Cellular Automata Modelling of the 2022 Keremeos Creek and Fry Creek Wildfires in British Columbia

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ABSTRACT

This project uses Cellular Automata (CA) to build a model of wildfire propagation using data of wildfires in British Columbia (BC) for 2022. Our model is inspired by previous CA wildfire models, and incorporates data on fuel types, road infrastructure, and topography to make a probabilistic model of wildfire spread for given ignition points under simulated wind conditions. Our model also incorporates stochastic processes to represent wildfire spotting. The project demonstrates the ability of CA models to represent fire propagation as a macro-phenomenon emerging from local interactions. Models were run five times each to capture different outcomes given the stochastic and probabilistic transition rules. Results show that the model results in comparable size, shape, and boundaries of the recorded wildfire perimeters given the same ignition points, though each ignition point can result in vastly different model outcomes given stochastic processes.

KEYWORDS

cellular automata; wildfire propagation; complex systems; British Columbia;

INTRODUCTION

Wildfire models are important for examining behaviour, propagation, and outcomes of wildfire and can be instrumental in planning mitigation efforts, emergency response, and evacuation. As described by Yassemi et al. (2008), CA is a mathematical modelling approach that uses a grid of cells with each cell representing a value within a defined set of values. The values of neighbouring cells influence the state of each cell according to a series of deterministic, probabilistic, or stochastic transition rules creating a successive set of new cells with the same or new values. Transitions rules are then reapplied on the raster output, modeling change over multiple iterations (or repetitions) of the model.

CA is useful for modelling wildfire as it is a 'bottom-up' phenomenon where broader patterns emerge from local combustion interactions. This project draws on the growing field of cellular automata models used to describe wildfires in British Columbia for 2022. Other models (Yassemi et al., 2008; Liu, et al., 2022) have successfully used factors such as cell proximity, combustibility, elevation, and wind to build their models. Liu, et al. used a separate data layer to show non-combustible areas such as major roads as inhibitors of wildfire spread. Boychuk et al. (2008) incorporate stochastic elements into their CA wildfire model to simulate wildfire spotting. Their results demonstrate wildfire's ability to traverse obstacles like roads and rivers.

Our model aims to address interactions of topography, wind, and fuel, the main factors influencing wildfire propagation, according to Bountzouklis, et al. (2022). This project incorporates data on topography, fuel, and built areas to create a suitability map, a neighbourhood window to represent wind conditions, while stochastic process represent wildfire spotting. Our model was calibrated using data for the 2022 Keremeos Creek Wildfire (K50863) (BC Wildfire Service 2023a, 2023b) (Figure 1), the same model was then applied to the Fly Creek (N71980) (Figure 2) of the same year.

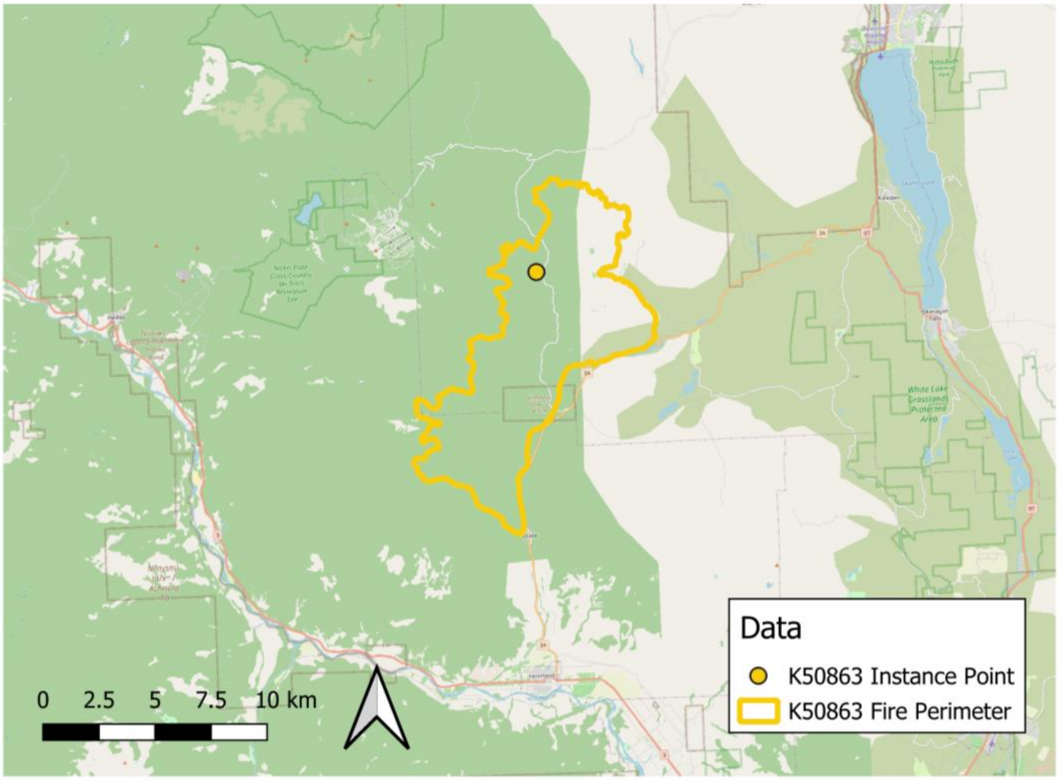


***Figure 1.** K50863 Perimeter and Incident Location (BC Open Data Catalogue, 2023a & 2023b) with Open Street Maps Basemap.

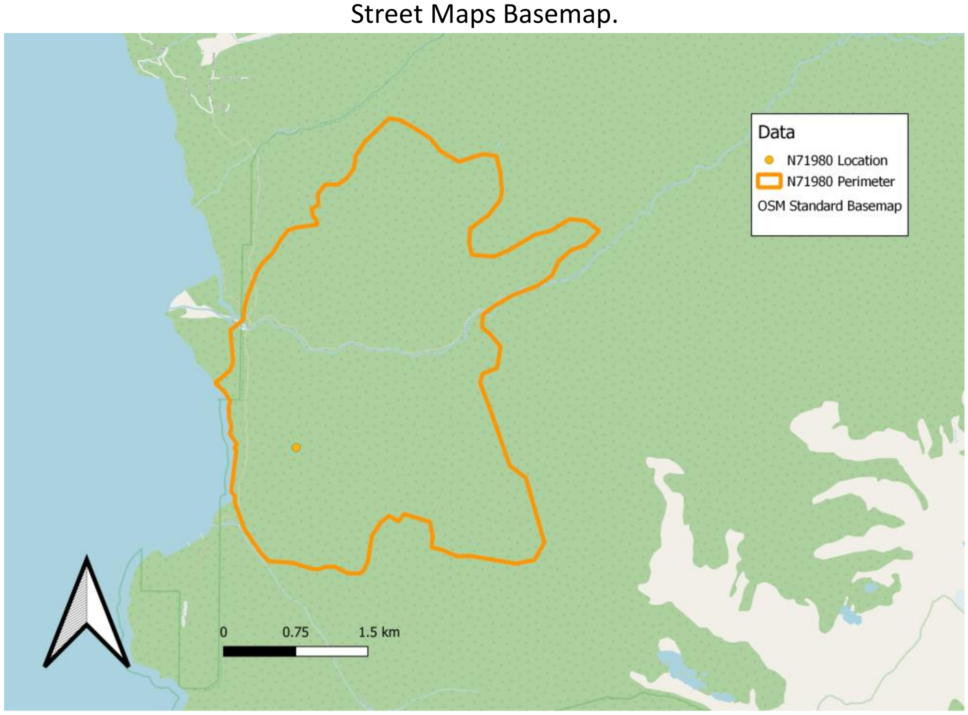


Figure 2. N71980 Perimeter and Incident Location (BC Open Data Catalogue, 2023a & 2023b) with Open Street Maps Basemap.

**All maps included in this paper make use of the NAD 1983 (2011) UTM Zone 11N CRS*

METHODS

Model

Suitability maps (Figure 6) were built for the study areas to assign each cell a probability of combustion based on fuel types, topography, and built areas. The project uses a 30m cell resolution as this is the resolution of the National Aeronautics and Space Administration’s Digital Elevation Model (NASA, 2015).

Fuel Types

Fuel type data from BC Wildfire Service (2022) is used to as our primary data source on combustibility. The data is current for the beginning of the 2022 fire season (Figure 5). The Initial Spread Index of the Canadian Forest Fire Behavior Prediction (FBP) System was used to determine the combustibility of different vegetation types (Figure 3). This index includes fuel types found in the study area and their rate of spread. From this index, fuel types were reclassified by flammability into high low and zero chance of ignition (non-vegetated and water) (Figure 4).

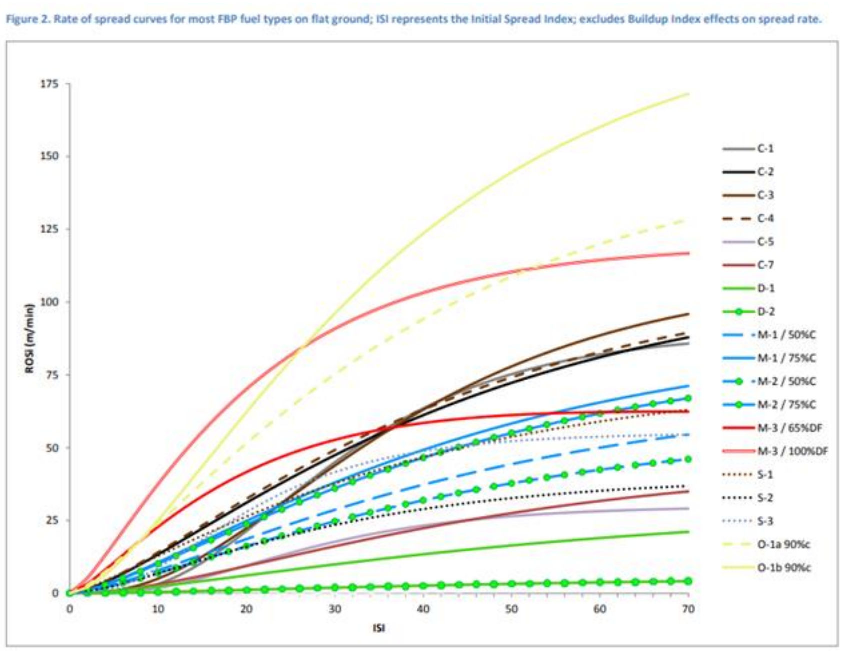


Figure 3. The ISI of Fuel Types was a Factor in the Suitability Map (Perrakis & Eade, 2015).

FBP Fuel Type	Assigned Value
N – Non-Vegetated	0
W—Water	0
D1 - Leafless Aspen	0.5
M1/2 - Boreal Mixedwood	0.5
C5 - Red and White Pine	0.5
C6 - Conifer Plantation	0.5
S1 - Jack or Lodgepole Pine Slash	0.5
S2 - White Spruce–Balsam Slash	0.5
C2 - Boreal Spruce	1
C3 - Mature Jack or Lodgepole Pine	1
C4 - Immature Jack or Lodgepole Pine	1

Figure 4. Assigned Values to FBP Fuel Types for Model Suitability Map where higher values represent higher probabilities for combustion.

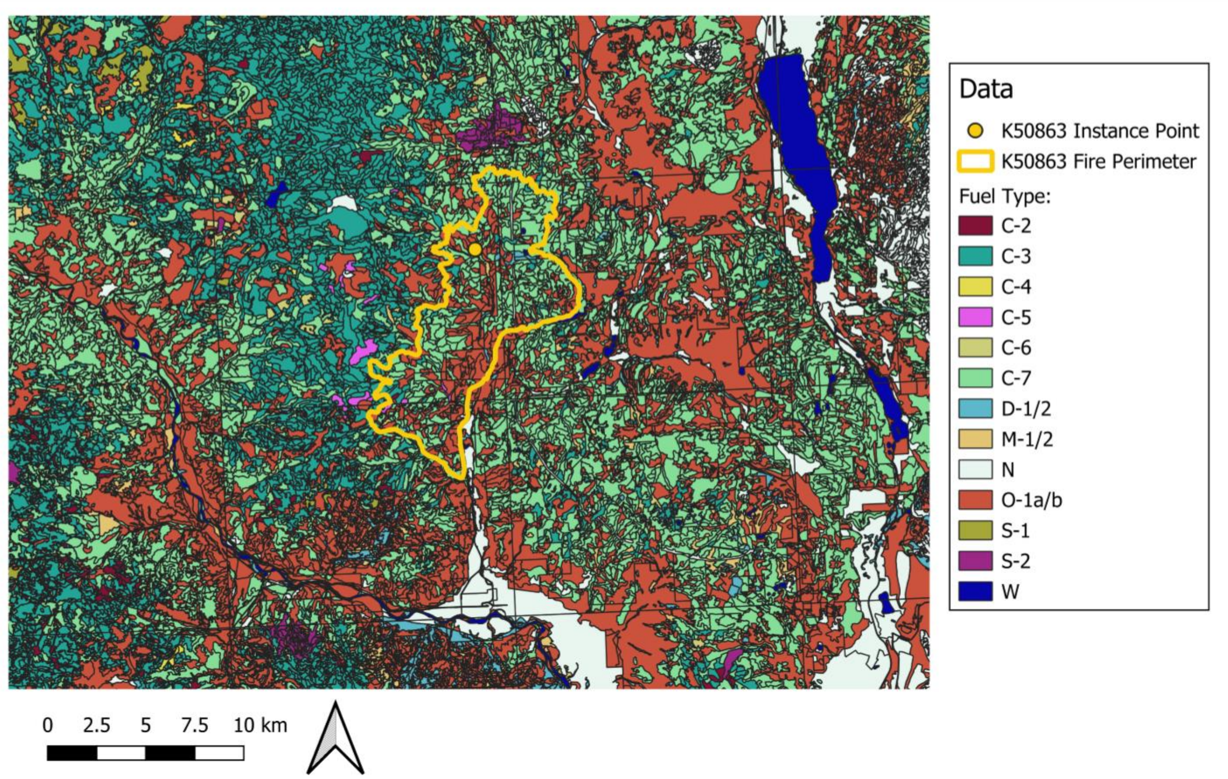


Figure 5. Map of Fuel Types (BC Wildfire Service, 2022) with K50863 Perimeter and Incident Location (BCOpen Data Catalogue 2023a & 2023b).

Neighbourhood

The neighbourhood function of a CA model represents which cells can influence transitions within the central cell. The neighborhood function of this model is used to represent wind. The neighbourhood window was based on data from Environment Canada weather stations in the region for maximum gust speed and gust direction for given days. These were used as an indicator of general wind conditions for the period. The neighbourhood shape means that regions downwind from ignited cells are more likely to catch fire. During sensitivity analysis, different neighbourhood windows and extents were tried. Experimentation arrived at the method described in Figure 9 to determine the neighbourhood windows (Figure 7, 8). Sensitivity analysis involved trying different variable modifiers v1 and v2 to determine the appropriate size and shape of the neighbourhood window for the model (Figure 9).

Stochastic Processes

Wildfire spotting is an unpredictable, stochastic process that is widely considered to be one of the most difficult problems in wildfire management (Martin & Hillen, 2016). Thus, stochastic transition rules within a set neighbourhood are used to represent wildfire spotting. Within our model cells within a certain proximity of combusting cells have a 10% chance of spontaneously combusting. This creates a unique model output each time the model is run.

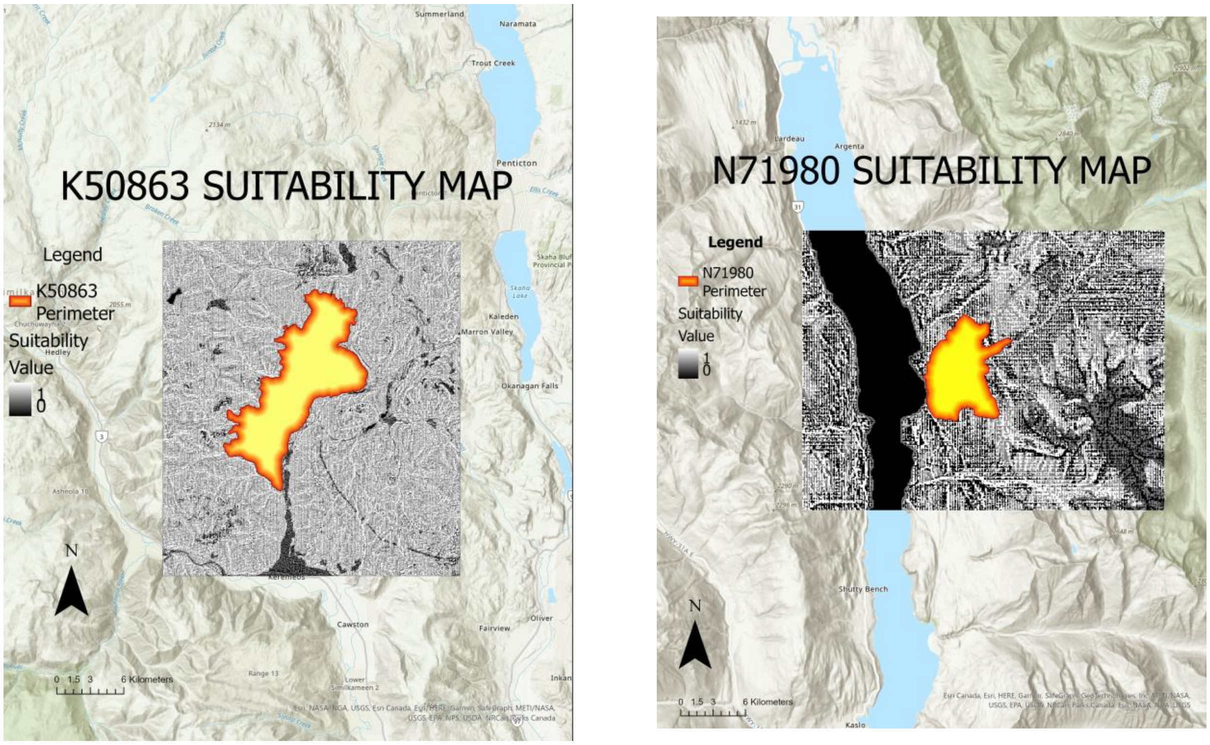
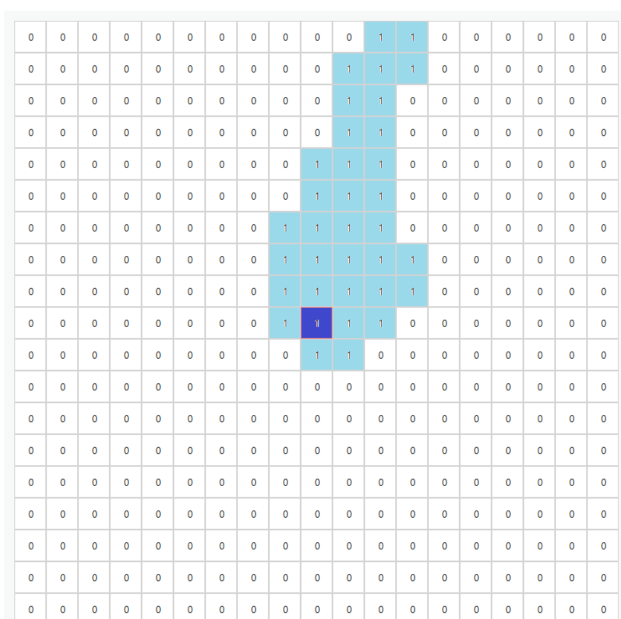


Figure 6. Suitability Maps for K50863 and N71980.



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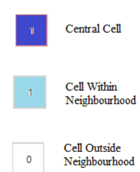

Figure 7. The Resultant 19x19 Neighborhood Applied to the Keremeos Creek Wildfire, The Window was Calculated using Average Wind Conditions for the Penticton Weather Station.

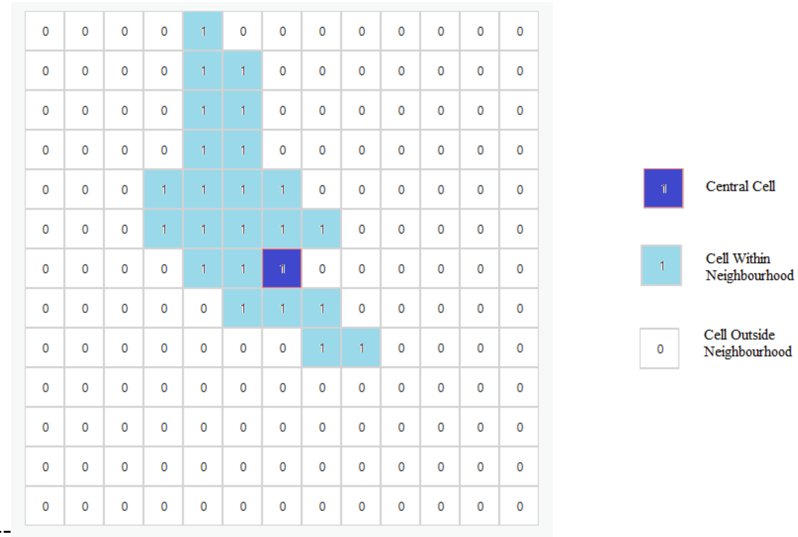

Figure 8. The Resultant 13x13 Neighborhood Window Applied to the Fry Creek Wildfire, The Window is Based on Compiled Weather Data from Golden and Nelson, BC.

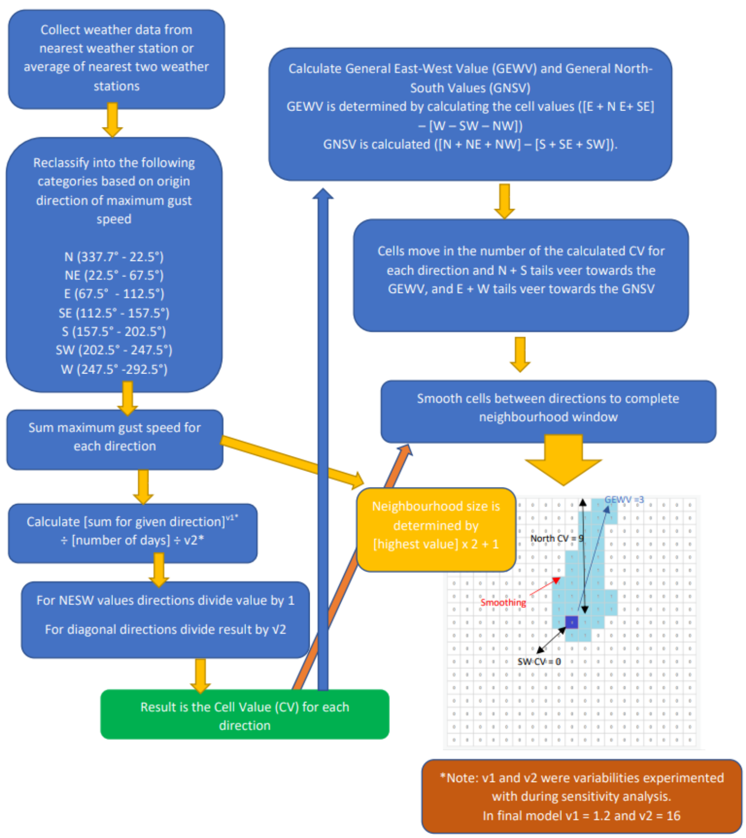

Figure 9. Workflow for Determining and Creating the Neighbourhood Window.

Temporal Scale

Each iteration of the model represents a period of one day.

Calibration & Validation

The model was calibrated using the K50863 fire with a 30m cell-size and extent of 771 columns by 869 rows. The fire perimeter grew for a period of 35 days between July 29 and September 2, 2022, given our temporal scale of one iteration per day, the calibration model was run for 35 iterations (Figure 10, 11). This calibrated model was then applied to another fire, the N71980 for model validation. The study area of N71980 is 534 columns by 412 rows using the same cell size. The fire began on September 1, 2022, and reached its maximum perimeter on September 15; therefore, the verification model uses 15 iterations with a one-day temporal scale (Figure 12, 13). Validation in a crucial step in CA modelling to assess how accurately the model can be applied to other scenarios. Satisfactory performance in model evaluation is a good indicator of a model's ability to represent wildfire outcomes.

RESULTS

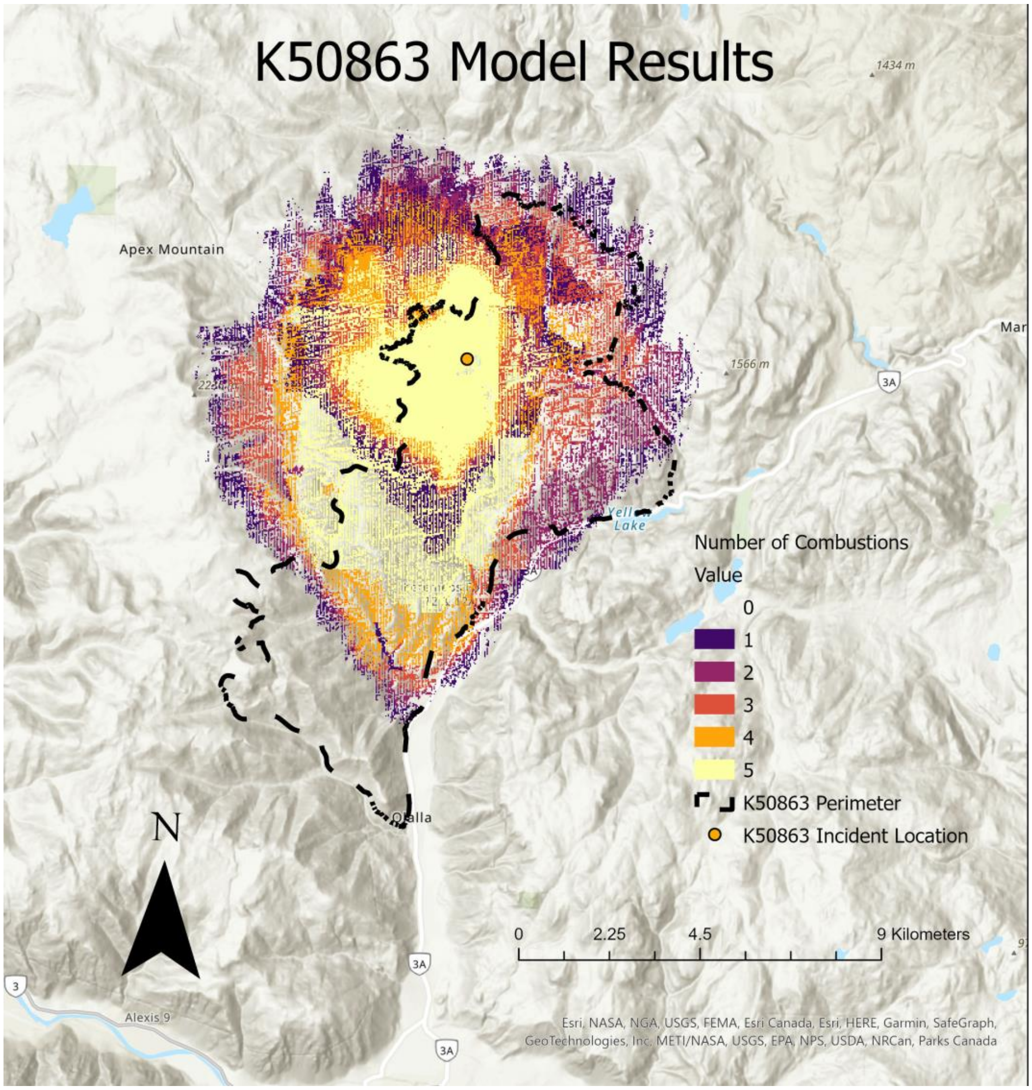

Figure 10. K50863 Model Results after 5 Model Runs Overlayed Together
(1 model iteration for K50863 is 35 iterations).

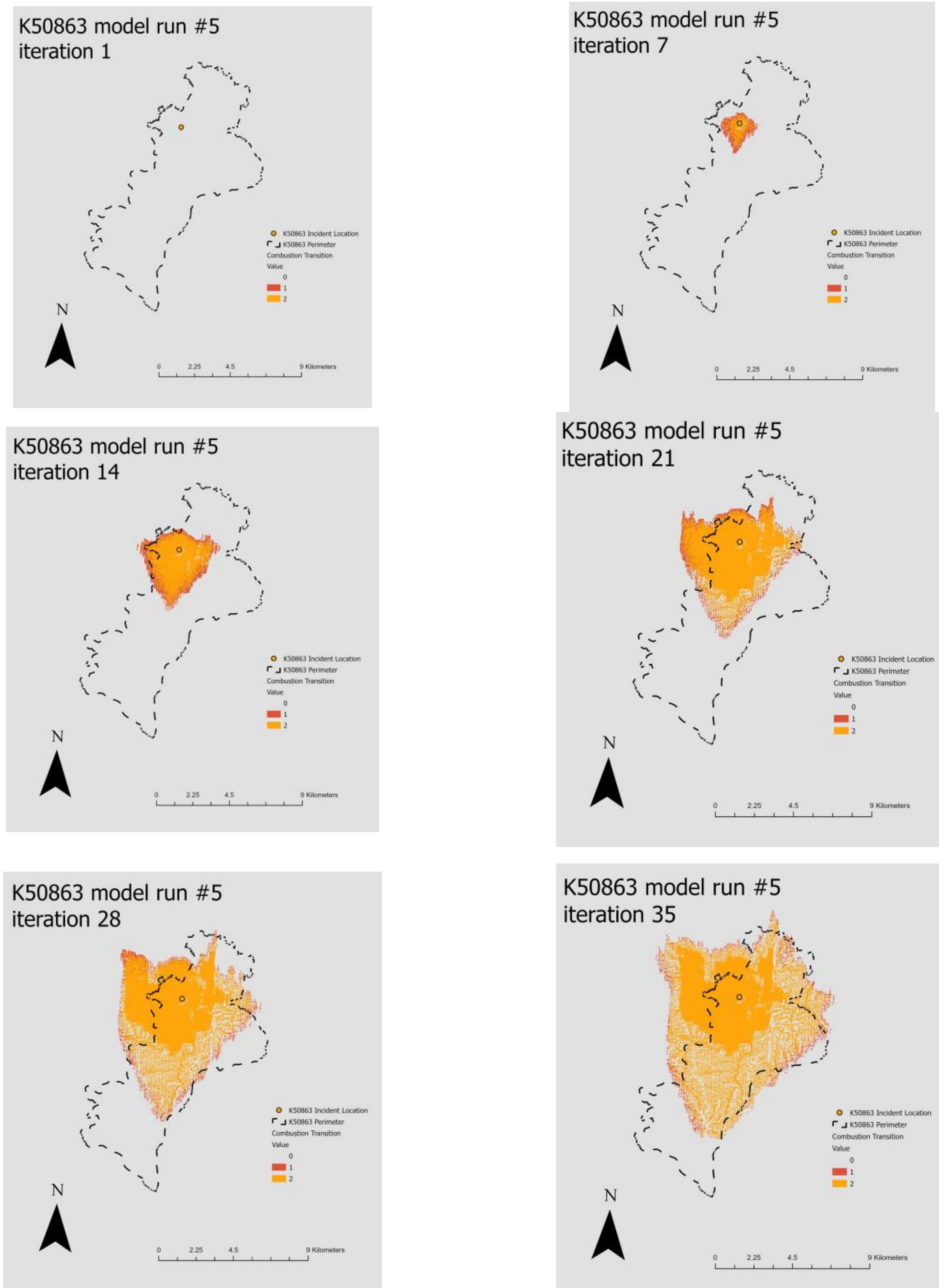

Figure 11. K50863 Model Results on Run 5 of iterations 1, 7, 14, 21, 28, 35.

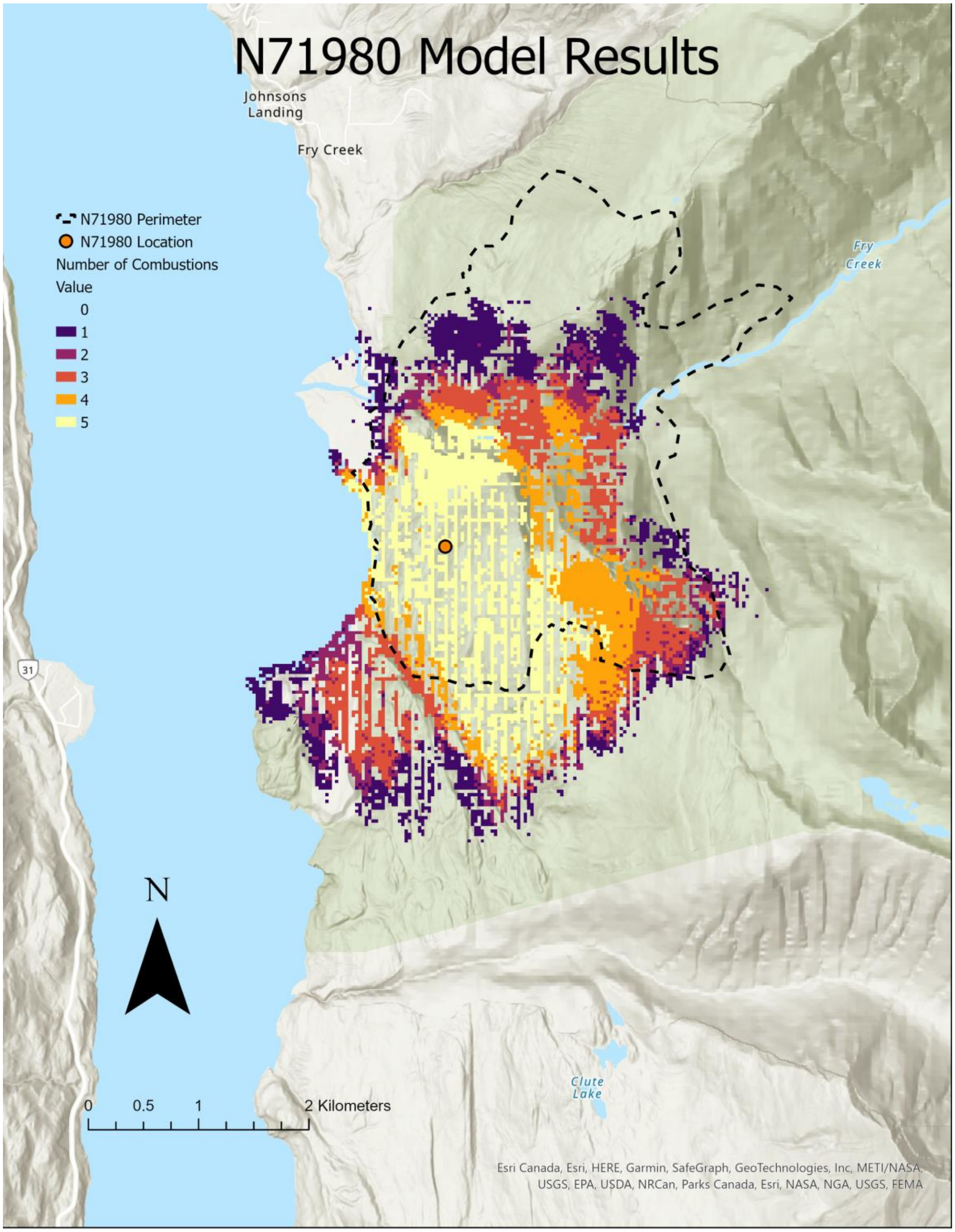

Figure 12. N71980 Model Results after 5 Model Runs Overlayed Together (1 model run for N71980 is 15 iterations).

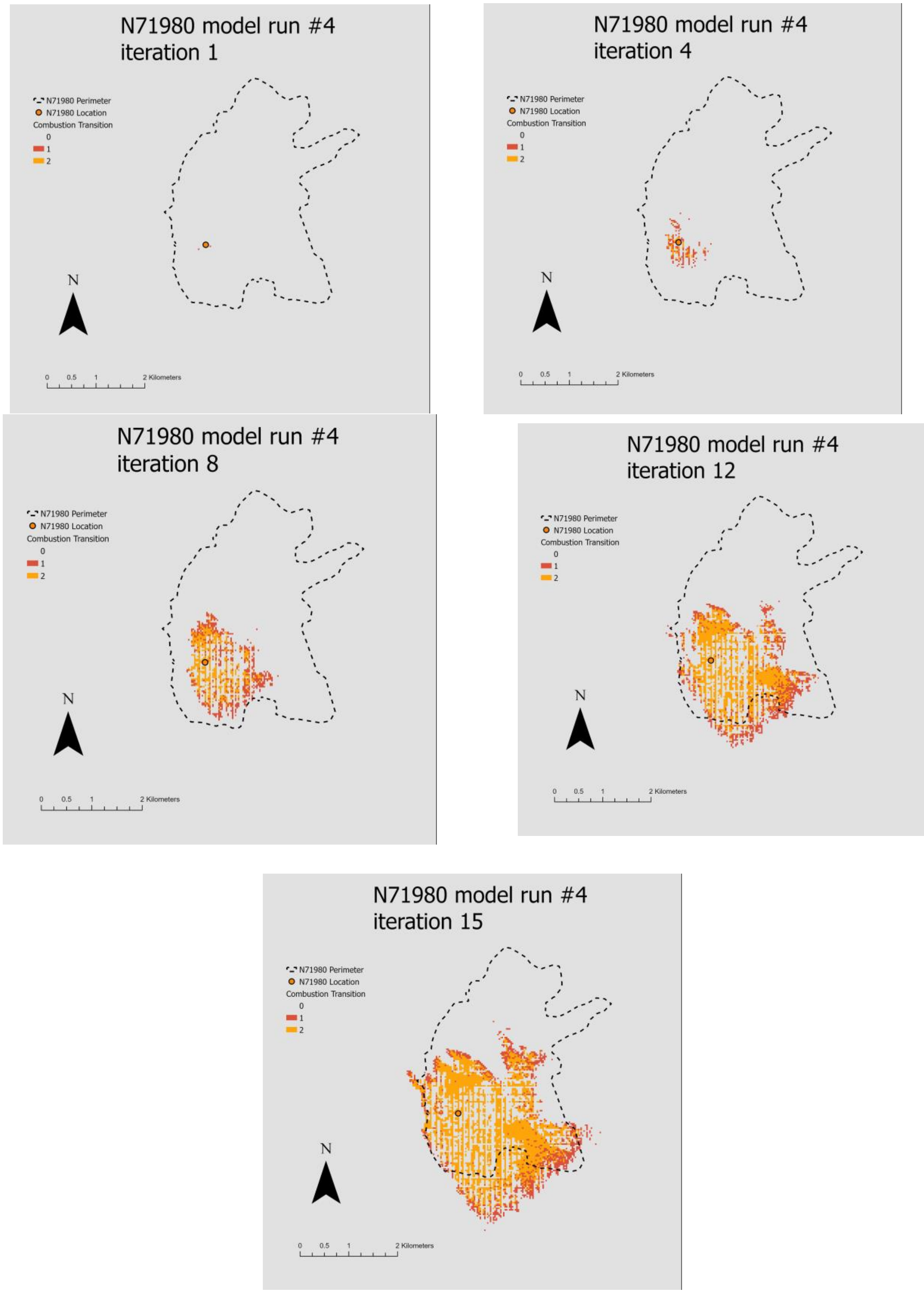

Figure 13. N71980 Model Results on Run 4 of iteration 1, 4, 8, 12, 15.

DISCUSSION

Visual evaluation of model outputs show they share boundaries with the recorded fire perimeters (Figure 10, 12) showing how topography, water features and the built environment define the boundaries of wildfire spread. The model succeeds in demonstrating interactions between data layers but has limitations. The one-day time increment is too large to capture the minute-by-minute permutations of real fires. The neighbourhood window is based on an aggregated sum of wind conditions. The window was calculated using the direction and speed of the maximum gust for each day within the period (Figure 7). These are used as indicators of prevalent wind conditions, but do not represent dynamic localized wind conditions in a realistic way.

The effect of slope was calculated using ArcGIS Pro's Surface Parameters tool. A value is assigned to each cell representing whether its neighboring cells elevations are higher than or lower than the central cell. This generalizes the process of fire movement, but more advanced programming of transition rules could better represent the influence of slope on fire propagation. The effects of wind and slope could be improved in future versions of this model but would require additional coding. Multiple runs of the model show how slight changes in stochastic mechanism of wildfire spotting produce vastly different outcomes over-time. Future improvements to this work including increasing the number of models runs to least 30 times to be considered statistically significant.

CONCLUSION

CA can capture how wildfire patterns emerge from local interactions under the influence of factors like fuel type, wind patterns and local topography. The model has limitations and is not an accurate representation of all wildfire processes but is able to represent the dynamic spatio-temporal development of wildfire using real-world data. Our results show how CA models can represent complex systems while using deterministic, probabilistic, and stochastic processes of multiple system components. However, wildfires are a dynamic complex system and there are characteristics of wildfire behaviour that CA is not able to capture completely. Certainly, this model helps us better understand and visualize the life cycle of a fire as it transitions from combusting to extinguished states, but wildfire behaviour is unpredictable. Our model is better intended to show how underlying factors influence wildfire behaviour, rather than a predictive tool. It shows how one fire ignition point could lead to many different outcomes. These forecasted outcomes help us better understand fire behaviour to improve mitigation and risk management practices in the future.

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REFERENCES

Bountzouklis, C., Fox, D. M., & Di Bernardino, E. (2022). Environmental factors affecting wildfire-burned areas in southeastern France, 1970–2019. *Natural Hazards and Earth System Sciences*, *22*(4), 1181–1200. https://doi.org/10.5194/nhess-22-1181-2022

Boychuk, D., Braun, W. J., Kulperger, R. J., Krougly, Z. L., & Stanford, D. A. (2007). A Stochastic Model for Forest Fire Growth. *INFOR. Information Systems and Operational Research*, *45*(1), 9–16. https://doi.org/10.3138/infor.45.1.9

Liu, L. *et al.* (2022). Establishment and Simulation of Forest Fire Spreading Model Based on Cellular Automata. In: Chu, SC., Chen, SH., Meng, Z., Ryu, K.H., Tsihrintzis, G.A. (eds) Advances in Intelligent Information Hiding and Multimedia Signal Processing. Smart Innovation, Systems and Technologies, vol 277. Springer, Singapore. https://doi.org/10.1007/978-981-19-1057-9_13

Martin, J.; & Hillen, T. (2016). The Spotting Distribution of Wildfires. *Applied Sciences*, *6*(6), 177. https://doi.org/10.3390/app6060177

Perrakis, D.D.B., & Eade, G. (2015). British Columbia Wildfire Fuel Typing and Fuel Type Layer Description. BC Wildfire Service HQ. www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/wildfire-management/fire-fuel-management/bcws_bc_provincial_fuel_type_layer_overview_2015_report.pdf

Yassemi, S., Dragićević, S., & Schmidt, M. (2008). Design and implementation of an integrated GIS-based cellular automata model to characterise forest fire behaviour. Ecological Modelling, 210(1), 71–84. https://doi.org/10.1016/j.ecolmodel.2007.07.020

DATA

BC Wildfire Service. (2023a). *Fire Incident Locations – Historical [Vector Dataset].* British Columbia Data Catalogue. https://catalogue.data.gov.bc.ca/dataset/fire-incident-locations-historical

BC Wildfire Service. (2023b). *Fire Perimeters – Historical [Vector Dataset]*. British Columbia Data Catalogue. https://catalogue.data.gov.bc.ca/dataset/fire-perimeters-historical

BC Wildfire Service. (2022). *BC Wildfire Fire Fuel Types – Public [Vector dataset].* British Columbia Data Catalogue. https://catalogue.data.gov.bc.ca/dataset/bc-wildfire-fire-fuel-types-public

ro. *Digital Road Atlas (DRA) - Master Partially-Attributed Roads [Vector Dataset]*. British Columbia Data Catalogue. https://catalogue.data.gov.bc.ca/dataset/digital-road-atlas-dra-master-partially-attributed-roads

Environment Canada. (2023). Historic weather data [CSV dataset]. https://climate.weather.gc.ca/climate_data/daily_data_e.html?StationID=50269

National Aeronautics and Space Administration (NASA). 2015. *Digital Elevation/Terrain Model* – N49W120 *[Satellite Raster Image]*. NASA EarthData Open Access for Open Science;

https://www.earthdata.nasa.gov/topics/land-surface/topography/terrain-elevation/digital-elevation-terrain-model-dem