:** Regions like Banff-Jasper-Rocky Mountain, Athabasca-Grande Prairie, and Calgary are classified as hotspots, displaying high centrality measures suggesting they are responsible in the event of a wildfire to spread it to other neighboring areas.
- **Common Causes of Wildfires:** The most common cause of fires is cooking and warming, by more than 7000 counts. Along with cooking, other common causes are OHV operations and debtis disposal All of these are preventable by proper education and training.
- **Impact of Climate Conditions:** Analysis of 2023 data revealed a strong correlation between higher temperatures and increased fire sizes. Seasonal patterns further highlighted May and June as peak months for fire activity, underlining the importance of fire management during these months.

Suggested Solutions

According to the analysis conducted, most of these fires can be prevented with the correct etiquette, training and key investments.

- **Policy and Public Awareness:** Significant investments into fire prevention teams and safe debris disposal could prevent hundreds if not thousands of fires. Also heavily investing in education about cooking and making bonfires in the forest would significantly reduce fires.
- **Resource Allocation:** Investing in more fire fighters in peak summer months and active monitoring could also prevent future fires.
- **Further Research:** Extend the study to analyze inter-provincial wildfire dynamics, providing a more comprehensive risk mitigation strategy. More availability of datasets could also improve research quality.

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