Reviewer 1

General comments

The authors present an interesting study that has practical implications for wildfire management in Canada and potentially beyond. The authors explore the discrimination of grassland wildfires from agricultural/managed) fires in South Central Canada. Using terrestrial datasets and high-resolution Landsat 8 data, the authors carefully construct and classify a dataset of MODIS fire clusters and explore the relationships between these two classes of fire and various environmental/meteorological variables using GAMs and regression tree (RT) models. The work results in a series of parameter thresholds and value ranges that appear to be useful for pinpointing periods when wildfires are most likely, and could likely be used to enhance operational wildfire management in future. This manuscript certainly merits publication in NHESS, however there are several areas where it could be improved prior to publication:

The narrative and structure could be improved throughout (see specific comments)

The methods need expanding, particularly with respect to the predictors chosen for inclusion in the models (some of this may be suited for inclusion in the supplementary materials).

3) Some of the results/discussion points could be elaborated on further, and the importance of this work better highlighted.

>>> We thank the reviewers for their careful reading of the manuscript, and we document our responses and revisions below.

Specific comments

Abstract I would specifically refer to MODIS in the abstract, so it is immediately clear to readers what your primary RS dataset is.

>>>We revised the abstract to read: " Daily polar orbiting satellite MODIS thermal detections since 2002 were used as the baseline for quantifying wildfire…"

1 Introduction

[39] For clarity I would amend to something like "…control) is somewhat limited, and can erroneously count responsible fire use…"

>>> Revised as suggested.

[44] also add precipitation here?

>>>Changed to : "Fire weather is quantified using daily temperature, precipitation, humidity, and wind speed…"

[65-70] It would be good to elaborate on the goals slightly here. From reviewing this paper, my understanding is that you are particularly trying to use the GAM for goal 1, and then goal 2 is informed by both models, so I would state this more explicitly. Also, related to this, I would probably address here (or perhaps in Section 2 somewhere, under the current structure possibly

in 2.4) why you are building 2 different models e.g. you use the tree approach primarily for explanation, and the GAM for both prediction & explanation? I don't think you clearly state anywhere your motivation for using 2 different approaches.

>>> We've added a whole section 2.1 that immediately follows the goals stated at the end of the introduction. The section more explicitly states the workflow. We explain the rationale for the simplified decision tree at the end of section 2.1: "These known agricultural and wildfire hotspot clusters and associated fields were then used to create a Generalized Additive Model (GAM), which was used to classify the unknown hotspot clusters into agricultural or wildfires and produce maps of their relative occurrence (goal 1). Additionally, a decision tree model was also built on the confirmed wildfire vs agricultural hotspot clusters, to provide simplified classification thresholds (goal 2) for use in fire operations and as the basis for potential public warning criteria."

[66] I would say "documented grassland wildfires" here just to make the focus completely clear.

>>>Changed to: "…to contrast that with documented grassland wildfires in the region."

2 Materials & Methods General comment on methods: A lot of my questions / comments on Section 2 relate to dataset attributes that are either not provided or found in different subsections of the text. You use a lot of different datasets from different sources in this study, so a concise 'datasets' or 'materials' subsection that provides a list of each of these with useful basic information (data source, spatio/temporal coverage, resolution etc, as relevant) at the beginning of Section 2 would be useful – then readers can find all this information in one place without having to move backwards and forwards through different sub-sections.

>>> We now provide Table 1, which summarizes the datasets and their properties. We thank the reviewers for this helpful suggestion.

2.1 Study Area

Figures 1 & 2: These figures are very nicely presented, however it is not immediately obvious which areas are the study area. At first, I thought it was all of the area for which landcover data are provided, i.e. including the forested regions. From looking at later figures, I think the Ecumene delineates the study area? I would suggest you consider changing the name of this to 'study area' for clarity, and change the colour of the boundary to something more obvious that the current grey, then maybe emphasise exactly where the study area is in the Figure 1 caption. Also, consider adding some of the info from the main body on the LC dataset to Figure 1 caption, and adding lines and/or ticks indicating lat/lon to these maps, as you refer to lat/lon locations in text – a reader not familiar with the region will have no context for this.

>>> Map insets have been modified to show only study area, all in black to help clarify study area. Lat/lon grid lines were added to maps. Caption revised to: "Remotely-sensed land cover data at 30 m resolution (Agriculture and Agri-Food Canada,

2018) of our study area as of 2010 compared to the extent of the ecumene. The study area extends past the ecumene to ensure all grass and agriculture are included. The majority of fires analyzed in this study occurred within the agricultural ecumene."

In figure 2 – What data is shown in this plot exactly? The full MODIS fire record (i.e. contains fires in non-grassland as well as grassland fires) or just data after the filtering step described on line 138? The label 'Grass hotspot clusters' – makes me think the latter? As with Fig 1, I would expand this caption to include this kind of detail for clarity, also probably adding: whether this map is post-persistent hotspot filtering; the specific MODIS product it was derived from; the associated MODIS dataset citation.

>>>Caption changed to: "Figure 2: Grass fire MODIS(MOD14A1 and MYD14A1)(Giglio, 2015) hotspot clusters in the study area from 2002–2018. These hotspot have been screened for persistent industrial heat sources and clustered as described in the methods."

2.2 Fire occurrence records

[93] I would consider stating the number of fires recorded over the study period from the CNFDB and evacuation dataset somewhere in this paragraph.

>>>Added: ". Eighty-four hotspot clusters representing wildfires were identified using the CNFDB and 15 additional hotspot clusters were identified using the evacuation record and were not otherwise recorded in the CNFDB." Added after clustering description.

[94] I find the logic a bit confusing in the sentence on lines 94-96 (starting 'in the agricultural zone…') – perhaps reword it? You say that large fires are included in the CNFDB, but also that the CNFDB is 'only a partial sample' of fires in the region – so maybe you should be highlighting the fires that are not captured in this region by the CNFDB, rather than those which are?

>>> Revised to: " In the agricultural zone, the CNFDB provides only a partial sample of wildfires in the region. The agricultural zone is not located in the provincial wildfire agencies area of responsibility, therefore, in this zone, only larger fires that required a mutual aid response from provincial agencies are documented in the database."

[106] what is the source of the FWI data? Presumably the official CFFDRS datasets, but worth clarifying here.

>>> We clarify the source of the FWI data as: "A 3-km grid of daily basic surface meteorology at 12:00 local time (air temperature, humidity, 10-m wind speed, and precipitation sum over prior 24 h) as well as Canadian Fire Weather Index system variables using inverse-distance weighting (Lee et al., 2002) was constructed. The rasters constructed use the same surface station data as McElhinny et al., 2020."

[101-110] I think you should probably state the number of total MODIS fire detections and introduce the clustering concept here with detail on the number of fire 'clusters' resulting from the clustering process described in the supplement.

>>> Revised as suggested. We rearranged the manuscript so the clustering process was introduced here and included the number of clusters.

2.3 Satellite grass curing

[125] I'm confused as to how exactly this metric works. Eq 1 is the widely used min/max scaling (aka normalisation) applied to the NDVI climatology, so high values should imply high 'greenness' i.e. low curing? As such it is confusing to refer to this metric as 'percent curing' (also indicated in your GAM figure panel (b) x-axis as 'per-pixel relative cured grass fraction (%)'). Inverting this relationship (or renaming it) might be more intuitive? Moreover, from reading line [188] in the results you say "high percent curing (i.e. low NDVI…" which seems to be the opposite of Eq. (1), so there seems to be some confusion regarding how this metric is calculated somewhere? Did you actually invert this metric but omit this detail from this section?

>>> Our mistake. The equations should have a 1 minus in front of it. That is a typographical error, and the equation in the analysis is correct. Low NDVI is high curing, and high curing corresponds to high fire potential. We use this curing fraction value to be consistent with the fire behaviour models, which using curing % from 0 to 100, rather than NDVI or greenness.

I would also add the comment you make in the Landsat figure (the first Figure 3) caption to the main text somewhere here – that extremely high curing values can (somewhat counterintuitively) reflect prior agricultural burning/ploughing activity rather than dry veg – as this an important observation.

>>> In the first paragraph of the results, we now state: "The curing fraction of the grass or agricultural residue is lower for wildfires compared to agricultural fires (Fig. 4b), which may be due to low NDVI(high curing) artifacts from tillage (Zhang et al., 2018) or adjacent previously burned area in the larger MODIS pixels. " We did not before add the comment on the previously burned area as we did in the figure caption.

[138] I do not think the paragraph starting 'All hotspot clusters…' belongs in Section 2.3 as it stands. You don't really mention 'fire clusters' until Section 2.4, so it should go after this point. However, if you altered the MODIS paragraph [lines 100-110] in Section 2.2 by briefly describing the clustering process (that you describe in detail in the supp. materials), then this 'All hotspot clusters…' paragraph could follow fit in 2.2. Furthermore, it is probably worth explicitly stating how variables were aggregated by clusters, rather than your current explanation in the supplement "An attribute was merged by max value, min value or mean, for each hotspot cluster, whichever was most appropriate" [line 39], as this not very detailed.

>>> Rearranged as suggested. Revised to include how variables were merged in supplementary material.

2.4 Classification of thermal detections

[145] more background information regarding (1) the model predictors and (2) model construction process is definitely required in Section 2 (some of which could go in the appendices, if necessary). For clarity purposes, I think you definitely need to explicitly state and describe all the predictors that were added to the two models, along with their source (information

could be in table form, and possibly a ‘datasets’ subsection as mentioned earlier), and where relevant, why those specific predictors were chosen over others. For example, FFMC, FWI, ISI often convey similar information -why was FFMC and not FWI or ISI chosen as predictors in the GAM, but ISI is used in the RT?

>>> We now clarify our choice in model selection inputs. For the GAM: “Variables included for consideration in the GAM include surface weather variables, day of year, satellite curing fraction, as well as the fuel moisture codes (FFMC, DMC, DC) from the Fire Weather Index system. Higher-order components of the Fire Weather Index System such as Initial Spread Index and Buildup Index were not used due to their derivation from fuel moisture codes and high correlation (Spearman’s $\rho > 0.7$) with those codes.” And for the classification tree, we clarify: “Additionally, classification trees were constructed using the *rpart* package (Therneau et al., 2019) to classify wildfires from thermal detections using a simple conditional threshold-type model for use as simplified warning criteria (maximum of two variables). Inputs directly related to hotspot detection were not included (i.e. FRP), as they are only obtained upon fire detection. Variables that integrate multiple weather factors into a single index (i.e. Initial Spread Index or Buildup Index) were considered.”

From reading the results section, I see that ‘hour of detection’ is derived from the MODIS dataset, however conceivably this could be information contained in the NFDB, and this sort of thing should be obvious from the methods. I would indicate any standardisation / scaling of variables used in models here – e.g. DMC and DC were presumably scaled, as indicated in Fig 5(d) and detailed in section 3.

>> We now clarify that the NFDB does not contain hour of detection data. We now clarify in section 2.2: “Off-nadir collections (Freeborn et al., 2014) were also utilized and the detection-specific detection hour was used.”

Did you test for and exclude any variables from the models based on collinearity using e.g. a simple correlation threshold? I assume you made some such decision here, as for example, you have omitted ISI & FWI as GLM predictors, and they are typically strongly correlated with e.g. FFMC. Similarly, I suspect RH and FFMC could be highly (negatively) correlated. Please explain how you addressed this.

>>> We now clarify this in the methods: “Higher-order components of the Fire Weather Index System such as Initial Spread Index and Buildup Index were not used due to their derivation from fuel moisture codes and high correlation (Spearman’s $\rho > 0.7$) with those codes. The high correlation ($\rho = -0.73$) between relative humidity and FFMC is noted, but both were used in the GAM. All other variables in the GAM were correlated $\rho < 0.5$, and thus suitable for landscape-level fire weather analysis and modelling (Parisien et al., 2012).”

[149] what is your reasoning for not including interaction terms? Is this something that was initially explored and found to be unimportant, or were they not considered for simplicity reasons? I would be surprised if there were no relevant interactions between at least some of the predictors you have chosen to use.]

>>> We've added the text to clarify our choice in GAM models: " The non-linear partial effects terms in GAM models have been found to be superior to linear models with interactions in the examination of wildfire-environment data (Woolford et al., 2010)."

[150] re: the argument for excluding curing from the RF model – does this logic not also extend to the GAM?
>>> That was included in error from a prior version of the manuscript. It has been deleted.

3 Results

[160-170] if you add a description of the predictor variables/datasets in Section 2, you can omit the 'background' info you include here: defining the DMC, explaining derivation of the FFMC, explaining the fact that FWI vars are observed at noon etc. These type of descriptions probably shouldn't appear in a results section.
>>> Agreed. We added a brief and relevant description of the fire weather metrics in the methods section: "A 3-km grid of daily basic surface meteorology at 12:00 (noon) local time (air temperature, humidity, 10-m wind speed, and precipitation sum over prior 24 h) as well as Canadian Fire Weather Index system variables using inverse-distance weighting (Lee et al., 2002) was constructed for every day during 2002-2018. The rasters constructed use the same surface station data as McElhinny et al., 2020. The primary Fire Weather Index variables used include the Fine Fuel Moisture Code, Initial Spread Index, Duff Moisture Code, and Drought Code (Lawson and Armitage, 2008). The Fine Fuel Moisture Code (FFMC) is a model of moisture content for fine dead vegetation material at the forest floor of a closed-canopy forest. The FFMC utilizes all of the above basic surface meteorology to estimate drying rate with an exponential drying rate (time to loss of 2/3 of moisture content) of 18 hours. It is used here as a proxy for the moisture content of dense matted grass thatch, with relative humidity alone a better proxy for the moisture content (Miller, 2019) and ignition capacity (Beverly and Wotton, 2007) of standing grass. High FFMC values indicate drier conditions, up to a maximum of 101. The Initial Spread Index (ISI) is the product of the FFMCand the square of wind speed and is proportional to the forward spread rate potential for grasslands and other open vegetated fuels (Hirsch, 1996). The Duff Moisture represents the moisture content of a forest organic soil layer as estimated by a simple precipitation and evaporation model. It has an exponential drying rate of 12 days, and can be considered a metric of the bi-weekly soil moisture budget. Similarly, the Drought Code is a vertical water budget model (Miller, 2020) for a soil column with a 100 mm soil water capacity (similarly, larger values indicate drier conditions). In this manner, the Drought Code has been shown to represent variations in surface water levels (Turner, 1972); a simple vertical water balance of precipitation and evaporation controls surface water extent in the prairies of Canada, where water routing to streamflow and groundwater infiltration is limited (Woo and Rowsell, 1993). As such, the Drought Code is a proxy for the extent of saturated soil areas (wetlands and other surface pond water) that when sufficiently dry, increase the continuity of fuels on the landscape."

[176] I would expand slightly here by highlighting what the significant splines show (I don't think you actually do this anywhere in the main body, but you do refer to the DoY criterion in the abstract?) e.g. wildfires are highly likely when: values of DoY < ~130, WS > 30, curing 65-85%.

>>> We thank you for that helpful comment, and we add the text in the GAM results section: "Day of Year analysis showed that wildfires are 75% or more of detections for days prior to early May. Wind speeds over 25 km h-1 or curing fractions between 50 and 85% were also indicators of the likelihood of hotspot cluster being a wildfire over 75%."

Figure 5: You should explain panels (a)-(c) in the caption – at the minute you only mention panel (d). e.g. what are the blue lines (confidence intervals?) and black 'dashes' next to the axes (some kind of rug plot/distribution?).

>> We now clarify in the figure caption that the axis ticks represent the marginal distribution of the data as a rug plot.

Panel (d) of Figure 5 is a table, and so should be presented as such in the main body rather than as a panel of this figure. From Section 2.4 you suggest hour of detection was incorporated as a spline not a linear predictor, but in (d) it is a linear predictor –which is correct?

>>> We now treat hour of detection as a linear predictor only. Panel (d) in the GAM plot is now Table 1.

Is there a reason why you didn't also include a plot of probability vs. FFMC in Figure 5 (as well as hour of day, if it was included as a spline?)

>>> We now treat FFMC as a linear predictor (appropriate for the variable at its high end of 80+ as observed here). This is reflected in the new Table 1 which is the GAM results.

As mentioned earlier, DMC and DC are scaled before being used in the model, so this should be stated in the methods.

>>> DMC and DC are not scaled, but rather we present the odds ratio of these linear predictors.

Why does RH have an asterisk next to it? I would not use this symbol here as you already use asterisks to signify significance in the same table, which is confusing.

>>> We have now switched over to superscript numbers for all footnotes in the Figure.

[184-201] decision tree results: This section is currently a bit confusing - I suggest it is restructured slightly, and some clarifications added. Firstly, how many fire clusters in total did you analyse here? I was expecting n=143 (113 wildfires + 41 agricultural fires stated on line 143, minus the 11 DC < 100 fires mentioned later) but adding up the denominators in Figure 6 it appears that n=95. Assuming I am reading Figure 6 correctly, shouldn't these two numbers match? After introducing the regression tree in Figure 6, It might be worth immediately stating the number of fires analysed, and that you removed the 11

low DC wildfires (plus any other filtering you did?) before discussing the specific results shown by the regression tree, so readers don't spend time looking for the 'missing' fires in figure 6.

>>> Moved the discussion of the low DC wildfires to just before discussing the results, as suggested.

[185] where is the 92 % accuracy figure from? Should this say 97 %? 92 % is not in Figure 6 or Table 1.

>>> Fixed that typo, thanks for noticing that.

[186] Not sure why you talk about FFMC here – was FFMC actually used in the regression tree model? It doesn't appear in Figure 6.

>>> Deleted. Included by accident from an earlier version of the manuscript.

[191] similarly, where does the 82 % value come from? not in Figure 6 or Table 1.

>>> The 82% refers to the model's sensitivity (which is given fractionally as 0.82) in Table 1. We've revised this to be consistent between the text and the table.

[192] I'm not sure about introducing Appendix A here, or actually including it in the paper at all (1) you don't really highlight what it adds to the study and (2) it uses the large fire dataset (>3000 fires) that you haven't really introduced yet.

>>> We include ~~Appendix A~~Figure S2 so the reader less familiar with the Canadian Fire Weather Index System is able to visualize the parameter space of surface meteorology past the critical ISI 15 threshold. The larger database it comes from is less important than the visualization of the parameter space shown, hence why we don't emphasize the larger database here, just cite the sample size.

[193-195] I would move the sentences comparing the GAM to the tree model, because you go from talking about just the tree model on line 192-3, to comparing the two models (193-195], and then back to discussing just the tree model [195-201], which is structurally hard to follow.

>>> Removed the comparison to the GAM in the text, as that is obvious in Table 1.

[203-215] this is interesting. Did you try including FRP & wind speed in the tree model? Seems like doing so could have added to tree classification skill?

>>> We did, but neither came out as significant in the model once ISI was introduced.

[217-220] this paragraph (GAM applied to all clusters) feels like it might work better following the other paragraph on the GAM [lines 175-183]

>>> Moved as suggested.

[218] should this point to what is labelled as Figure 7 (the one with with two panel plots) rather than Figure 8?
>>>Revised as suggested.

Figures 7, 8 and 9: These are interesting figures, but you do not have much on them in either the results or discussion section (and in the case of figure 8, the 'avg. no. days per year figure', I don't think you mention this figure at all!). Some explanation is definitely required, otherwise why are they here?
>>> Explanation of figures 7-9 added to results.

4 Discussion

General comment on discussion:

Overall, you make some interesting points here, but several of them feel like they need expanding upon. I feel like you also don't draw much from the 'final' outputs of the study (Figures 7-9) – surely these results warrant discussion? Also, this paper clearly has important implications for operational fire management in grassland/agricultural complexes of Canada (and possibly beyond) – while you do mention this, I think you should try to highlight this aspect further in the discussion.
>>> More discussion on Figs 7-9 was added in the very last paragraph of the discussion.

[222] this paragraph might go better in the introduction/datasets sections of the paper, as it is effectively a justification of why you chose to examine MODIS rather than other options
>>> Moved to methods and material section.

[232] "> 7500 fires" this statistic is from which dataset?
>>> Revised to "In all likelihood, many of the roughly 7 500 wildfire hotspot clusters classified by the GAM over 17 years…"

[244-252] I'm not sure what the key point you are trying to highlight here is, so this probably needs clarifying. I think your main point is that FFMC is a reasonable proxy for grassland moisture content/fire occurrence in the study area? If this is the case, it is interesting to me that (1) FFMC is not significant in the GAM and (2) FFMC is not included in the decision tree model (Fig 6), and this observation might merit further discussion here.
>>> We've modified this section to remove the focus on the FFMC (which underlies the ISI metric used in the decision tree), and revised this as: "Both the GAM as well as the classification tree point the combination of critically dry fuel and wind as the drivers of wildfire occurrence in the region. In the GAM model, both low RH (as a proxy for standing grass moisture), alongside indicators of bi-weekly (DMC) to monthly (DC) moisture deficit are significant in predicting wildfire occurrence as linear predictors, with a wind threshold in the range of 30 km h^{-1}. In the Canadian Fire Weather Index System, fine fuel moisture (mostly driven by low RH) is combined with wind speeds to calculate the Initial Spread Index as a single heuristic

(~~Appendix A~~Figure S2), and thus comes out as the strongest indicator of wildfire. Lindley et al., 2011 found no such moisture deficit as a driver of wildfire occurrence, and instead found that RH alone below 25 % and particularly below 20 % as responsible for most grassland wildfires in west Texas. In our study region, RH alone however is not an ideal proxy for fuel moisture across the wide range of air temperatures found in the region during wildfire, as RH alone does not account for variable vapour pressure deficit at different temperatures (Srock et al., 2018) that drives the equilibrium moisture content of standing grasses (Miller, 2019). Moreover, the extensive shallow water bodies in the region may contribute during periods of higher moisture surplus (i.e. low DMC and DC) to a fragmentation of fuel continuity, similar to the function of larger lakes to the north in Canada (Nielsen et al., 2016). "

[261-266] Interesting observation, and this makes intuitive sense because managed fires that escape and become wildfires are probably usually the ones that reach the suppression limit. You should probably expand on this slightly though: (1) you could justifiably highlight that this adds to the validity of your work, as you have derived thresholds from a 'top down' RS/modelling approach that agree well with physical, bottom up observations of fire behaviour. (2) maybe you draw this out further? e.g. what might this finding have any applied fire management implications?
>>> We don't here to to over-extend this analysis, but your point is well taken, and we've added the text to the end of that paragraph: "This correspondence of our remotely sensed records (confirmed by fire reports solely of date and time, not of reported fire behaviour) and the operational models in the Canadian Forest Fire Danger Rating System lends confidence to the application of our approach in public safety and awareness messaging."

[268-276] You highlight an important point - that grasslands are increasing, and likely to keep doing so under climate change and current agricultural conversion trends. But you do not then use these points to highlight the importance of the work you have done here, and that it will be increasingly important in future – I think you should definitely emphasise this!
>>> Revised to include: "The expansion of grasslands and agriculture into currently forested areas will substantially change the fire regime in these areas, highlighting the importance of understanding the current grassland and agriculture area fire regime. Understanding how fire regimes could change with climate change will help fire managers make long term fire management decisions."

5 Conclusion
[283] maybe rephrase to say "a noon ISI threshold of > 15 was the most powerful threshold for discriminating wildfires from agricultural fires, while grass curing…"
>>>Revised as suggested.

Supplementary materials
[8] do you mean UTC rather than UTM date and time?

>>>Revised as suggested.

[39] How were each variable aggregated by fire cluster? E.g. FRP average vs max might be important to know…
>>> Revised to: "An attribute was merged by max value or mean, for each hotspot cluster. FFMC, DMC, DC, ISI, BUI, FWI, precipitation, relative humidity, wind speed, temperature, hour of detection, percent cured and NDVI were merged by mean. HFI and FRP were merged by max values."

[40] the 5% buffer you describe here, is this the same buffer you indicate in eq S2, or is this an additional buffer?
>>> Revised to: "Five percent was added to the buffer radius to fix this."

[117-122] this paragraph contains useful detail justification on the number of clusters you used. I would integrate at least some of this information into the main body, as it is important.
>>> We appreciate the comment, but feel the details on the clustering methodology is too detailed for the main text, and we would like to keep it in the appendix,

Technical corrections
Figures: Figure numbers are often incorrect in captions, and in places throughout the text. Please review and amend. Also consider generally expanding figure captions to include more information on the features of the figures or datasets used etc (see specific comments on figures where I believe these could be improved).
>>> Figure captions were expanded and figure numbers corrected.

[60] consider deleting "…despite higher spread rates: : :". Probably adds to an unnecessarily long sentence
>>>Revised as suggested

[87] "..northern fringe of agriculture.." - not sure if this applies to both areas (i.e. the 'main' southern Prairie area and the distinct northern agri-forest area?) or just the main southern one, please clarify
>>>Revised to: "… At the fringe of agriculture…"

[96] "agencies" should have an apostrophe?
>>>Revised as suggested.

[Figure 4] is labelled as figure 2. You refer to panel letters (a, b etc) in the text but they are missing from the figure. I think this shows results for fire clusters, not MODIS pixel detections – make this clear in the caption and text. Also, the 'Day of year' panel only extends slightly beyond DoY 300 – is this intentional?

(maybe there is never fire after this date?)
>>> This is the default axis limits in the GAM plotting function in R. The minimum value of the day of year field is 98, and the maximum is 298.

[150] is 'Additionally' a better word choice here than 'Alternately' as you build both models?
>>> Revised as suggested.

[155] I think you are referring to fire clusters here – if so, I would make this obvious by saying 'distribution of agricultural vs. wildfire clusters'
>>> Revised to: "…distribution of agricultural vs wildfire hotspot clusters…"

[173] I would state the median no. of pixels for agricultural fires here for comparison to the median wildfire pixels
>>> Revised to : "The median number of thermal detection points per wildfire was 2 but as high as 55, in contrast with agricultural fires where the median number of thermal detections is also 2 but the maximum is 6."

[178] should this say "increased rate of wildfire likelihood per integer increase in predictor value"?
>>> Revised as suggested

[257] I'm not very familiar with the use of odds ratios, so ignore this comment if it has a different technical interpretation - but might this be better phrased as "…results in the increase in the odds of a wildfire over an agricultural fire by 2.45…"?
>>> yes, we've revised this to : "Relative humidity and DC were found to be significant in the GAM model as linear predictors, with odds ratios (increased likelihood of a fire being classified as a wildfire per integer increase in predictor value) of 0.31 per unit increase in RH, and 1.008 per unit of DC. " It is important in odds ratios to state the increasing likelihood of a detection being a wildfire per unit change of the variable of interest.

[273] I think you want 'exacerbated' rather than 'exasperated' here?
>>> revised as suggested

Reviewer 2: Overall, I think this paper is trying to advance natural hazards - specifically fire science - in using remote sensing and data science to attribute and predict wildland vs. human caused fire. I would recommend the authors refine the terminology.
I look forward to reading a revised version.

General comments: 1. Landsat 8 is not an acronym and should not be capitalised.

>>>Fixed as suggested.

Referring to all non-wildland fires as agricultural fires becomes confusing later on, especially when trying to explain how the curing data set was included in the regression tree [much of the agricultural landscape was exempted from the curing assessment because < 40% open fuels].

>>> We now clarify in the methods that the trees are uncommon in the region outside of shelterbelts: “Within the agricultural ecumene, the vast majority of the region constitutes open fuels (Figure 1), and little tree cover exists outside of shelter belt plantations which exist as single rows of trees (Piwowar et al., 2016). “

The term ‘responsible use of fire’ is used to encompass a large amount of human-caused burning. Is this a legal or statute-based definition? This is not a common term in fire science. Also, burning of crop residues is not necessarily considered an appropriate thing for this ecosystem.

The Province of Alberta has shifted to no-burn management of crop residues, treating burning as a last resort: https://open.alberta.ca/dataset/dd5ca66a-09f6-4aeb-8bb9-21babed92780/resource/3b67de8e-7377-406c-94d7-25f3efaee710/download/mar2017-unharvested-crops-fs.pdf

>> We adopt a terminology similar to Lewis et al 2018, where “use of fire” is specific to the low-intensity application of fire in an informal context by community members, not in a formal prescribed fire context. This isn’t a definition based on legal statute. As we discuss later in the paper, burning of post-harvest flax residue may be in part responsible for higher fire activity in the eastern portion of our study region.

Why was 2002 (Terra only) MODIS active fire product included when the combined (Aqua and Terra) MODIS active fire product is available starting in 2003? How were these differences in number of detections accounted for when determining the clusters? Was the 2002 Terra-only MODIS active fire useful?

>>> Only 3 of 140 hotspot clusters were from 2002, so we did not go to the effort of normalizing the lower detection rate of having only one MODIS instrument. For the density analysis across the landscape, since we had autumn 2002 included and the density data in Figure 6 is an average over the 2002-2018 period, we similarly did not normalize for such a small effect.

Paragraph 265: The thesis statement of this paragraph may need to be re-written “ The thresholds at which agricultural fire detections are overtaken by wildfires occurs at fire intensity thresholds that correspond to the limits of ground-based wildfire suppression.” Is this a result or a qualitative observation or an assumption that fits into the description of the CFFDRS is the following sentence? Please consider re-phrasing this paragraph.

>> Rephrased to: “The thresholds shown here in the classification tree and GAM models correspond to modelled fire intensity conditions at the upper limits of ground-based wildfire suppression.”

I do not understand how this fits into the study or the findings. Perhaps, again, it is an issue with referring to grass fires as agricultural fires. This reads as the CFFDRS for native grasslands. Is that correct?

>>> We now clarify the relationship between agricultural debris and fire behaviour models in Canada: “The grass fire spread model in the Canadian Forest Fire Danger Rating System utilizes Australian experimental grass fire data that has been shown to approximate fire behaviour in wheat crops, with the matted (or cut) grass model approximating spring (cured) post-harvest debris (Cruz et al., 2020).”

Is the last paragraph in the discussion section implying increasing agricultural fires with climate change? Did this study find increasing agricultural fires? And if so, in grasslands or croplands?

>>> We now clarify that there has been no observed trends in fire activity in the region, though wildfire activity is expected to increase in the surrounding forest regions: “In addition to this likely grassland and cropland expansion, projections of increasingly common critical fire weather conditions (Wang et al., 2015) is likely to shift the fire regime to one of more open fuel burning. However, no change in the rate of fire detections (undifferentiated between wildfires and agricultural burning) has been detected between 1981-2000(Riaño et al., 2007) nor 1998-2015 (Andela et al., 2017).”

A classification scheme to determine wildfires from the satellite record in the cool grasslands of southern Canada: considerations for fire occurrence modelling and warning criteria

Dan K. Thompson[1], Kimberly Morrison[1]

[1]Canadian Forest Service, Northern Forestry Centre, Natural Resources Canada, Edmonton, Canada

Correspondence to: Dan K. Thompson (Daniel.Thompson@canada.ca)

Abstract. Daily polar orbiting satellite MODIS thermal detections since 2002 were used as the baseline for quantifying wildfire activity in the mixed grass and agricultural lands of southernmost central Canada. This satellite thermal detection record includes both the responsible use of fire (e.g. for clearing crop residues, grassland ecosystem management, and traditional burning), as well as wildfires in grasslands and agricultural lands that pose a risk to communities and other values. A database of known wildfire evacuations and fires otherwise requiring suppression assistance from provincial forest fire agencies was used to train a model that classified satellite fire detections based on weather, seasonality, and other environmental conditions. A separate dataset of high-resolution (~~LANDSAT~~ Landsat 8 thermal anomalies) of responsible agricultural fire use (e.g. crop residue burning) was collected and used to train the classification model to the converse. Key common attributes of wildfires in the region included occurrence on or before the first week of May with high rates of grass curing, wind speeds over 30~~21~~ km h^{-1}, relative humidity values typically below 40% and fires that are detected in the mid-afternoon or evening. Overall, grassland wildfire is found to be restricted to a small number of days per year, allowing for the future development of public awareness and warning systems targeted to the identified subset of weather and phenological conditions.

1 Introduction

Wildfire is a widespread and commonplace phenomenon in Canada, with contexts ranging from an integral component of traditional land use (Lewis et al., 2018), a purely natural disturbance (i.e. lightning ignition) process with little human impact (Whitman et al., 2018), to a devastating natural hazard to communities (Christianson et al., 2019). Fire (both human and natural ignition) is most common in Canada in its interior, west of the Great Lakes and east of the Rocky Mountains, where a belt of high fire frequency extends from the subarctic forests of the Deh Cho (Mackenzie Valley) through to the drier southern boreal forest-grassland transition (Boulanger et al., 2014). Within this broad north-south transect, the density of values at risk varies greatly, from sparse communities in the northern forest with limited industrial activities to a dense matrix of industry with dispersed agriculture and rural habitation (Johnston and Flannigan, 2018). At the southern limit of the boreal forest in western Canada, climatic limitations to widespread forests created a natural ecotone towards a more open deciduous forest and grass parkland (Hogg, 1994; Zoltai, 1975), which has been almost entirely converted to intensive agriculture with a steady rate of increasing agricultural conversion (Hobson et al., 2002). This is in contrast to the United States, where extensive natural grasslands intermix with dry conifer forests in areas of greater wildfire occurrence (Gartner et al., 2012). In Canada, at the southern forest limit and further south, the wildland-urban interface transitions to widespread human agriculture and only patches of broadleaf (deciduous) aspen forest (Hogg, 1994). Though smaller, localized grasslands in a larger matrix of forest are readily integrated into local wildfire likelihood assessments (Parisien et al., 2013), large-scale assessments of wildfire likelihood are often based on modelling that utilizes forest fire management agency records (Parisien et al., 2013; Stockdale et al., 2019), and therefore exclude wildfires in agricultural areas where no such land management agency records exist. In this primarily agricultural region, controlled agricultural burning is commonly used to burn off excess crop residue (Chen et al., 2005). The use of a purely thermal remote sensing approach to determine the risk of wildfire (Rogers et al., 2015) (i.e. fires being actively suppressed but not under control) is somewhat limited, and can erroneously ~~can~~ count responsible fire use in agriculture as wildfire occurrence.

In Canada, both forest fire and grass fire likelihood and spread are predicted using a common system, the Canadian Forest Fire Danger Rating System (CFFDRS), developed and maintained by the Canadian Forest Service starting in the 1930s. The system allows for the prediction of grass fire rate of spread (metres/minute), fire intensity (equivalent to flame height), and expected growth rate (fire size over time). Fire weather is quantified using daily temperature, precipitation, humidity, and wind speed, with grass curing (the ratio of dead grass to live grass) being a critical variable that controls grass fire behaviour. Under the Canadian Fire Weather Index System (Van Wagner, 1987), the fire danger classes for public awareness (i.e., Low, High, Extreme, etc.) are based on a scaling of the expected head fire intensity of an idealized pine stand with a pine needle surface fuel bed. In this type of forest, wind speed, humidity, and drought will impact fire behaviour, but the lack of deciduous trees or understory vegetation negate seasonal phenology beyond needle flush. When this Fire Weather Index scheme is then applied across regions dominated by grasslands, agriculture, or deciduous tree or shrubs, the Fire Weather Index alone and associated Fire Danger classes need to be adjusted for leaf-on or greenup conditions (Alexander, 2010; Chéret and Denux, 2011).

Recent research in Australia has highlighted the importance of grass fuel loading as a negative influence on fire rate of spread, whereby a doubling of grass fuel load from the standard assumption of 0.35 kg of fuel m^{-2} to 0.70 kg m^{-2} results in a 10 % reduction in spread rate (Cruz et al., 2018). Conversely, a 50 % reduction in fuel load results in between a 10–30 % increase in spread rate; flame height (proportional to fireline intensity) increased to the power of 0.60 with increased fuel loading however, meaning a doubling of fuel loading results in a 50 % increase in flame height. Accordingly, under dry conditions, light agricultural residues may burn with high rates of spread though lower flame heights, while higher fuel loads in agricultural residues would likely burn slower but with substantially larger flames. In mixed forest and open grass-type fuel landscapes, the lower intensity of grass fires ~~despite the higher spread rates~~ typically results in higher rates of successful fire suppression for grasslands in empirical (Finney et al., 2009) and modelling (Reimer et al., 2019) studies compared to standing forest. Rapid fuel moisture gains during typical night-time periods results in limited nocturnal fire activity potential (Kidnie and Wotton, 2015) except during exceptional periods of sustained wind and very low humidity (Lindley et al., 2019).

The overall goal of this study is to examine the differing environmental conditions most common during agricultural fires, and to contrast that with documented grassland wildfires in the region. The first specific goal is to apply a classification model to historical fire thermal detections (2002–2018) in order to determine the relative densities of agricultural burning and smaller, mostly undocumented grassland wildfires. The second goal is to develop an initial data-driven wildfire occurrence criteria usable for public warning specific to grassland and agricultural regions of southern Canada.

2 Materials and Methods

2.1 Summary of datasets

MODIS thermal detections were used as a spatially unbiased record of fire activity in the study area. Each thermal detection was then associated with gridded data including grass curing (NDVI), as well as surface weather and fire weather variables from the Canadian Fire Weather Index (FWI) S~~s~~ystem. These thermal detections were then clustered and classified where possible into confirmed agricultural (Landsat 8, (Kato et al., 2018)) or wildfire using a fire occurrence database (Hanes et al., 2018) or evacuation records largely from media reports (Beverly and Bothwell, 2011). These known agricultural and wildfire hotspot clusters and associated fields were then used to create a Generalized Additive Model (GAM), which was used to classify the unknown hotspot clusters into agricultural or wildfires and produce maps of their relative occurrence (goal 1). Additionally, a decision tree model was also built on the confirmed wildfire vs agricultural hotspot clusters, to provide simplified classification thresholds (goal 2) for use in fire operations and as the basis for potential public warning criteria.

~~**Table 1: Summary of datasets used in study.**~~

~~Dataset~~	~~Spatial Resolution~~	~~Temporal Resolution~~	~~Derived Data~~	~~Product Number/Source~~	~~Time Frame~~
~~Land cover~~	~~30 m~~	~~As of 2010~~	~~Grass cover~~	~~(Agriculture and Agri-Food Canada, 2018)~~	~~2010~~
~~MODIS thermal detections~~	~~1 km~~	~~Twice daily~~	~~Hotspot clusters~~	~~MOD14A1 and MYD14A1~~	~~2002-2018~~
~~MODIS NDVI~~	~~250 m~~	~~16 day composite~~	~~Grass curing~~	~~MOD13Q1 and MYD13Q1~~	~~2002-2018~~
~~Landsat 8 thermal detections~~	~~30 m~~	~~16 days~~	~~Confirmed agricultural fires~~	~~(Kato et al., 2018)~~	~~2013-2018~~
~~Weather and fire weather~~	~~3 km grid~~	~~12pm LST daily~~	~~Model input~~	~~(McElhinny et al., 2020)†~~	~~2002-2018~~
~~CNFDB~~	~~N/A~~	~~N/A~~	~~Confirmed wildfires~~	~~(Hanes et al., 2018)~~	~~2002-2017~~
~~Canadian Wildfire Evacuation Database~~	~~N/A~~	~~N/A~~	~~Confirmed wildfires~~	~~(Beverly and Bothwell, 2011)‡~~	~~2002-2018~~

~~† The station data used in McElhinny et al (2020) were interpolated on a 3-km grid using an inverse distance weighting approach.~~

~~‡ The methodology of Beverly and Bothwell (2011) was applied to search for fires in the Prairie region of Canada, which were excluded from this publication. Evacuations were catalogued from 2002-2018. See supplementary data.~~

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2.2~~1~~ Study Area

The study area encompasses the entire primary agriculture zone of central-western Canada (Prairies) as well as the forest-agriculture mix that extends north (to 58º N at its furthest point) and east to (as far as 96º W) where the shallow granitic soils of the Canadian Shield are found (Fig. 1). The southern limit of the study area is the United States border at 49º N, and the western limit is the continuous forest and protected areas of the Rocky Mountains. The climate of the region is cool and continental, with mean annual temperature ranging from 0.6º C in Peace River to 5.9º C at Lethbridge. The number of frost-free days is as few as 119 in Peace River, and as many as 132 in areas east of Lethbridge. Foehn winds (locally known as Chinooks) on the eastern side of the Rocky Mountains cause periodic temperature increases above freezing during winter, allowing for occasional winter ~~grass~~ fires in grass and other open, fine fuels. Snowmelt typically occurs in March-April in the southern extent, and April- early May further north. Annual precipitation varies from close to 600 mm in the easternmost edge of the study area near Winnipeg to as little as 316 mm in areas northeast of Lethbridge. Precipitation is heavily weighted to convective precipitation in the months of June-August. April and October are typically the two driest snow-free months.

Overall, 42 % of the study area is agricultural land or grasslands. Land ownership in the agricultural area is almost entirely privately held, with the exception of First Nations reserves (1.6 %), parks and protected areas (2.4 %), and provincial grazing reserves (1.8 %). Wildfire response is primarily volunteer-driven at the local community level (McGee et al., 2015). At the fringe of agriculture, private land is intermixed with provincially (sub-national) owned lands that are managed primarily for timber, and wildfire response is entirely the responsibility of provincial fire management agencies outside of settlement boundaries. Remotely-sensed land cover data at 30 m resolution (Agriculture and Agri-Food Canada, 2018) was used to distinguish forested areas from open fuels (including permanent croplands, pastures, native grasslands, and treeless wetlands) all of which share similar phenology and flammability. Broadleaf crops vs cereals were not distinguished.

2.3~~2~~ Fire occurrence records

In the forest-agriculture mix, we used comprehensive fire history records from wildfire management agencies, as compiled in the Canadian National Fire Database (CNFDB) (Hanes et al., 2018). In the agricultural zone, the CNFDB provides only a partial ~~sample~~sample of wildfires in the region. The agricultural zone is not located in the provincial wildfire agencies' area of responsibility, therefore in this zone, only larger fires that required a mutual aid response from provincial agencies are documented in the database. ~~In the agricultural zone, the CNFDB provides only a partial sample of wildfires in the region, as larger fires that required a mutual aid response from provincial agencies are documented in the database, despite not being located in the provincial wildfire agencies area of responsibility.~~ Additional reporting on wildfire occurrence in the agricultural zone is provided by the Canadian Wildfire Evacuation Database (Beverly and Bothwell, 2011), which since 2010 has collected information on wildfire evacuation in grassland areas in addition to forest fires dating back to the 1980s.

Records from fire management agencies and evacuations provide a partial sample of the true extent of wildfires in the agricultural zone, and capture completely the occurrence of wildfire in the provincial forest. Remotely-sensed thermal detection of active wildfire from the polar-orbiting NASA Aqua and Terra satellites that pass over Canada at nominally 13:~~0~~30~~h~~ local time (with a 01:30 overnight overpass) were used as a spatially unbiased (but time-limited) sample of fire activity in the area (Fig. 2). Off-nadir collections (Freeborn et al., 2014) were also utilized and the detection-specific detection hour was used. A standard MODIS collection from 2002-2018 (MOD14A1 and MYD14A1) (Giglio, 2015) with 1 km resolution was screened for persistent industrial heat sources.

These~~se~~ MODIS thermal detections were merged into hotspot clusters based on the detection's track and scan distance~~, in an attempt~~ to group detections from the same fire together (see supplementary material).

~~Attributes were merged by max value or mean, for each hotspot cluster.~~

~~and combined with a~~A 3-km grid of daily basic surface meteorology at 12:00 (noon) local time (air temperature, humidity, 10-m wind speed, and precipitation sum over prior 24 h) as well as Canadian Fire Weather Index S~~s~~ystem variables using inverse-distance weighting (Lee et al., 2002) was constructed for every day during 2002-2018. The rasters constructed use the same surface station data as ~~(M~~McElhinny et al.~~,~~ (2020~~)~~). The primary Fire Weather Index variables used include the Fine Fuel Moisture Code, Initial Spread Index, Duff Moisture Code, and Drought Code (Lawson and Armitage, 2008). The Fine Fuel Moisture Code (FFMC) is a model of moisture content for fine dead vegetation material at the forest floor of a closed-canopy forest. The FFMC utilizes all of the above basic surface meteorology to estimate drying rate with an exponential drying rate (time to loss of 2/3 of moisture content) of 18 hours. It is used here as a proxy for the moisture content of dense matted ~~to produce a database of fire thermal detections that spans both the responsible use of fire in land clearing and vegetation management, as well as out of control wildfire (Fig. 2). Thermal detections associated with fire agency records or evacuations (see supplementary materials for details) were set aside for later model creation and validation.~~grass thatch, with relative humidity alone a better proxy for the moisture content (Miller, 2019) and ignition capacity (Beverly and Wotton, 2007) of standing grass. High FFMC values indicate drier conditions, up to a maximum of 101. The Initial Spread Index (ISI) is the product of the FFMC and the square of wind speed and is proportional to the forward spread rate potential for grasslands and other open vegetated fuels (Hirsch, 1996). ISI is calculated daily and represents the peak potential rate of spread typically found in the later afternoon at the daily temperature maximum. The Duff Moisture Code (DMC) represents the moisture content of a forest organic soil layer as estimated by a simple precipitation and evaporation model. It has an exponential drying rate of 12 days, and can be considered a metric of the bi-weekly soil moisture budget. Similarly, the Drought Code (DC) is a simple vertical water budget model (Miller, 2020) for a soil column with a 100 mm soil water capacity (similarly, larger values indicate drier conditions). In this manner, the ~~Drought Code~~DC has been shown to represent variations in surface water levels (Turner, 1972); a simple vertical water balance of precipitation and evaporation controls surface water extent in the prairies of Canada, where water routing to streamflow and groundwater infiltration is limited (Woo and Rowsell, 1993). As such, the

~~Drought Code~~ DC is a proxy for the extent of saturated soil areas– (wetlands and other surface pond water) that when sufficiently dry, increase the continuity of fuels on the landscape.

~~The dataset used in this study~~We purposely utilized the longer-duration MODIS dataset from 2002 onwards, rather than the shorter duration VIIRS dataset from 2012 onwards. Though both sensors are capable of fire detection in the mid-wave infrared, VIIRS is in theory capable of detecting smaller or less intense agricultural fires (Johnston et al., 2018; Zhang et al., 2017) which offers little advantage when the goal is the detection of larger wildfires in the region. Moreover, one of the goals of this study is to examine broad spatial trends in fire occurrence ~~(Fig. 87)~~, where a longer record is ideal. Recently launched geostationary weather-oriented earth observation platforms such as GOES 16/17, Meteosat, and Himawari offer many advantages for monitoring short-lived wildfires, with scan rates every 10–15 minutes (Hall et al., 2019). The northern latitude of the study area (49–59° N) causes a severe degradation of the pixel size of GOES geostationary fire detections to 4 km and limited ~~FRP resolving~~ capacity in accurately resolving fire radiative power (Hall et al., 2019). The dataset and classification criteria presented here can assist in improving the confidence in real-time wildfire detection in these areas with widespread intentional fire use in agriculture on the landscape.

~~These MODIS thermal detections were merged into hotspot clusters based on the detection's track and scan distance, in an attempt to group detections from the same fire together (see supplementary material). Attributes were merged by max value or mean, for each hotspot cluster.~~

All hotspot clusters with less than 40 % open fuels (grasslands, croplands, and treeless wetlands) were too influenced by fire behaviour in forests, and were ~~not considered~~excluded from the dataset~~ grass fires and were eliminated from this study~~. Within the agricultural ecumene, the vast majority of the region constitutes open fuels (Fig.~~ure~~ 1), and little tree cover exists outside of shelter belt plantations which exist as single rows of trees (Piwowar et al., 2016). ~~It was noted that there were several hotspot clusters remaining near Fort McMurray, an area known not to have much grass. These clusters were also~~Area burned in forest-shrub-grass mixes typical of post-fire regeneration were eliminated from this study, as ~~they looked to be in a previously burned area dominated by shrubs, grass, and aspen, rather than a prairie grassland.~~their suppression, land ownership, and vegetation ecology more closely mirror forests than grasslands (Whitman et al., 2019). This resulted in a total of 24 297 MODIS hotspot clusters containing a total of 44 324 thermal detections. The CNFDB and evacuation database were used to classify these hotspot clusters as wildfires where possible. Eighty-four~~four~~ hotspot clusters representing ~~65~~ wildfires were identified using the CNFDB and 15 additional hotspot clusters were identified using the evacuation records and were not otherwise recorded in the CNFDB.

The responsible use of fire in the region includes traditional burning by First Nations (Lewis et al., 2018), prescribed burning by fire management agencies to reduce fuel loads in grasslands (McGee et al., 2015), burning of crop residues (Chen et al., 2005), and pile burning during land clearing operations where residual tree biomass is burned during agricultural land conversion (Hobson et al., 2002). Other than prescribed burning, no official documentation exists for this type of fire use, and could otherwise be conflated with wildfires as documented by remote sensing. In order to discriminate between responsible fire use and wildfires, we used the 30 m short-wave infrared thermal detections from the ~~LANDSAT~~ Landsat 8 satellite (Kato et al., 2018) in order to classify clusters of thermal detections as responsible fire use if they correspond to geometric patterns associated with prescribed burning or other controlled fire (Fig. 3). A total of 41 ~~LANDSAT~~ Landsat hotspot clusters were manually classified in this manner; fire weather and land cover ~~was~~ were associated with these detections similar to the MODIS detections. These ~~LANDSAT~~ Landsat detections are limited in spatial scale as the satellite only returns over an area every two weeks, so these records are at best a small sample of the entire fire activity in the region (approximately 1/14, or 7 %), and only a small sample of ~~LANDSAT~~ Landsat data was used in this study. All responsible use of fire is referred to as agricultural fire in this paper.

2.4~~3~~ Satellite grass curing

Grass curing (the fraction of dead grass with moisture content controlled by atmospheric conditions) is the primary control on the fire spread potential in grass fuels, overriding all other factors (Cruz et al., 2015). However, capturing the complexities of plant phenology in the simple daily weather scheme used by the Fire Weather Index S~~s~~ystem or similar scheme is challenging (Jolly et al., 2005). For this retrospective analysis, we leverage satellite greenness as a proxy for grass curing, similar to (Pickell et al., 2017). In this study, we leverage historical 16-day composite NDVI (MOD13Q1 and MYD13Q1) (Didan et al., 2015) at 250 m resolution. A simple linear transform was used to convert between NDVI and percent curing:

$$P_{curing} = \left(1 - \frac{NDVI_t - \min(NDVI)}{\max(NDVI) - \min(NDVI)}\right) \times 100 \cancel{\frac{NDVI_t - \min(NDVI)}{\max(NDVI) - \min(NDVI)}} \quad (1)$$

Where $NDVI_t$ is the measured NDVI at time t, $min(NDVI)$ represents the per-pixel minimum snow-free NDVI value, and $max(NDVI)$ is the per-pixel maximum NDVI climatology. Both the min and max values are based on the average of the annual maxima and minima from 2002 to 2014 (*i.e.* n = 12 per pixel for both min and max calculations).

~~All hotspot clusters with less than 40 % open fuels (grasslands, croplands, and treeless wetlands) were not considered grass fires and were eliminated from this study. It was noted that there were several hotspot clusters remaining near Fort McMurray, an area known not to have much grass. These clusters were also eliminated from this study, as they looked to be in a previously burned area dominated by shrubs, grass, and aspen, rather than a prairie grassland.~~

2.5~~4~~ Classification of thermal detections

In total, 99 ~~113~~ MODIS clusters (representing 386 ~~576~~ total individual hotspots) were associated with documented wildfire, and 41 MODIS clusters (representing 104 total individual hotspots), confirmed to be agricultural controlled burning via ~~LANDSAT~~ Landsat imagery, were classified as agriculture fire use. Variables included for consideration in the GAM include surface weather variables, day of year, satellite curing fraction, as well as the fuel moisture codes (FFMC, DMC, DC) from the Fire Weather Index S~~s~~ystem. Higher-order components of the Fire Weather Index System such as Initial Spread Index and Buildup Index were not used due to their derivation from fuel moisture codes and high correlation (Spearman's $\rho > 0.7$) with those codes. The high correlation ($\rho = -0.73$) between relative humidity and FFMC is noted, but both were used in the GAM. All other variables in the GAM were correlated $\rho < 0.5$, and thus suitable for landscape-level fire weather analysis and modelling (Parisien et al., 2012). ~~These data were~~This data was then used to build models to classify the remaining hotspot clusters as either agriculture fire or wildfire using Generalized Additive Models (GAM) as binomial models (binary of wildfire or not) without interaction surfaces were built using the R package *mcgv* (Wood, 2019), with splines used for variables with an expected non-linear response such as ignition d~~D~~ay of y~~Y~~ear, hour of detection (from MODIS), wind speed, and curing (Eq. ~~(~~1~~)~~). The non-linear partial effects terms in GAM models have been found to be superior to linear models with interactions in the examination of wildfire-environment data (Woolford et al., 2010). This model was validated using leave-one-out cross validation. These GAMs account for multiple non-linear responses but not interactions between predictors. Additionally~~Alternately~~, classification~~regression~~ trees were constructed using the *rpart* package (Therneau et al., 2019) to classify wildfires from thermal detections using a simple conditional threshold-type model for use as simplified warning criteria (maximum of two variables). Inputs directly related to hotspot detection were not included (i.e. FRP), as they are only obtained upon fire detection. Variables that integrate multiple weather factors into a single index (i.e. Initial Spread Index or Buildup Index) were considered.~~. Percent grass curing was not used in the model, as it is highly site-specific compared to the weather variables that vary only regionally on a given day. As a result, only wildfires and agricultural fires with moderate to high curing (>40 %) were used to build the regression tree.~~

2.6~~5~~ Analysis of classified clusters

The large dataset of hotspot clusters classified by the GAM were separated back into their individual hotspots (44 324), and used as a proxy for total fire on the landscape (a combination of fire size and fire occurrence). These classified hotspots were used to explore spatial and temporal patterns of agricultural and wildfires in the study area ~~(Fig. 7 and 9)~~.

The thresholds determined by both the~~the~~ decision tree model and GAM were used to produce a ~~burn days raster~~map representing the number of potential grassland wildfire days per year. ~~Every 3 km grid cell, from April through October, 2002-2015, within the ecumene was classified into whether it was conducive to wildfire or not. To be considered conducive to~~

~~wildfire, a day needed an ISI >= 15 and percent curing >= 75 %. This was done for everyday within the mentioned time frame, summed and averaged by year (Fig. 8).~~

3. Results

Environmental, remotely sensed, and weather variables related to the distribution of agricultural vs wildfire hotspot clusters are shown in Fig. 4. Both fire types (agricultural vs wildfires) show a strong peak in the spring period after snow melt (Day of Year, Fig. 4a), centred on late April and early May, with a slightly earlier peak for wildfires. The curing fraction of the grass or agricultural residue is lower for wildfires compared to agricultural fires (Fig. 4b), which may be due to low NDVI(high curing) artifacts from tillage (Zhang et al., 2018) or adjacent previously burned area in the larger MODIS pixels. The hour of first detection (Fig. 4c) is largely limited by the 13:00~~h~~ local time overpass at nadir for MODIS. Night-time fire detections at 1am local (01:00) overpass are rare even for the wildfires. Pre-fire drying conditions as parameterized in the Fire Weather Index System (~~Duff Moisture Code (~~DMC~~)~~ and ~~Drought Code (~~DC)~~)~~ show much larger right skews for wildfires. In the case of the DMC (Fig. 4d), ~~which represents the moisture content of the forest floor beyond 2 cm depth,~~ 26% of the wildfire data have DMC values beyond the maximum DMC for agricultural burning of 67 (approx. 17 days without rain exceeding 1.5 mm). DC (Fig. 4e) shows a similar trend: 5% of agricultural fires have a DC of 470 or greater compared to 27% of wildfires. Observed fire weather values ~~(noon local standard time measurements of surface weather on the day of first fire detection)~~ showed a meaningfully larger number of wildfires when relative humidity (Fig. 4f) was below 20 %, more agricultural fires when noon air temperatures are below 10°C (Fig. 4g), and far more wildfires when noon 10-m wind speeds exceed 25 km h^{-1} (Fig. 4h). ~~The noon temperature, relative humidity, and wind speed form the basis of the calculation of the~~ Fine Fuel Moisture Code (Fig. 4i) ~~which~~ showed~~s~~ a peak for agricultural burning at FFMC 90 versus 92 for wildfires. Finally, the natural logarithm of the Fire Radiative Power (FRP) of the MODIS detection (Fig. 4j) showed far more variance in wildfires compared to agricultural fires. No agricultural fires exceeded 400 MW in the sample of confirmed agricultural fires. The median number of thermal detection points per wildfire was 2 but as high as 55, in contrast with agricultural fires where the median number of thermal detections is also 2 but ~~e~~ the maximum ~~number of thermal detections in a cluster~~ is 6. Only 16 % of wildfires contained more than 6 hotspots in a cluster.

The above variables were assessed in a binomial generalized additive model, shown in Fig. 5. The GAM model was able to explain 6~~8~~4 % of the variance in the data, with strong non-linear predictors in Day of Year, curing, and wind speed. Day of Year analysis showed that wildfires are 75 % or more of detections for days prior to early May. Wind speeds over 25 km h^{-1} or curing fractions between 50 and 85 % were also indicators of the likelihood of hotspot cluster being a wildfire~~-~~. ~~Hour of detection, r~~Relative humidity and DC were found to be significant in the GAM model as linear predictors, with odds ratios (increased likelihood ~~rate~~ of a ~~of wild~~fire being classified as a wildfire ~~likelihood~~ per integer increase in predictor value) of

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~~1.32x per hour~~, ~~-~~0.31~~1.17x~~ per unit ~~decrease~~ increase in RH, and ~~2~~1.~~45x~~ 008 per ~~hundred~~ unit ~~ofs of~~ DC. Essentially, a single integer percentage increase in relative humidity, keeping all other measures constant, makes the odds of a hotspots detection being a wildfire drop by one third. Similarly, a 100 unit increase in ~~Drought Code~~ DC (on a scale roughly from 0 to 700) makes the odds of a thermal detection being a wildfire increase by 80%. Despite the lack of interactions between predictors in all GAM models, the model had a high overall predictive power ~~when tested using a leave-one-out framework~~, with sensitivity of 0.86~~2 %~~ (true positive rate), specificity (true negative rate) of 0.90~~87 %~~, an area under receiver operating characteristic curve (AUC) of 0.89~~88~~, and a Critical Success Index of 0.87~~78~~ (Table 3~~1~~). The cutoff of the overall GAM model binomial output of 0.667~~30~~ provided the optimal model performance. When the GAM model is applied to the 24 297 hotspots clusters in the entire MODIS dataset, 30 % of hotspot clusters were detected under conditions that are most similar to documented wildfires. These hotspots have a strong regional gradient with more wildfires in the eastern portion of the study area (Fig. 6).

~~2978The seasonal and spatial patterns along lines of equal longitude are portrayed in a Hovmoller time-longitude diagram in Fig. 99. For both agricultural and wildfires there is a concentration of fires in the spring (around weeks 17 to 21, late March to late April) and between longitudes 100-105° W. Agricultural fires have an additional concentration of hotspots in week 43 (late September).~~

A simple decision tree was constructed from the same 140 classified hotspots ~~dataset~~ to look at simple threshold-based classification schemes. (Fig. 7). An Initial Spread Index (ISI) (proportional to the fire's potential or modelled rate of spread based on weather alone) was found to be the strongest predictor, with 53 of 54 hotspot clusters being wildfires when ISI is greater than or equal to 17. For fires with ISI <17, high curing (i.e. low NDVI, indicative of plowed fields in the vicinity or recent adjacent agricultural burning) over 87 % was a strong indicator of controlled agricultural burning, with 21 of 25 hotspot clusters being agricultural burning. Detection hour during or after 14:00 local time (indicating an intense fire detected in a later off-nadir satellite overpass) was also a meaningful indicator of a wildfire event, with 15 of 16 clusters being confirmed wildfires. For detections prior to 14:00 local time, an ~~Initial Spread Index~~ISI of 11 or greater provided a moderately strong indicator of a wildfire, with 18 of 22 hotspot clusters detected being wildfires. For hotspots clusters with an ISI below 11, there was no meaningful discrimination between agricultural fires and wildfires. Overall, this decision tree model had an AUC of 0.75~~85~~, and a favourable True Positive Rate of 0.77~~81~~ ~~and~~with a lower True Negative Rate of 0.71~~90~~ (Table 3). The Critical Success Index of this particular classification model 0.68~~82~~ and overall Accuracy of 0.75~~86~~.

The decision tree model was used to analyze the number of potential wildfire days per year given the criteria laid out in Fig 7. Geographic patterns of potential wildfire days (Fig. 8) is the opposite of observed densities of both agricultural and wildfire (Fig. 6), with more days conducive to wildfires in the west of the study area. The seasonal and spatial patterns along lines of equal longitude are portrayed in a Hovmoller time-longitude diagram in Fig. 9. For both agricultural and wildfires there is a

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concentration of fires in the spring (around weeks 17 to 21, late March to late April) and between longitudes 100-105° W. Agricultural fires have an additional concentration of hotspots in week 43 (late September).

~~A simple decision tree was constructed from the same dataset to look at simple threshold-based classification schemes. (Fig. 69). A total of 9 out of 99 wildfire hotspot clusters (primarily from early May of 2009) occurred at reportedly low values of DC (<50). A DC of 50 is below the minimum DC recorded for agricultural fires (which generally have DC that is lower that wildfires), inclusion of DC in classification tree would have resulted in a terminal node of wildfires at a very low DC with no regard for ISI. This would lead to the false conclusion that all detections with a low (wet) DC are wildfires. These observations were included in the classification tree, but DC was not included in the classification model construction. Therefore, the classification tree should be used with caution at very low DC levels (<50). An Initial Spread Index (ISI) (proportional to the fire's rate of spread) was found to be the strongest predictor, with 972 % accuracy in predicting wildfires vs agricultural fires. Next, the Fine Fuel Moisture Code was also found to correctly classify 98 % of fire detections when wildfires are classified ISI >=15. For fires with ISI <15, high percent curing (*i.e.* low NDVI, indicative of plowed fields in the vicinity or recent adjacent agricultural burning) over 86 % was a strong indicator of controlled agricultural burning, with 84 % accuracy. In areas with lower NDVI/curing values, ISI values >= 11 (but under 15) were wildfires 90 % of the time, and lower ISI values showed no meaningful pattern, with 58 % being agricultural burns. Overall, the single threshold of ISI >= 15 appears to be the best balance between simplicity and accuracy, as it correctly identifies 82 % of all the fires with little commission of only one agricultural fire. The complete range of meteorological conditions resulting in an ISI >= 15 are shown in Appendix A. Overall, this decision tree model had an lower AUC of 0.78 compared to the GAM, where as the decision tree hadand a higher favourable True Positive Rate of 0.95 and a far lowerthough a less favourable True Negative Rate of 0.60 (Table 13). However, tThe Critical Success Index of of this particular classification model 0.82 and overall Accuracy of 0.85 is slightly better than the GAM. A total of 11 wildfires in early May of 2009 occurred at reportedly low values of DC (<100). A DC of 100 is far below the minimum DC recorded for agricultural fires (which generally have DC that is lower that wildfires), and resulted in a terminal node of wildfires at a very low DC with no regard for ISI. This would lead to the false conclusion that all detections with a low (wet) DC are wildfires. These observations were not included in the decision tree. Therefore, the decision tree should be considered applicable when DCs exceed 100, a moisture condition range at which overwinter precipitation measurements can induce uncertainty into spring DC values (Chavardès et al., 2019)(Hanes et al., 2020).~~

In addition to the classification tree ~~s~~ presented in Fig. ~~69~~7, some properties of wildfires show meaningful ~~extreme values~~breakpoints beyond which all agricultural fires values with or without meaningful differences to overall distribution (Fig. 4) or as a linear predictor in the GAM (Fig. 5). Median FRP between all agricultural burns (39 MW) and all wildfires (59 MW) are similar, and a non-parametric Mann-Whitney *U* test on the two samples did not differ significantly (Mann–Whitney $U = 1860$, $n_1 = 113$, $n_2 = 41$, $p < 0.44$ two-tailed). However, on the higher end of FRP, wildfires showed a much larger right skew to the FRP values, with the 99th percentile of agricultural fire FRP of 233 MW, while this corresponded to

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the 86th percentile of wildfire FRP (or the largest 14% of the wildfire data). With the maximum observed wildfire FRP being 1174 MW, this allows for an additional logical scheme to discriminate wildfires from agricultural burning not captured in the above decision tree, where MODIS hotspot FRP values > 233 MW can be confidently classified as wildfires. Similarly, median noon wind speeds between agricultural fires (15.5 km h^{-1}) and wildfires (21.2 km h^{-1}) were similar, though distributions differed significantly (Mann–Whitney $U = 1387$, $n_1 = 113$ $n_2 = 41$, $p = 0.0001$ two-tailed). Some 30% of wildfire wind speeds exceeded the 90th percentile of agricultural fire wind speeds (22 km h^{-1}), allowing for an additional simple classification consideration for fire thermal detections during periods of high wind speed.

~~When the GAM model is applied to the 24,316 hotspots clusters in the entire MODIS dataset, 30 % of hotspot clusterss were detected under conditions that are most similar to documented wildfires. These hotspots (Fig. 8), these have a strong regional gradient with more wildfires in the eastern portion of the study area (Fig. 7). The trend is reversed for burn days, with more days conducive to wildfires in the west of the study area (Fig. 8).~~

~~The seasonal and spatial patterns along lines of equal longitude are portrayed in a Hovmoller diagram in Fig. 9. For both agricultural and wildfires there is a concentration of fires in the spring (around weeks 17 to 21, late March to late April) and between longitudes 100-105°W. Agricultural fires have an additional concentration of hotspots in week 43 (late September).~~

4. Discussion

~~The dataset used in this study purposely utilized the longer-duration MODIS dataset from 2002 onwards, rather than the shorter duration VIIRS dataset from 2012 onwards. Though both sensors are capable of fire detection in the midwave infrared, VIIRS is in theory capable of detecting smaller or less intense agricultural fires (Johnston et al., 2018; Zhang et al., 2017) which offers little advantage when the goal is the detection of larger wildfires in the region. Moreover, one of the goals of this study is to examine broad spatial trends in fire occurrence (Fig. 8), where a longer record is ideal. Recently launched geostationary weather-oriented earth observation platforms such as GOES, Meteosat, and Himawari offer many advantages for monitoring short-lived wildfires, with scan rates every 10–15 minutes (Hall et al., 2019). The northern latitude of the study area (49–59° N) causes a severe degradation of the pixel size of GOES geostationary fire detections to 4 km and limited FRP resolving capacity (Hall et al., 2019). The dataset and classification criteria presented here can assist in improving the confidence in real-time wildfire detection in these areas with widespread fire use on the landscape.~~

In all likelihood, many of the~~se~~ roughly ~~>~~7 500 wildfire ~~s~~ hotspot clusters classified by the GAM ~~identified~~ over 17 years (or 441 fires per year over a 115 Mha study area) are smaller, briefly out of control fires where agricultural burning gets beyond direct suppression and burns over a number of adjacent agricultural fields until the wildfire encounters a roadway (typically over 10 m of fuel-free width), which readily stops most wildfires in grass and agricultural residue fuels (Cheney, and Sullivan, 2008). Given the generally widespread dispersed population density of the area, the vast majority of wildfires in the region are detected and reported by the public (McGee et al., 2015), such that satellites as the first mode of wildfire detection is of limited utility in the region, compared to more northerly and remote areas (Johnston et al., 2018). However, satellites provide a consistent technique for medium-resolution fire extent reporting and mapping that can prove useful for emergency managers (Lindley et al., 2019). Moreover, wildfire growth modelling (Sá et al., 2017) and smoke dispersion forecasts (Chen et al., 2019) require real-time analysis and forecasting initialized using remotely-sensed fire detections.

Both the GAM as well as the classification tree point to the combination of critically dry fuel and wind as the drivers of wildfire occurrence in the region. In the GAM model, both low RH (as a proxy for standing grass moisture), alongside indicators of bi-weekly (DMC) to monthly (DC) moisture deficit are significant in predicting wildfire occurrence as linear predictors, with a wind threshold in the range of 30 km h^{-1}. In the Canadian Fire Weather Index System, fine fuel moisture (mostly driven by low RH) is combined with wind speeds to calculate the Initial Spread Index as a single heuristic (Figure S2), and thus comes out as the strongest indicator of wildfire~~This is in contrast with~~. ~~(~~Lindley et al., 2011~~)~~ ~~who~~ found no such moisture deficit as a driver of wildfire occurrence, and instead found that RH alone ~~thresholds~~ below 25 % and particularly below 20 % as~~re~~ responsible for most grassland wildfires in west Texas. In our study region, RH alone however is not an ideal proxy for fuel moisture across the wide range of air temperatures found in the region during wildfire, as RH alone does not account for variable vapour pressure deficit at different temperatures (Srock et al., 2018) that drives the equilibrium moisture content of standing grasses (Miller, 2019). Moreover, the extensive shallow water bodies in the region may contribute during periods of higher moisture surplus (i.e. low DMC and DC) to a fragmentation of fuel continuity, similar to the function of larger lakes to the north in Canada (Nielsen et al., 2016).~~The interaction of temperature and vapour pressure is parameterized to some extent in the FFMC (Van Wagner, 1987).~~

While more complex classification models with additional predictors were easily built using the *rpart* package, the goal in the classification tree model is to create a parsimonious model with simple application in short range (same day to 3 day outlook) guidance whether environmental conditions (grass curing, humidity, and wind speed) are sufficiently similar to historical wildfire occurrence. The classification tree presented in Fig.~~ure~~ 7~~9~~ is by no means the sole model that meets objectives for Critical Success Index and model accuracy. A high False Alarm Rate as present in the classification tree shown in Fig.~~ure~~ 7~~9~~ would be far more problematic in natural hazards such as tornadoes that require a sheltering response upon a false alarm (Ripberger et al., 2015). In this particular regional context, the criteria established to differentiate between agricultural fires and wildfires is more akin to the threshold beyond which responsible fire use activities should not occur due to dry and windy conditions, rather than triggering a sheltering response. The adoption of any formal warning criteria requires a robust consultation process with regional stakeholders and is not within scope here. Rather, the data acquired and analyzed here provides for the efficient creation of future warning products in the region.

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~~Grass dries much quicker than the forest floor, meaning the largest discrepancy between forest floor (FFMC) and open grass moisture content lies within 2–3 days after rainfall where grass is drier, after which the moisture content in the FFMC and a Grass Fuel Moisture Content model are similar (Kidnie and Wotton, 2015). In the decision tree model (Fig. 6), RH is not directly included, though FFMC values over 93 are found only during periods of low RH and multiple days since rainfall. This is in contrast with (Lindley et al., 2011) who found that RH thresholds below 25 % and particularly below 20 % are responsible for most grassland wildfires in west Texas. RH however is not an ideal proxy for fuel moisture across the wide range of air temperatures found in the region, as RH alone does not account for variable vapour pressure deficit at different temperatures (Srock et al., 2018). The interaction of temperature and vapour pressure is parameterized to some extent in the FFMC (Van Wagner, 1987).~~

The study region is often impacted by prolonged dry periods. The study region experienced profound drought in the 1999–2005 period (Hanesiak et al., 2011) that corresponds to the start of the study period. Drought Code (representing a simple water balance of precipitation minus evaporation) ~~itself~~ was a weak linear (p = 0.084)~~minor~~ ~~first-order~~ predictor of grassland wildfire in this dataset, and may be considered mechanistically similar to the Palmer Drought Severity Index widely used in grassland and agricultural water availability studies (Hanesiak et al., 2011)~~, as an increase of 100 DC units (DC is wettest at zero and reaches ~700 in late summer droughts) results in the odds of a wildfire over an agricultural fire increase by 2.45 times~~. Similarly, Duff Moisture Code as another weak linear indicator of wildfire detection, though a model as the drying of a forest floor organic soil, is still a metric of rainfall deficit relative to evaporation over the prior two weeks. ~~In addition to the absolute value of the DC, d~~Drought itself in the grasslands and agricultural areas of North America results in significant reductions in NDVI (Gu et al., 2007) that therefore directly increases grass curing as estimated in this study (Eq. (1)) and hence lengthens the seasonal window of grassland wildfire susceptibility.

~~The thresholds at which agricultural fire detections are overtaken by wildfires~~The thresholds shown here in the classification tree and GAM models ~~occurs a~~correspond to modelled~~t~~ fire intensity ~~thresholds that~~conditions at the upper ~~correspond to the~~ limits of ground-based wildfire suppression. The grass fire spread model in the Canadian Forest Fire Danger Rating System utilizes Australian experimental grass fire data that has been shown to approximate fire behaviour in wheat crops, with the matted (or cut) grass model approximating spring (cured) post-harvest debris (Cruz et al., 2020). Following the Canadian Forest Fire Danger Rating System (Forestry Canada Fire Danger Rating Group, 1992) for an O-1a (matted grass) fuel type, ~~Initial Spread Index~~ISI values of 1~~5~~7 (Fig. 7) with grass curing ~~between~~of ~~75–80~~ 80 % ~~(Fig. 65)~~, the resultant spread rate is~~of~~ 38~~24~~ m min^{-1} (~~1~~2.~~4~~3 km h^{-1}). ~~and~~ This intensity of approximately 4000~~2 500~~ kW m^{-1} (flames 2 m long) is near the upper limit of suppression, particularly when fire sizes exceed 2~~–3~~ ha at the time of initial suppression action (Hirsch et al., 1998). This correspondence of our remotely sensed records (confirmed by fire reports solely of date and time, not of reported fire behaviour) and the operational models in the Canadian Forest Fire Danger Rating System lends confidence to the application of our approach in public safety and awareness messaging.

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Under climate change, the agricultural and grassland region of Canada is anticipated to move northward (Schneider et al., 2009), though this rate of transition will be dampened in wetland~~peatland~~ areas (Schneider et al., 2016) and those not disturbed by wildfire (Stralberg et al., 2018). Natural grasslands are expected to increase particularly in areas of rapidly accelerating fire occurrence, where younger forests disturbed by severe wildfire are prone to large increases in grass cover (Whitman et al., 2019). Moreover, a dense grass cover is problematic in recently planted forests north of the study region, as it can outcompete tree seedlings (Lieffers et al., 1993), and is likely to be exacerbated ~~exasperated~~ by the expected lower overall canopy density (Lieffers and Stadt, 1994) brought about by a drier future climate (McDowell and Allen, 2015). Active conversion of forest to agricultural lands is likely to continue (Hobson et al., 2002), as is the natural expansion of grasslands on drier, south-facing (solar-exposed) slopes in the boreal forest ~~where their range is currently limited to at high latitudes~~ (Sanborn, 2010). In addition to this likely grassland and cropland expansion, projections of increasingly common critical fire weather conditions (Wang et al., 2015) is likely to shift the fire regime to one of more open fuel burning. However, no change in the rate of fire detections (undifferentiated between wildfires and agricultural burning) has been detected between 1981-2000 (Riaño et al., 2007) nor 1998-2015 (Andela et al., 2017) in the region.

The expansion of grasslands and agriculture into currently forested areas will substantially change the fire regime in these areas, highlighting the importance of understanding the current grassland and agriculture area fire regime. With grassland expansion into forest, forest fire suppression will have to incorporate elements of the grass fire regime. A key feature of the temporal nature of the grassland fire regime shown (Fig. 9~~8~~) is the prevalence of wildfire in the month of April, far before traditional forest fire suppression crews are trained and active (Tymstra et al., 2019). The occurrence of autumnal wildfire is much smaller than that in the spring (Fig. 9~~8~~), but similarly requires resources for wildfire suppression in a region where the fire season has traditionally ended in early September (Hanes et al., 2018).

~~. Understanding how fire regimes could change with climate change will help fire managers make long term fire management decisions.~~

~~To further understand the fire regimes of our study area we looked at east west gradients in both grass fire weather and the amount of fire on the landscape.~~Regional contrasts in this grassland-agricultural fire landscape are revealed in the spatial analysis. Larger amounts of both agricultural and wildfire in the east of the study area (Fig. 6), despite fewer burn days (Fig~~s~~. 8~~7and 8~~), may~~could~~ be due to differences in ~~burning culture~~agricultural practices or more flax agriculture.~~.~~ Farmers are more likely to burn flax crop residue as it can be difficult to remove by other methods (~~Y.~~ Chen et al., 2005). ~~This increase in~~Higher rates of agricultural burning may also lead to increased ~~wildfires as there are more ignitions on the landscape, which could escape~~wildfires via escaped fires from crop burning. Further work is required to better understand the contributions of vegetation and fire ignition that results in east-west gradients in both wildfire and agricultural activity observed here that contrasts directly with the number of potential wildfire activity days.~~Additionally, since there are more days conducive to wildfire in the western portion of our study area, any ignition is more likely to lead to a wildfire.~~

5. Conclusions

A classification scheme was developed to discriminate remotely sensed agricultural fires vs wildfires in the southern grasslands of continental Canada through an analysis of historical wildfires and documented agricultural fires. Effective schemes for discriminating fire types were produced using continuous data (Generalized Additive Models) as well as threshold-based classification trees. A combination of weather, vegetation condition, and temporal variables provided the best predictors. ~~–~~A noon Initial Spread Index threshold of >= 17~~5~~ was the most powerful threshold from the decision tree model for discriminating wildfires from agricultural fires, while grass curing values ~~Initial Spread Index values exceeding 15 at noon on the day of the fire was the most powerful threshold for identifying wildfires, grass curing values~~ between 60–85 % w~~a~~ere ~~s~~ the best non-linear spline predictor in the GAM. Fire Radiative Power was effective in discriminating wildfires only in the 14 % of wildfires with very high FRP values that exceeded the highest documented FRP in the agricultural fire dataset. ~~Similar~~Minor discrimination utility was seen in the Drought Code and Duff Moisture Code precipitation deficit metrics. Classification of a large dataset of historical wildfire detections revealed a strong regional contrast in fire activity that is the inverse of the number of days with wildfire-conducive weather. Overall, the majority of the most power predictors of grassland wildfire stem from weather observations and remotely sensed metrics of the pre-fire environment, and are thus available for forecasting and real-time classification of satellite thermal detections. This work provides a foundation from which future public warning products can be derived.

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Data availability: Landsat thermal detection thumbnails detailing patterns of hotspot detections as well as data used to build the model and apply it across the study area is available at https://doi.org/10.5281/zenodo.3764192.

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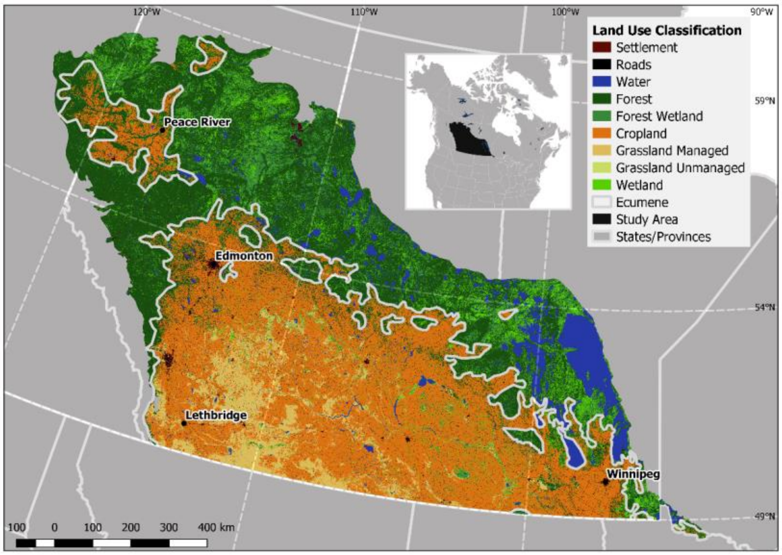
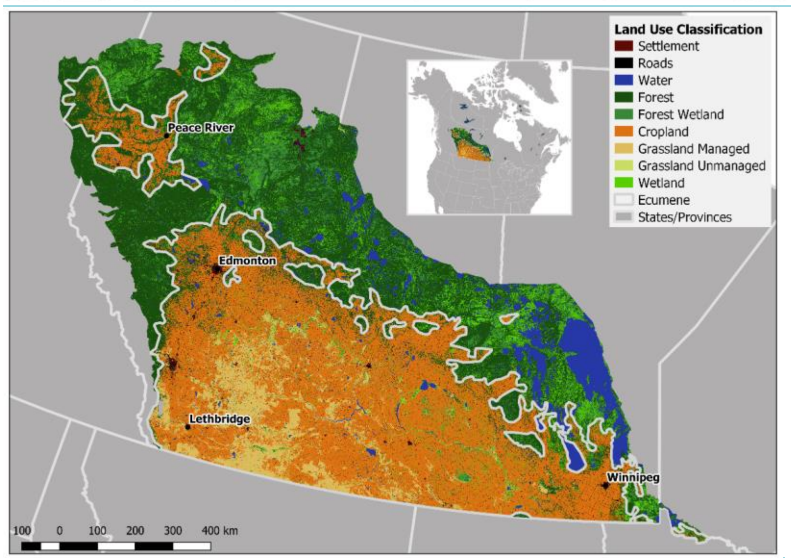


120°W
110°W
100°W
90°W
59°N
54°N
49°N
Land Use Classification
Settlement
Roads
Water
Forest
Forest Wetland
Cropland
Grassland Managed
Grassland Unmanaged
Wetland
Ecumene
Study Area
States/Provinces
Peace River
Edmonton
Lethbridge
Winnipeg
100 0 100 200 300 400 km



Land Use Classification
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Cropland
Grassland Managed
Grassland Unmanaged
Wetland
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States/Provinces
Peace River
Edmonton
Lethbridge
Winnipeg
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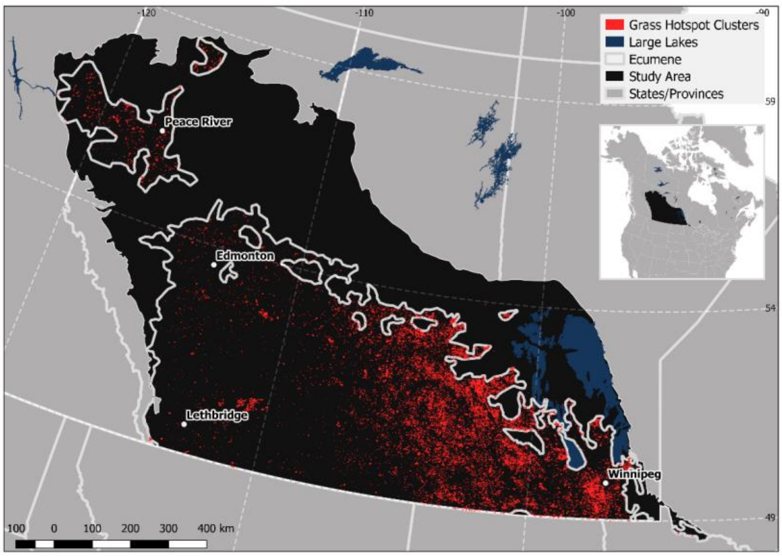
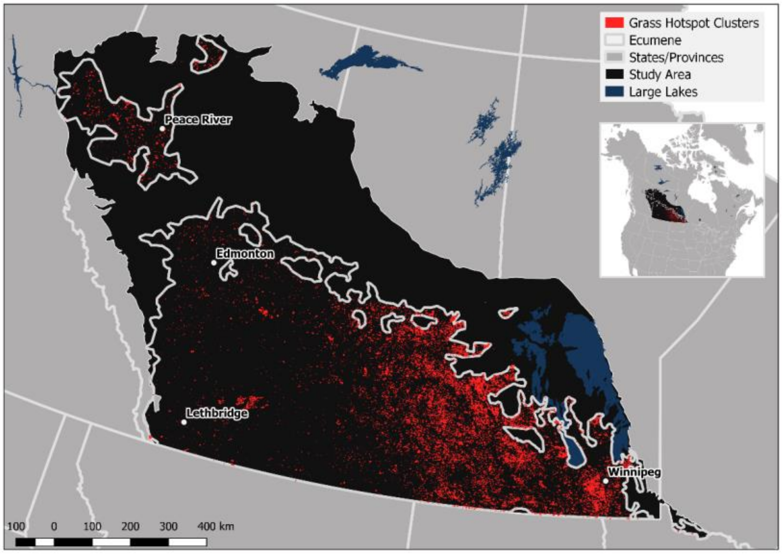
Figure 1. ~~Landcover~~ Remotely-sensed land cover data at 30 m resolution (Agriculture and Agri-Food Canada, 2018) of our study area as of 2010 compared to the extent of the ecumene. The study area extends past the ecumene to ensure all minor area of grass and agriculture are included. ~~and study area extent.~~



-120
-110
-100
-90
Grass Hotspot Clusters
Large Lakes
Ecumene
Study Area
States/Provinces
59
54
49
Peace River
Edmonton
Lethbridge
Winnipeg
100 0 100 200 300 400 km



Grass Hotspot Clusters
Ecumene
States/Provinces
Study Area
Large Lakes
Peace River
Edmonton
Lethbridge
Winnipeg
100 0 100 200 300 400 km

Figure 2: Grass fire MODIS(MOD14A1 and MYD14A1)(Giglio, 2015) hotspots clusters in the study area from 2002–2018. These hotspot have been screened for persistent industrial heat sources and clustered as described in the methods. The study area extends past the ecumene to ensure all minor areas of grass and agriculture are included. However, the vast majority of hotspot clusters are present within the ecumene.

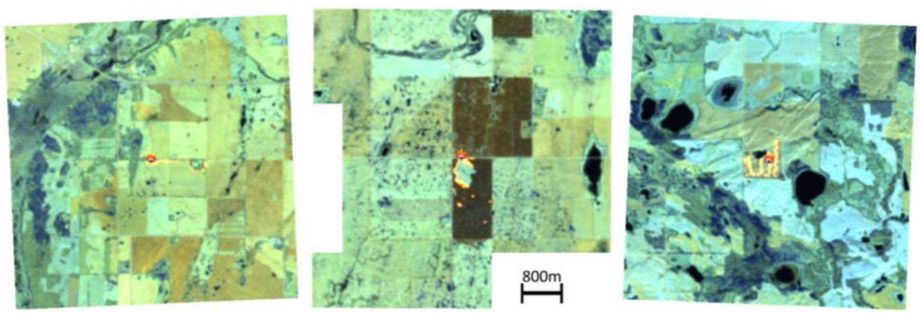


Figure 3. Examples of processed Landsat 8 images indicating fire detections considered agriculture burns. Note the regular geometric patterns of the fires, specifically the line ignitions patterns and the burning of specific fields. The presence of previously burned fields is shown north of the active fire in the centre panel, which is registered in this study as low NDVI and very high rates of curing.

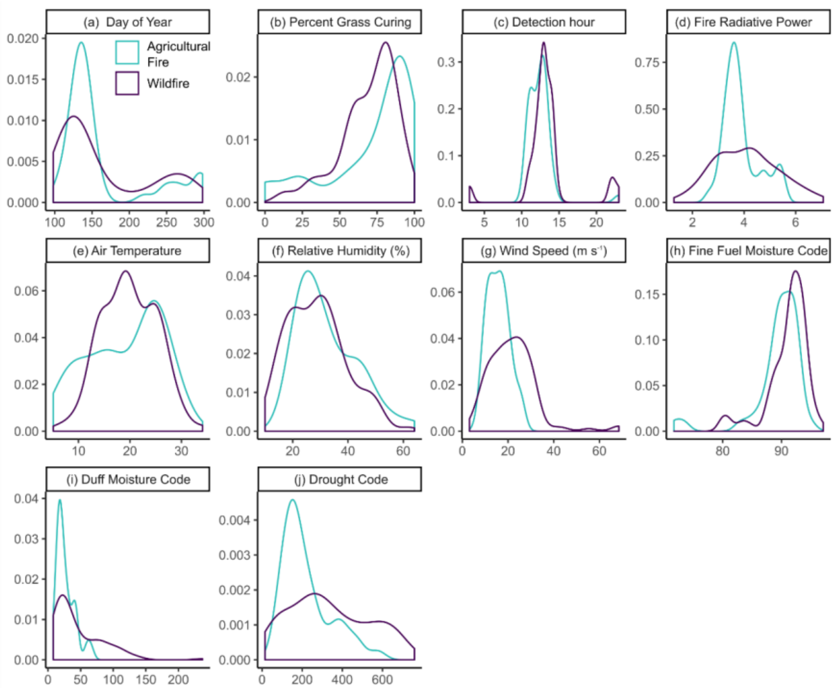


Figure 4. Distribution of hotspot cluster properties between wildfires (purple) and agricultural fires (blue). Fire Radiative Power is given in MW and transformed by the natural logarithm.~~Figure 4: Distribution of fire detection properties between wildfires (purple) and agricultural fires (blue).~~

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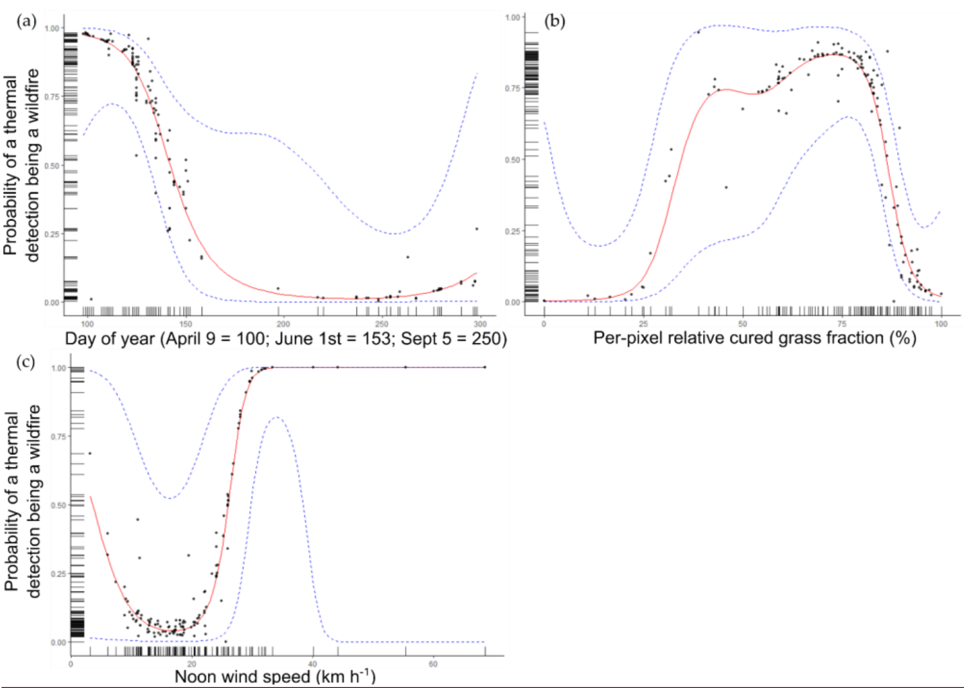
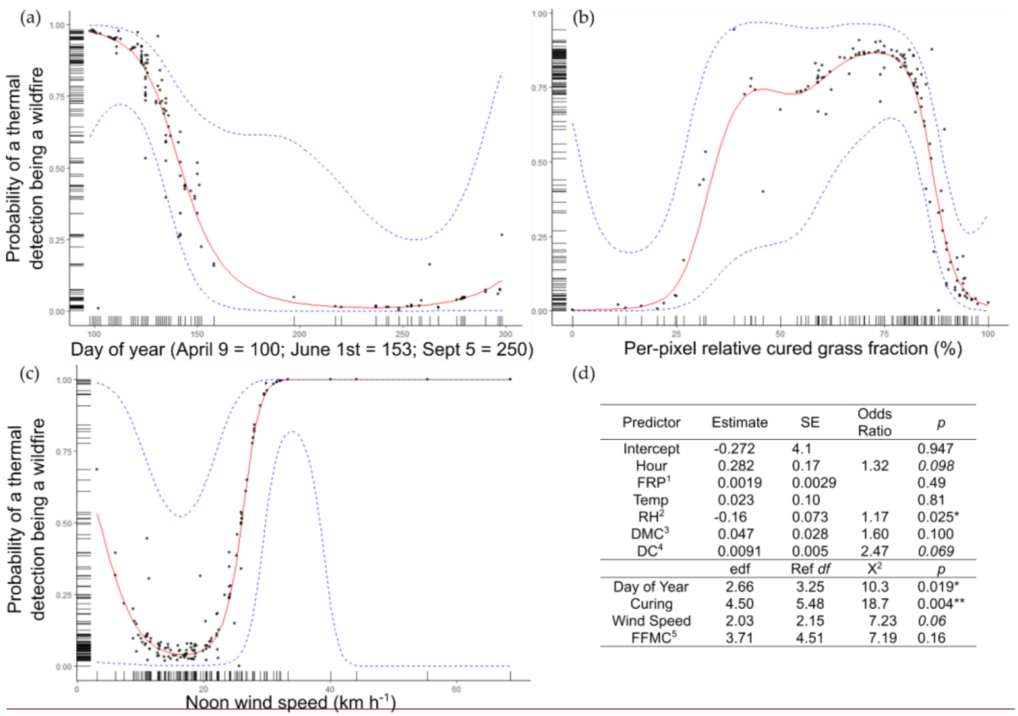

(a)
(b)
(c)
Probability of a thermal detection being a wildfire
Day of year (April 9 = 100; June 1st = 153; Sept 5 = 250)
Per-pixel relative cured grass fraction (%)
Noon wind speed (km h-1)



Predictor	Estimate	SE	Odds Ratio	*p*
Intercept	-0.272	4.1		0.947
Hour	0.282	0.17	1.32	*0.098*
FRP[1]	0.0019	0.0029		0.49
Temp	0.023	0.10		0.81
RH[2]	-0.16	0.073	1.17	0.025*
DMC[3]	0.047	0.028	1.60	0.100
DC[4]	0.0091	0.005	2.47	*0.069*
	edf	Ref *df*	X^2	*p*
Day of Year	2.66	3.25	10.3	0.019*
Curing	4.50	5.48	18.7	0.004**
Wind Speed	2.03	2.15	7.23	*0.06*
FFMC[5]	3.71	4.51	7.19	0.16

Figure 5: Generalized Additive Model outputs for a binomial model of agricultural fire vs wildfire. The ticks along each plot axis show the marginal distribution of the data. ~~The linear portions of the GAM coefficients (logit-transformed) are shown with Z values in panel (d), and the spline portions of the GAM are shown with X^2 (Chi-square) estimates in (d). Predictors significant at $p < 0.01$ are shown with **, $p < 0.05$ with *, and $0.1 > p > 0.05$ shown in italics. Logit-transformed parameter estimates of the GAM and Odds Ratios shown in panel (d). FRP = Fire Radiative Power; RH* = noon relative humidity, odds ratio shown as (estimate×−1), or odds ratio per unit decrease in RH; DMC† = Duff Moisture Code per 10 units; DC‡ = Drought Code per 100 units; FFMC = Fine Fuel Moisture Code.~~

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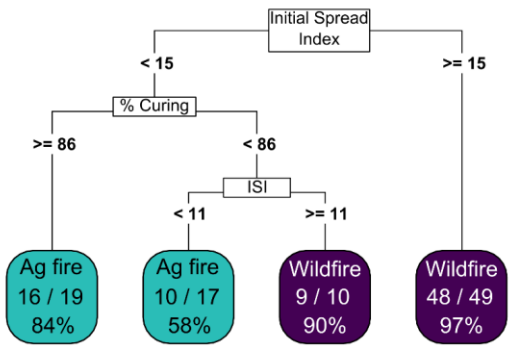
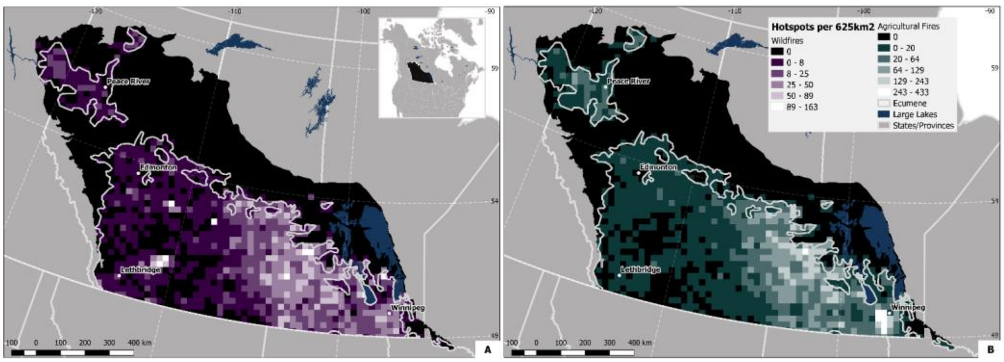


~~Figure 6. Simple decision tree scheme for the classification of agricultural vs wildfires, valid only for a subset of the dataset with Drought Codes exceeding 100. The first set of numbers in each terminal node is the number of correctly classified records divided by the total number of records in that node. The accuracy of each node is also given. Note that high rates of curing > 86% is associated with plowed fields or those previously burned in agricultural fires in the days prior (see Fig. 3).~~



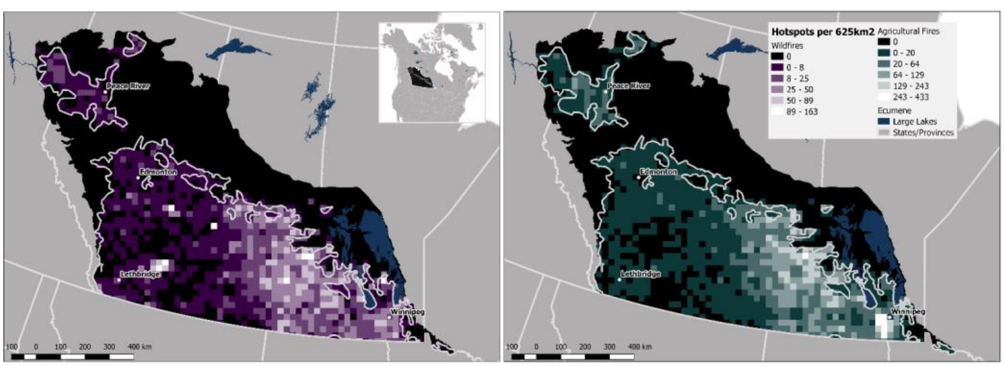


Figure ~~7~~6. (a) Cumulative occurrence of wildfire hotspot detections per~~r 625 km^2 pixel)~~25km square cell ~~-~~in the study region from 2002–2018~~. A wildfire may contain one or more hotspots~~. Panel (b) Cumulative occurrence of agricultural fire hotspot detections in the study region from 2002–2018. Discrimination between wildfire and agricultural fire hotspots conducted using the Generalized Additive Model (GAM).

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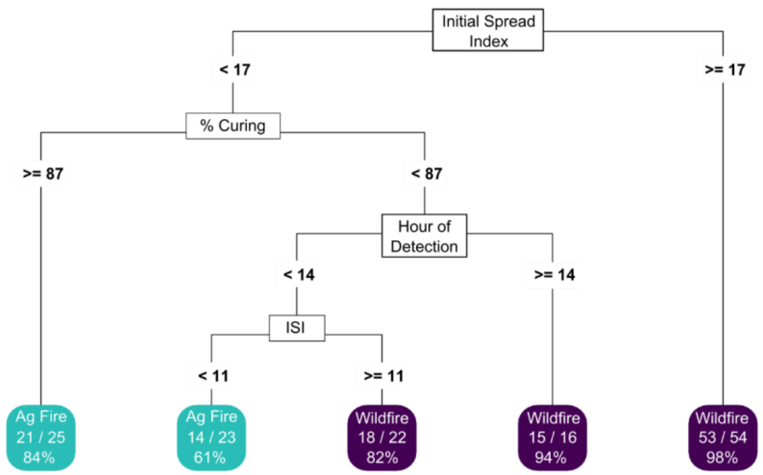

Figure 7. Simple decision tree scheme for the classification of agricultural vs wildfires. The first set of numbers in each terminal node is the number of correctly classified records divided by the total number of records in that node. The accuracy of each node is also given. Note that high rates of curing is associated with plowed fields or those previously burned in agricultural fires in the days prior (see Fig. 5).

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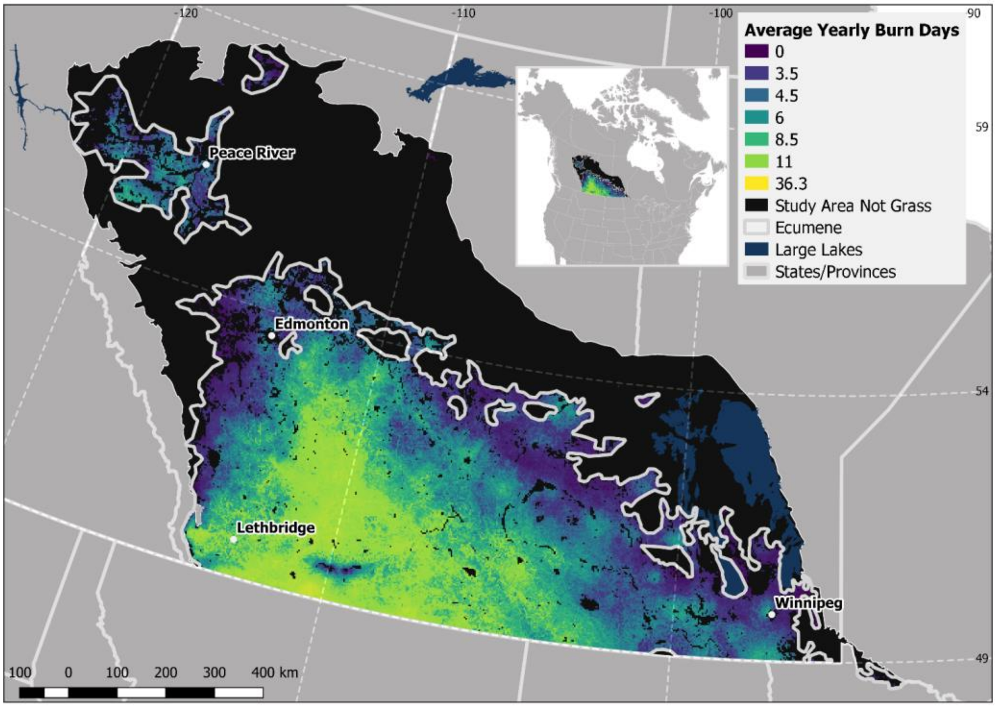
Average Yearly Burn Days
0
3.5
4.5
6
8.5
11
36.3
Study Area Not Grass
Ecumene
Large Lakes
States/Provinces
Peace River
Edmonton
Lethbridge
Winnipeg
-120
-110
-100
90
59
54
49
100 0 100 200 300 400 km

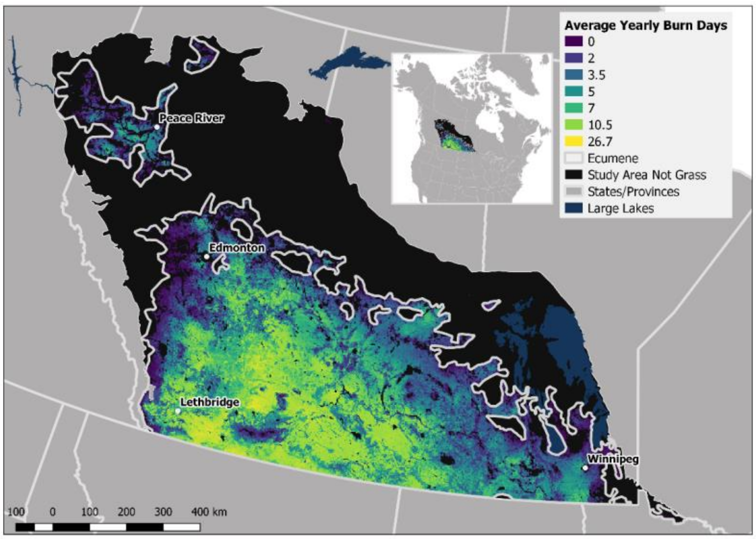

Figure ~~87~~8. Average number of days per year (2002–2015, April–September~~8~~) where the fire weather and environmental conditions meet or exceed an Initial Spread Index of 17 or greater as well as grass curing between 60 and 85~~0~~ % ~~the criteria in Fig. 6 for a grassland wildfire~~.

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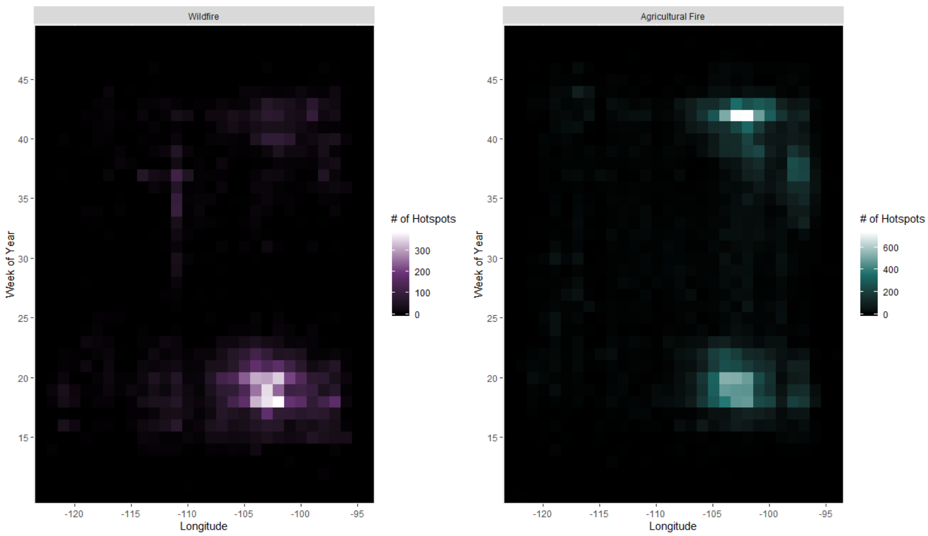
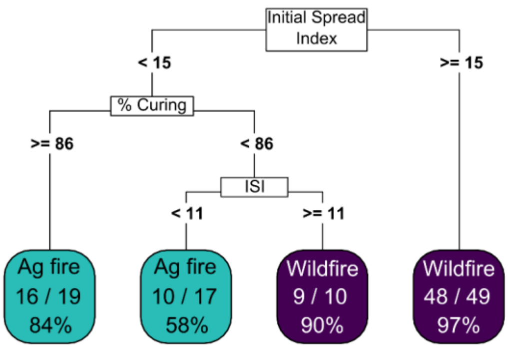


Figure ~~9~~89. Hovmoller diagram showing seasonal patterns of wildfire vs agricultural fire. In this diagram, the number of hotspot detections is summed across all latitudes within a longitude bin (x-axis), and is shown over time (y-axis). Values are the cumulative sum of detections from 2002–2018.



~~Figure 69. Simple decision tree scheme for the classification of agricultural vs wildfires, valid only for a subset of the dataset with Drought Codes exceeding 100. The first set of numbers in each terminal node is the number of correctly classified records~~

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~~divided by the total number of records in that node. The accuracy of each node is also given. Note that high rates of curing ≥ 86% is associated with plowed fields or those previously burned in agricultural fires in the days prior (see Fig. 3).~~

Table 1: Summary of datasets used in study.

Dataset	Spatial Resolution	Temporal Resolution	Derived Data	Product Number/Source	Time Frame
Land cover	30 m	As of 2010	Grass cover	(Agriculture and Agri-Food Canada, 2018)	2010
MODIS thermal detections	1 km	Twice daily	Hotspot clusters	MOD14A1 and MYD14A1	2002-2018
MODIS NDVI	250 m	16 day composite	Grass curing	MOD13Q1 and MYD13Q1	2002-2018
Landsat 8 thermal detections	30 m	16 days	Confirmed agricultural fires	(Kato et al., 2018)	2013-2018
Weather and fire weather	3 km grid	12pm LST daily	Model input	(McElhinny et al., 2020)†	2002-2018
Canadian National Fire Database	N/A	N/A	Confirmed wildfires	(Hanes et al., 2018)	2002-2017
Canadian Wildfire Evacuation Database	N/A	N/A	Confirmed wildfires	(Beverly and Bothwell, 2011)‡	2002-2018

† The station data used in McElhinny et al (2020) were interpolated on a 3-km grid using an inverse distance weighting approach.
‡ The methodology of Beverly and Bothwell (2011) was applied to search for fires in the Prairie region of Canada, which were excluded from this publication. Evacuations were catalogued from 2002-2018. See supplementary data.

Table 2. The linear predictors of the GAM predicting if a hotspot cluster is a wildfire (coefficients given in logit space) alongside their odds ~~ratios~~ for predictors with $p < 0.10$. Smooth of the GAM are shown with X^2 (Chi-square). [1]FRP = maximum Fire Radiative Power of a cluster (natural log-transformed); [2]RH = noon relative humidity (%),~~y, odds ratio shown as (estimate×−1), or~~ odds ratio per unit in~~de~~crease in RH; [3]FFMC = Fine Fuel Moisture Code; [4]DMC = Duff Moisture Code.

Linear Predictor	Estimate	SE	Odds Ratio	*p*
Intercept	14.5~~2.4~~	11.~~4~~6		0.21~~7~~
Detection hour	0.26~~29~~	0.144~~1~~	1.29	0.06~~10~~
[1]~~FRP~~ln(FRP)	-0.30~~0.003~~	0.~~00~~230		0.~~23~~32
Air Temperature	0.05~~04~~	0.078~~0~~		0.48~~53~~
[2]RH	-0.163~~46~~	0.061	0.31~~1.15~~	0.016~~7~~

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[3]FFMC	-0.148~~37~~	0.118~~7~~		0.21~~3~~
[4]DMC	0.039~~1~~	0.022~~1~~	1.04	0.080~~14~~
Drought Code	0.008	0.004~~5~~	1.008	0.083~~95~~
Smooth Terms	*edf*	Ref *df*	X^2	*p*
Day of Year	3.1~~2.9~~	3.~~6~~8	14~~3.8~~4	0.00~~5~~4
Curing	4.1~~6~~	5.0~~6~~	17.7~~20.1~~	0.004~~1~~
Wind Speed	2.0	2.1	9.4~~8.1~~	0.03~~6~~4

Table ~~1~~3. Generalized Additive Model (cutoff 0.66~~70~~) and Decision Tree model performance metrics (n = 140 in both models). Sensitivity, Specificity, and AUC (Area Under receiver operating characteristic Curve) were calculated using a leave-one-out cross validation. Miss Rate through to Accuracy Statistics were calculated using all data to train the model tested against itself.

Metric	GAM	Decision Tree
True Positive Rate – ~~-~~ Sensitivity	0.87~~82~~	0.77~~98~~
True Negative Rate – Specificity	0.85~~87~~	0.71~~48~~
AUC	0.89~~88~~	0.74~~74~~
False Negative Rate	0.14~~17~~	0.23~~01~~
False Positive Rate	0.15~~2~~	0.29~~51~~
False Discovery Rate	0.06~~5~~	0.13~~15~~
False Omission	0.28~~32~~	0.44~~09~~
Critical Success Index	0.81~~78~~	0.68~~82~~
Accuracy	0.86~~84~~	0.75~~85~~

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~~Appendix A. Observation density biplots of the fire weather associated with thermal detections (*n* = 3036) where the Initial Spread Index of the Canadian Fire Weather Index System is 15 or higher (3036 of 24316 total observations, or 12%). Panel A: noon vapour pressure deficit vs wind speed (both local noon standard time) for all observations of ISI 15 or higher. Panel B: relative humidity vs wind speed for the same subset. Panel C: Fine Fuel Moisture Code vs wind speed.~~