fire

Supplementary Material

Considerations for Categorizing and Visualizing Numerical Information: A Case Study of Fire Occurrence Prediction Models in the Province of Ontario, Canada

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1. Other Applications of the Method

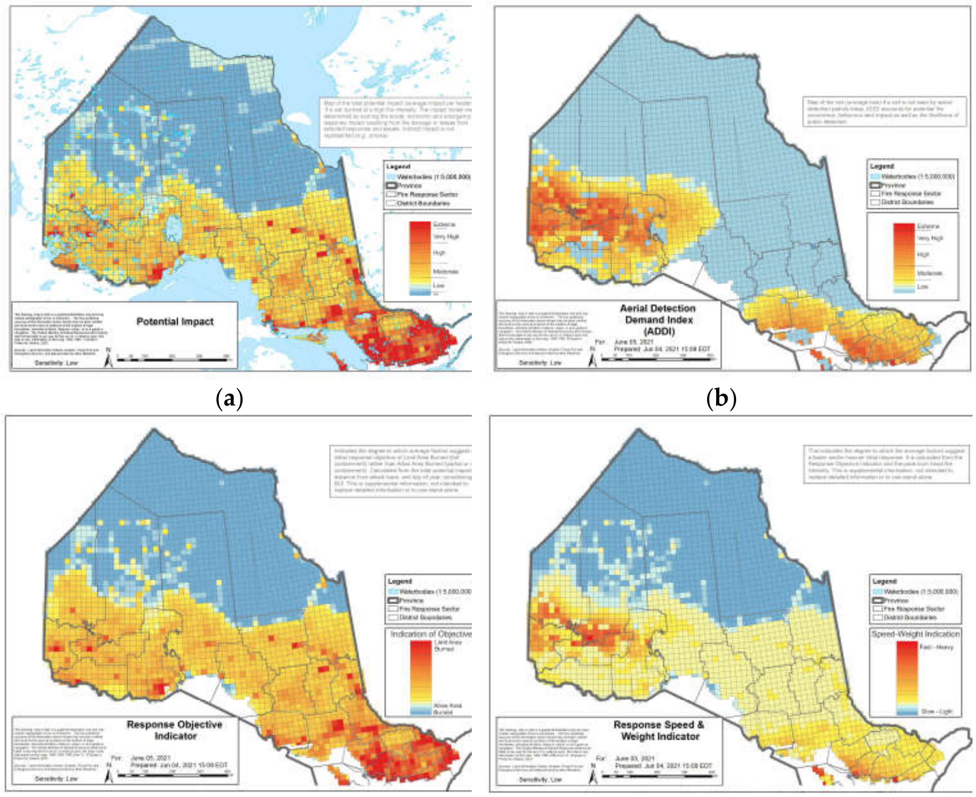
Although our method was developed for fire occurrence prediction (FOP) model outputs, we believe that many of the features and principles can be useful for other applications in fire management and beyond. The design options of the method are in retrospect simple and logical. For example, where appropriate, use:

- Truncation, where resolution is not needed at the end(s) of the range
- Nonlinear category boundaries, to have relatively higher resolution in some part(s) of the range
- Colours, to show the data clearly, and colour psychology, to draw suitable attention to them

The design options, their interactions and the need to make trade-offs among their effects seem generally applicable to many different datasets. The specific design options chosen would of course depend entirely on the specific application.

Applications of our method to other fire management decision support model outputs are shown in Figure S1. All these examples use roughly the same design options as for FOP, but with different truncations and parameter settings for the paper's Equation 1. In all cases, decision-makers are more sensitive to differences at low values of the indicators than at high values, so the class boundaries are smaller at the low end than at the high end. In all cases, the same colour sequence is used, although with different adjective descriptors in some cases. Figure S1a shows data which indicate the potential impact to resources and assets if they were burned by high-intensity fire [1]. The highest impacts are in dense urban areas. This and the following indicators are described in detail in their respective cited references. Figure S1b shows data that indicate the value of seeing cells by aerial detection today [2]. The indicator's driving factors include FOP, the potential impact in Figure S1a, fire intensity and the probability of public detection. Figure S1c shows data indicative of the degree to which the factors indicate that the initial response objective for a fire will be complete containment rather than partial or nil containment [3]. The indicator's driving factors include the potential impact in Figure S1a, fuel moisture conditions as the end of the fire season approaches and a surrogate for the response cost. Figure S1d shows data that indicate the relative speed and weight of initial attack for a fire, given a full-response objective [3]. The indicator's driving factors include the potential impact in Figure S1a and the fire intensity.

To illustrate the effect of our method, we show examples of the evolution over several years of our classification and colouring schemes (Figure S2a–d). Figure S2a is an early prototype of the holdover lightning-caused fire occurrence prediction map. Of the four categories, the red (Extreme) category is relatively rare, and the blue–green–yellow sequence draws progressively less attention to the rising level of concern. Figure S2b is an early prototype of a combined human- and lighting-caused map with 10 classes using the traditional green–yellow–orange–red sequence and the inconsistent scaling shown in the paper's Figure 6. That caused the human-caused, lighting-caused and total fire maps to have different colouring for any given FOP magnitude. Figure S2c used the same categories and scaling as Figure S2b, but with a colour palette that accommodates some types of colour vision deficiency, and alludes to being a "heat map" for the level of concern. Figure S2d is an example of the current classification and colouring scheme.



(**a**) (**b**) (**c**) (**d**)

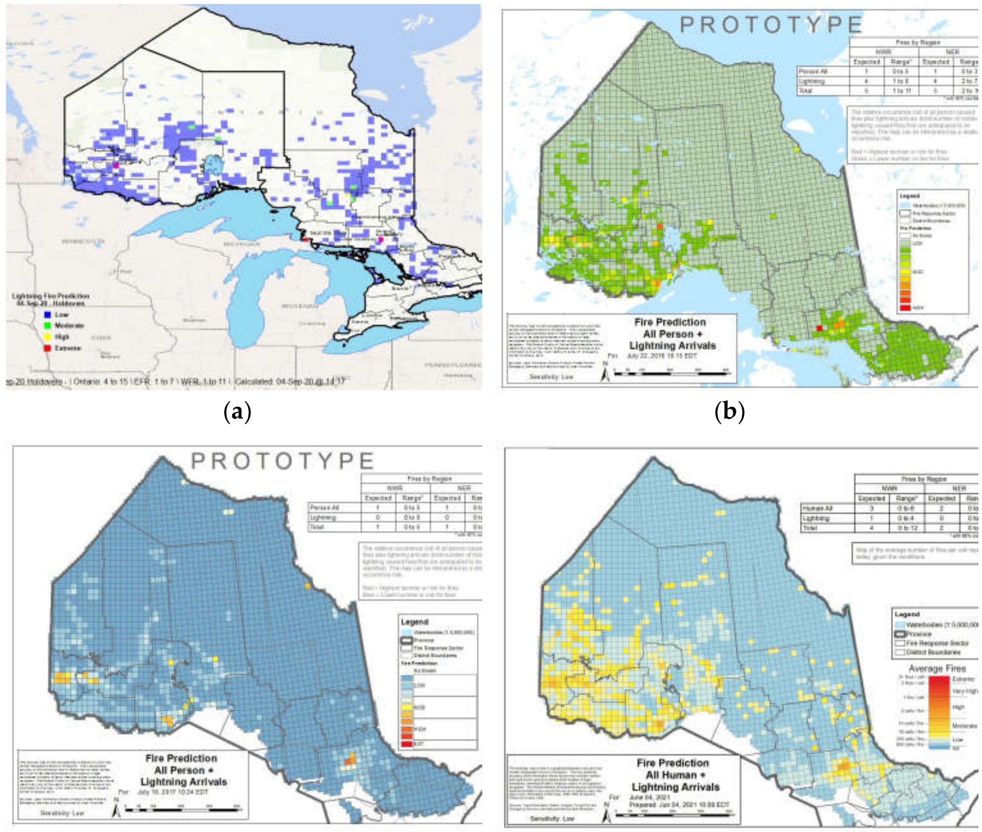
Figure S1. Examples of other model outputs that we categorized and coloured using the method presented in this paper: (**a**) indicator of the potential impact to resources and assets, if burned by a high-intensity fire [1]; (**b**) indicator of the value of seeing cells by aerial detection today [2]; (**c**) indicator of the degree to which factors indicate that the initial response objective for a fire will be complete containment rather than partial or nil containment [3]; (**d**) indicator of the speed and weight of initial attack for a fire, given a full-response objective [3].

2. Classification of Numbers for Operational Significance

The principle of simplifying information for speed of understanding can be applied to numerical data that are not necessarily coloured and mapped. For example, there may be no operational significance for differences of 5, 10 or more points for some Fire Weather Index (FWI) System [4] outputs in some parts of their ranges—for example, when the Drought Code (DC) gets into the hundreds. Decision-makers routinely look at tables that have hundreds of observed and forecast weather and FWI System outputs. As a demonstration, scan the following sample of 10 DC values. The first row is given in the usual precision of the nearest integer, and the second row is rounded to the nearest 10. Given that DC is associated with depth of burn and difficulty of extinguishment, which is faster and easier to absorb and use in this context?

- Station: A B C D E F G H I J
- DC: 146 179 257 272 294 323 222 325 326 178
- DC: 150 180 260 270 290 320 220 330 330 180

Note that displaying DC to integers has the benefit of showing the dynamic behaviour of the model—for example, that the DC rises by 4–6 points without precipitation, depending on other conditions.



(**a**) (**b**)

(**c**) (**d**)

Figure S2. Examples of earlier classification and colouring schemes that show the evolution of our method: (**a**) a 4-category scheme; (**b**) a 10-category scheme with the traditional green–yellow–orange–red sequence; (**c**) the same categories and scaling as for Figure S2b, but with colouring that accommodates some types of colour vision deficiency; (**d**) the current scheme.

3. Additional Considerations for the Spatial Display of Data

We noted that our case study used maps with a predetermined 20 km × 20 km resolution. We did not test other resolutions, but resolution seems to affect the results and should be considered. We illustrate with an example how the spatial resolution can affect the appearance of the mapped information. Figure S3 shows the same underlying data—the Fire Behaviour Prediction System's [5] fuel type—mapped at four different resolutions. Each gives a distinctly different impression about the landscape. There is no perfect resolution; they are all approximations. What is best for a particular application will likely depend on (1) the meaning and purpose of the data being displayed and (2) the nature and scale of decisions being informed.

We used a different dataset to demonstrate the averaging of fine-scale, heterogeneous data to the coarse-scale grid. Figure S4 shows data from a model of the potential impacts to resources and assets, if burned by a high-intensity fire [1]; at 100 m × 100 m (1 ha) and 20 km × 20 km (40,000 ha) resolutions. The high spatial variation within cells is understood by decision-makers but not seen in the coarse grid. This averaging is a necessary simplification for the decision-makers to be able to use the vast amount of information for province-wide preparedness planning. This highlights the need to design visualizations for the decision-making scale, for example, regional preparedness vs response to specific fires.

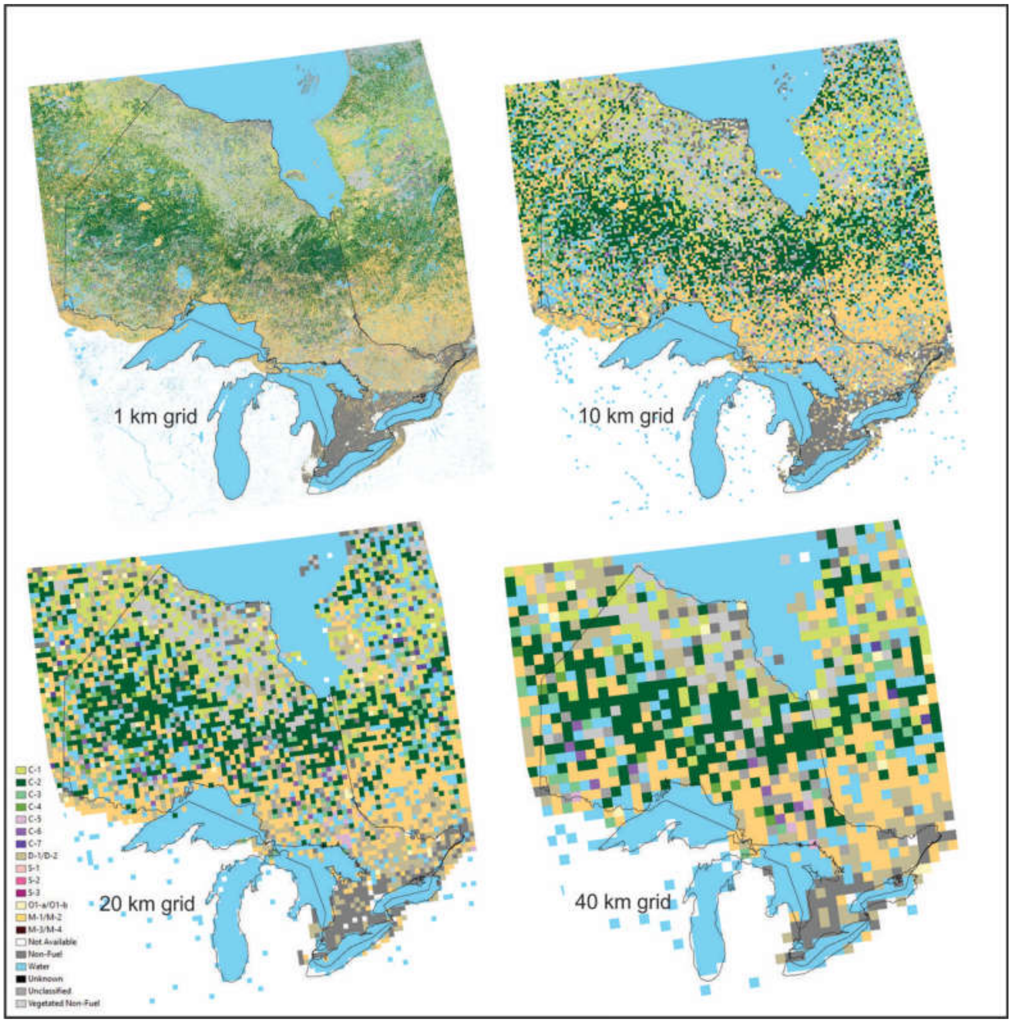


Figure S3. Mapping of the same underlying fuel type data at four different resolutions: 1, 10, 20 and 40 km. The fuel types are defined in [5], but those details are not relevant for the demonstration that each resolution gives a distinctly different impression about the landscape.

In this context, it is important to remember another consideration in designing the display of spatial data. The above cases involved simplifying spatial information when there is too much spatial data, i.e., reducing resolution by averaging. In contrast, interpolation involves the opposite case, where there is too little spatial data, so gaps are filled using interpolation. The reminder is to use appropriate interpolation methods, as demonstrated by [6]. Operational maps can look significantly different when the data are interpolated differently. We showed the use of the point data in combination with interpolation in fire operations for FWI System outputs (see the paper's Figure 1b). In addition to overcoming the coarseness of categorization, showing the data points arguably addresses the limitations of interpolation and highlights some of the uncertainty between the data points. A detailed review of the current FWI classification methods is outlined in [7].

A final consideration is that there are alternatives to the choropleth maps used so far. The nonlinear scale used to categorize FOP maps was customized for the needs of detection planning and other decisions, where actions vary relatively less at the higher FOP magnitudes. In contrast, when planning for heavy initial attack workloads, low FOP magnitudes are of lower concern, while high magnitudes are critical. For that decision, it may be useful to design a separate FOP map with a different scale and colouring to draw attention accordingly. Alternatively, different visualizations, such as simulated three-dimensional maps (Figure S5), may be effective for highlighting peak FOP areas of concern. It may be necessary, however, to make three-dimensional maps interactive, since the parts of the map may be obscured by three-dimensional imagery "in front", necessitating a change in the viewing angle. See [8] for an example of this when visualizing daily time series of FWI over multiple years.

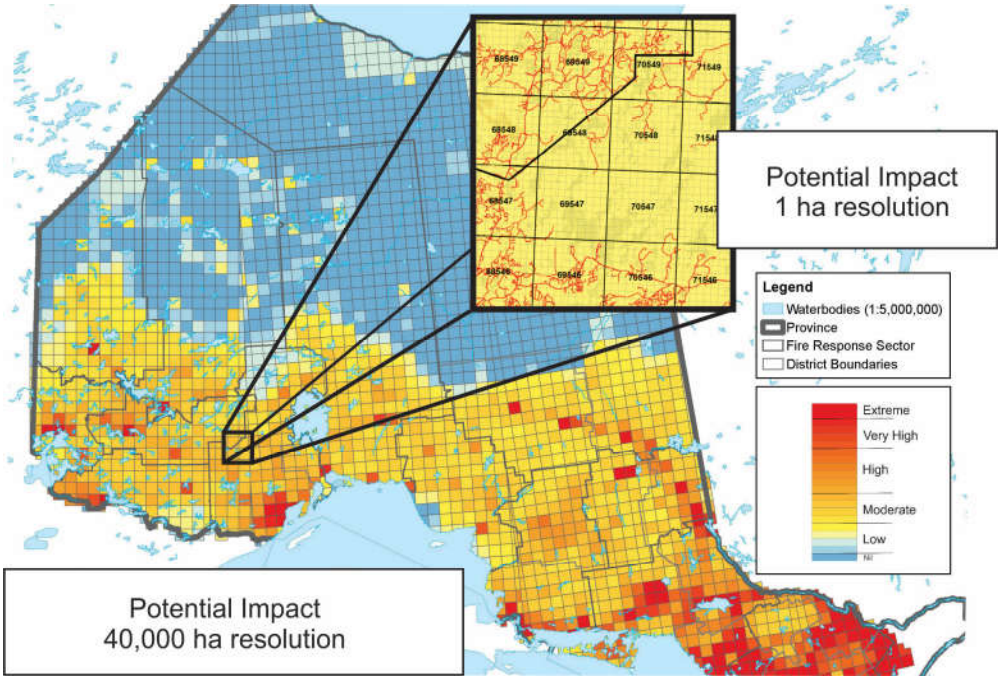


Figure S4. Comparison of the impact factor at different spatial resolutions—20 km × 20 km (40,000 ha) and 100 m × 100 m (1 ha)—using the same numerical and colouring scales for display. A 20 km × 20 km cell that has a moderate average impact has many areas within it that have impacts ranging from low to extreme.

The additional considerations outlined in this section are beyond the scope of our method, but merit at least an ad hoc inclusion in the design process.

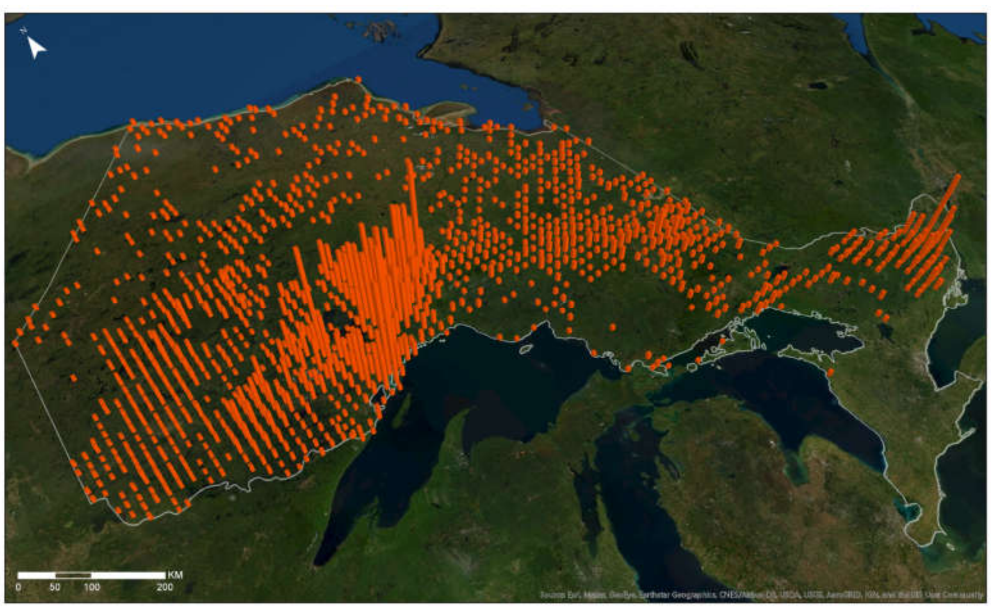


Figure S5. An example of a total human- and lightning-caused fire occurrence prediction displayed using a simulated 3-dimensional map. This may be an effective alternative to choropleth maps for displaying peaks of concern.

4. Larger Versions of Maps

Figures S6, S7 and S8 are larger versions of the maps in the paper's Figure 7a–c.

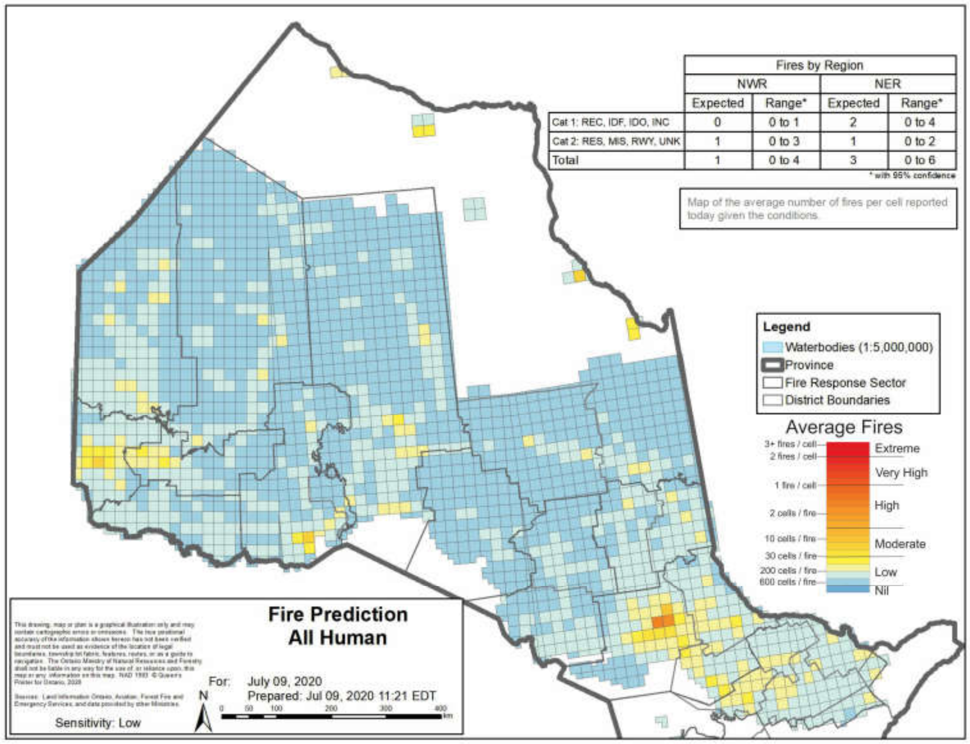


Figure S6. A larger version of the paper's Figure 7a.

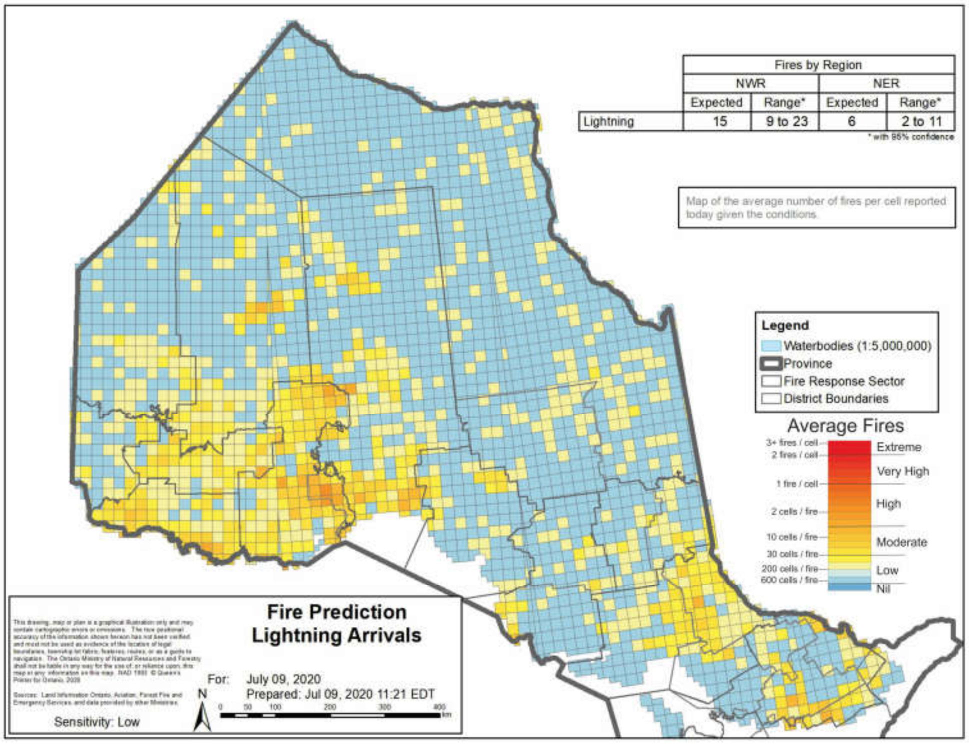


Figure S7. A larger version of the paper's Figure 7b.

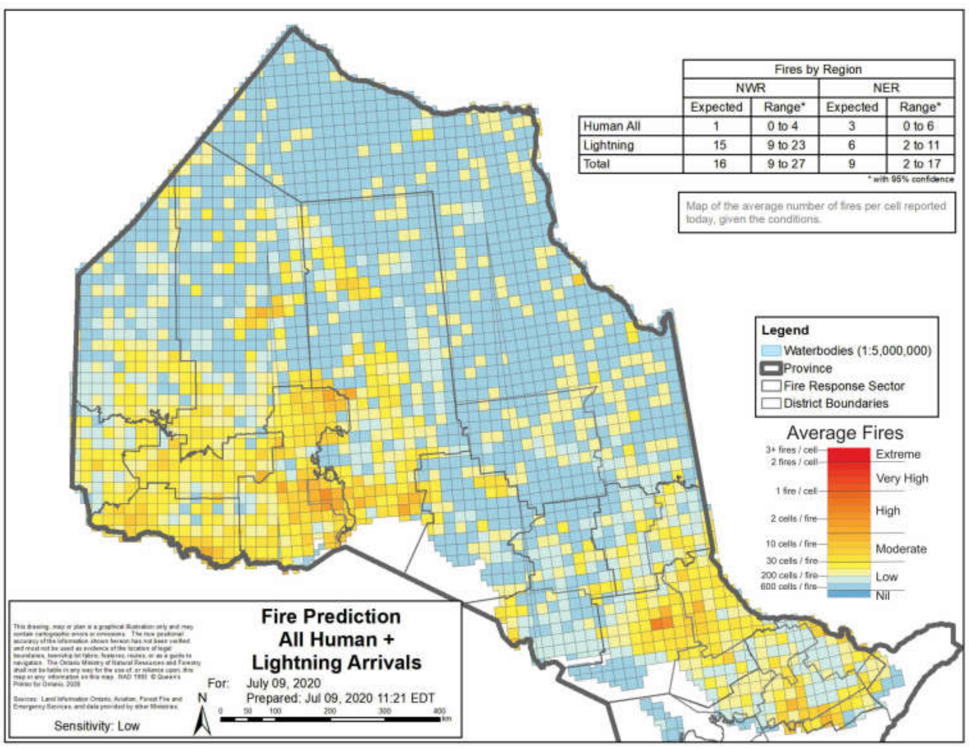


Figure S8. A larger version of the paper's Figure 7c.

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