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Commentary on the article "Burn probability simulation and subsequent wildland fire activity in Alberta, Canada – Implications for risk assessment and strategic planning" by J.L. Beverly and N. McLoughlin

Monte Carlo simulations using wildland fire spread models have been conducted to produce numerical estimates of fire likelihood, project potential fire effects, and produce event sets of realistic wildfires (Parisien et al., 2019). The application of these methods has greatly expanded over the last few decades as a result of increased computation capabilities, available data, and our fundamental understanding of landscape fire dynamics. In their recently published article, Beverly and McLoughlin (2019) attempt to assess the accuracy of fire likelihood outputs (hereafter "burn probability" [BP]) they produced for five large areas in Alberta, Canada, by testing the "correspondence between observed burned areas and pre-fire burn probability maps" in order to "explore how the expectations of decision-makers influenced our assessment of map accuracy." To do so, they superimposed BP estimates computed with the Burn-P3 fire simulation model (Parisien et al., 2005) with areas recently burned by wildfire from the reference year used in Burn-P3 until 2017. Their results show a moderate statistical preference of recent burns for high-probability areas in three study areas and no preference in the remaining two. This leads them to conclude that "the use of these maps for research or other applications should be approached with caution and consideration of their shortcomings and apparent limitations." In dismissing the accuracy of the BP estimates, they are sending an erroneous message to managers and the research community that BP maps are not useful.

We agree with Beverly and McLoughlin (hereafter B & M) that assessing the skill of BP models—or any model—is necessary, but we argue that the manner in which their evaluation was executed undermines (or even invalidates) some of their conclusions regarding the utility and potential accuracy of fire simulation model outputs. We display and discuss three major weaknesses in B & M's analysis: (1) the inappropriate method of assessing accuracy, (2) a misinterpretation of BP outputs, and (3) data quality considerations. Finally, we propose ways in which a discussion on assessing BP model skill could move forward.

1. Inappropriate method of assessing accuracy

We should first provide a brief overview of how BP is calculated. In models such as Burn-P3 (Parisien et al., 2005) and FSim (Finney et al., 2011), the ignition and growth of individual wildfires are simulated during a single pseudo-year (termed "iteration") according to the natural variability one could expect within a fire season. Model inputs are usually derived from historical databases representing wildfire patterns, fuels, and weather and modeling processes simulate substantial year-to-year variation. Some iterations, therefore, yield many wildfires that can burn large proportions of the landscape, whereas others may simulate none or few (similar to fire seasons observed in the real world). Model runs are carried out for a large number of iterations (typically 10^4 to 10^6); that is, until the outputs have reached a "stable" estimate of pixel-wise BP. Numerous outputs can be obtained from these models, one of which is a measure of BP that, depending on the model formulation, measures a conditional (i.e., given an ignition in a study area; e.g., Ager et al., 2010) or annualized probability (Scott et al., 2013). Other outputs include maps of potential fire behavior components (e.g., fire intensity, fuel consumption) and mapped ignitions and perimeters of the simulated wildfires. Post-processing of model outputs has been used to investigate a wide range of wildfire management issues, including strategic placement of fuel treatments (Thompson et al., 2017), risk transmission to the urban interface (Haas et al., 2014), and conservation of critical habitat (Ager et al., 2007).

B & M use Burn-P3 to generate BP maps for five study areas and then compare BP values with subsequent observations of wildfire that occurred during two- (n = 2 study areas), four- (n = 2), or thirteen-year periods (n = 1) (Fig. 1). In their assessment of model skill, B & M imply that model "performance" is contingent on observations of burned areas coincident with high BP. Although this presumption may appear sensible, it suffers from at least three related conceptual flaws.

The first flaw is illustrated in Fig. 2. Areas of high BP in Burn-P3 outputs represent "fire sinks" on the landscape; that is, locations where many fires may originate, converge, or intersect (Ager et al., 2012). Areas of high BP are the result of many (hundreds or thousands) overlapping simulated fires. When the full extent (i.e., the fireshed) of all of the fires that burn into, or originate from, a given area of high probability is displayed, it is clear that most of these fires also burn large areas of low and moderate BP across the landscape. While it is reasonable to expect model outputs to reflect real-world fire activity, it is highly unreasonable to expect that the area burned by observed individual wildfires will constrain themselves to a particular range of BP values on the map: many wildfires (and especially large ones) will burn across lands with a wide range of BP values. Indeed, the simulated perimeters used to produce the BP maps themselves do not perfectly align with high BP areas (Fig. 2c, d). Therefore, it is not surprising that B & M found that "large portions of burned areas observed in the years following burn probability simulations occurred in locations where burn probabilities were relatively low." Large fires burn under extreme conditions and may cover vast areas that, under moderate conditions, are generally of low flammability (and low BP) due to a lack of fuels (e.g., urban areas, broadleaf stands, recently burned forests). An example of one such fire from B & M's set of observed fires that burned indiscriminately across the landscape is evident in the FTMC study area (Fig. 1).

The second flaw is in the attempted comparison of burned areas with probabilities. Ideally, burned areas (units of hectares) need to be compared with burned areas, and probabilities (units related to time, i.e., per year) compared with probabilities. Instead, B & M go to great

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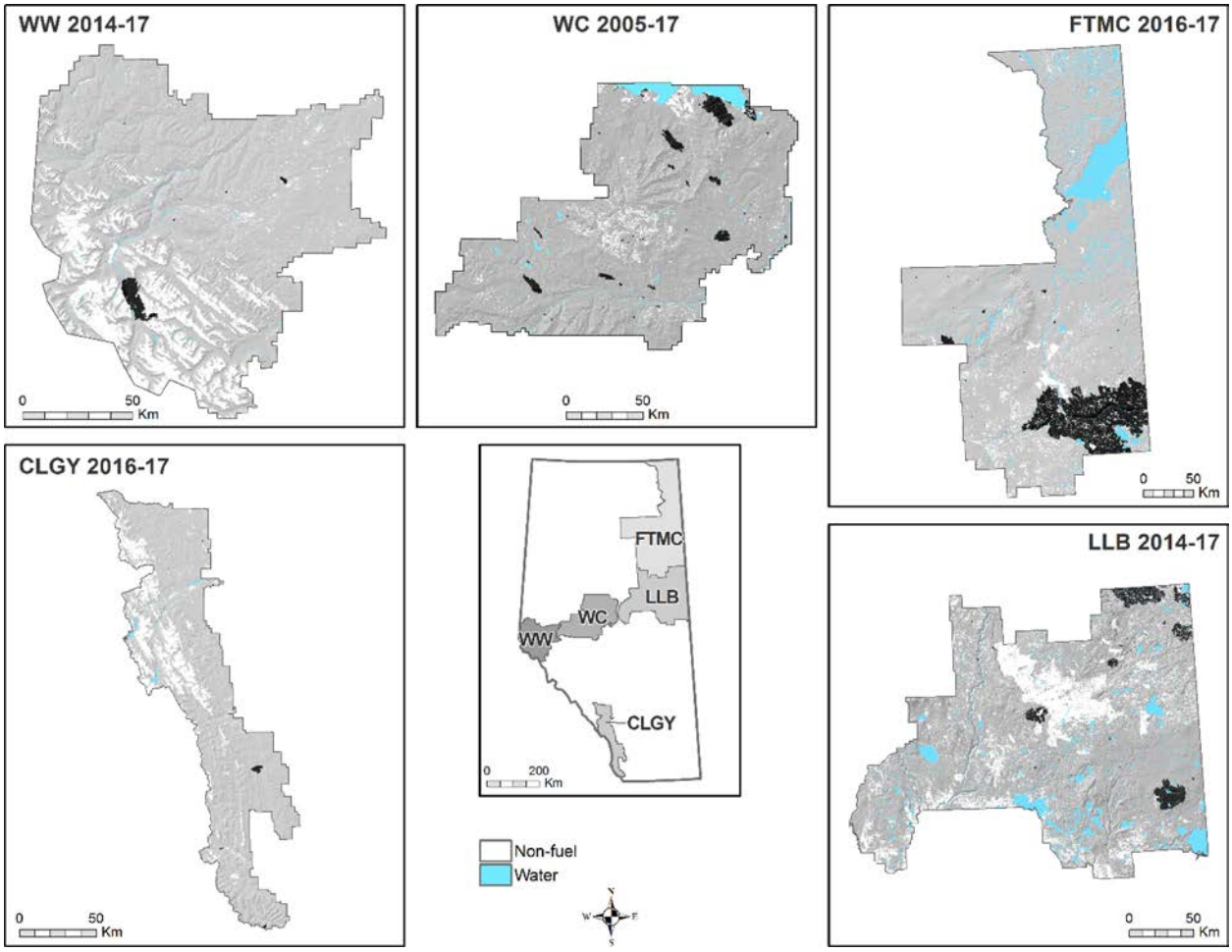

Fig. 1. The five study areas from Beverly and McLoughlin (2019) in Alberta, Canada. The areas burned by wildfire in their evaluation period are shown in black, while areas displayed as non-fuel in their analysis are shown in white.

lengths to compare proportional burned area within subjectively determined classified bins of probabilities. Although B & M claim that the perceived accuracy of estimated BP outputs varies according to aspects of symbology (e.g., number of bins of values, where one places the value breaks), this is based on the false premise that one can compare areas to probabilities. One option for comparison is to use the observed burned areas to estimate empirical BPs, and then compare those probabilities with simulated values. As an illustration, we calculated observed BPs from burned areas estimated from 2013 to 2017 by the Monitoring Trends in Burn Severity (MTBS) large-fire perimeter dataset (Eidenshink et al., 2007) as the proportion of 50 × 50-km grid cells for the conterminous US. We compared these observed BPs with BPs simulated for 10,000 iterations for the same domain using landscape data representing 2012 conditions (Short et al., 2016) (Fig. 3a). Binomial confidence intervals (95%) were calculated for these simulated BPs (the standard normal approximation, Brown et al., 2001) for a hypothetical 100- and 10,000-year observational sample. This illustrates the decreasing confidence (i.e., wider confidence intervals) with both the smaller sample size and lower likelihood of burning (Fig. 3b). We attempted to plot confidence intervals for 2013–2017, a period of similar length to the evaluation period used by B & M. However, the confidence intervals for this period of observations were not informative because (as plotted on logarithmic axes) the upper-bound is about 0.5 and the lower bound is 0.0 for nearly all predicted BPs, meaning that all 5-year estimates of BP are within the confidence bands. In fact, even though the hypothetical 100-year example represents an infeasibly long observational record, it still has confidence intervals sufficiently wide as to encompass most of the actual 5-year estimates. Our conclusion is that the variation in BPs of rare fire events ($BP < 0.1$) is so great that quantitative comparisons are mostly meaningless with short-duration event sets similar in length to those used by B & M (four out of five study areas in B & M included ≤ 4 years of fire data). The method we used to compare observed BPs to estimated BPs thereby highlights an important third flaw (below).

This related conceptual flaw concerns the stochastic nature of wildfire occurrence: individual wildfires can (and do) occur in low-BP areas because of chance alone. Even if the superimposition of a handful of observed burned areas and BP were a valid measure of model evaluation—flaws #1 and #2 show that it is not—, one should never expect a particular outcome for a stochastic process. For example, just as one would not expect six rolls of a die to yield a one, a two, a three, a four, a five, and a six, we cannot expect individual wildfires to occur exclusively within a particular BP range. In fact, recent wildfires across the conterminous US do not all occur in high-BP areas (Fig. 3a). To illustrate the effect of stochasticity, we recreated B & M's results on the burned area proportions by BP class (Fig. 5 in B & M) in Fig. 4 using simulated data from two previously published studies that used Burn-P3, one in the relatively flat boreal forest of northeast Alberta (Stockdale et al., 2019) and one in the rugged terrain of south-central British Columbia (Wang et al., 2016). For each of these, we drew 50 random samples of two, four, and 13 years (i.e., iterations) of simulated fire data and evaluated how the area burned corresponded to the BP values using a quantile classification scheme, which was found to be the most "accurate" representation of data according to B & M. Of course,

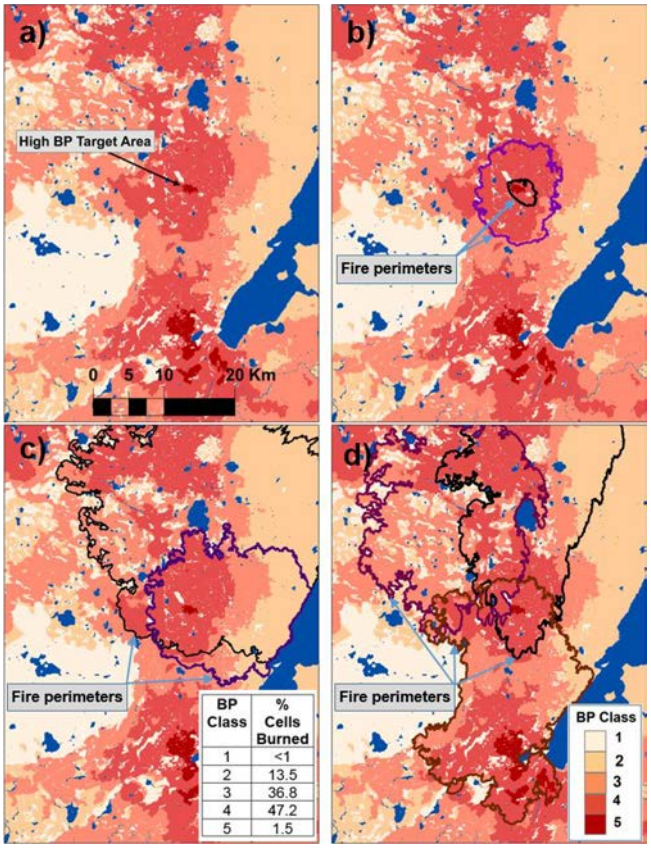

Fig. 2. Validation methods of Burn-P3 outputs in Beverly and McLoughlin (2019) presume significant overlap of real-world fires with areas of high burn probability (BP). Panel A shows a section of a BP map (Stockdale et al 2019), classified by quantiles into 5 classes (1–5, low to high). A small high-BP target area is indicated with the arrow for reference. Panel B: B & M's accuracy analysis implies that fires should occur as the black or purple outlines: largely falling within classes 4 or 5, as shown with these two sample wildfires drawn from the simulations. Panel C: these simulated fires burn large areas of BP classes 2 and 3, and would be considered "poorly predicted fires" according to the authors. Panel D shows three more simulated fires derived from this event set of fires used to create this BP map. In total, 236 individual modeled fires intersected the target area, ranging from 71 to 138,978 ha in size (mean 21,600 ha). The embedded table shows the number of cells burned by all 236 fires combined in each BP class. Most fires that burn through the area of high BP also burn large other areas of the landscape.

there is an important difference between observed data that occurred over a multi-year time period and simulated wildfires burning on a landscape that is "reset" at each iteration. Nevertheless, the results in Fig. 4 show that many simulated fire perimeters from these randomly selected iterations—the very same data that were used to compute the BP maps—occur in the low-BP classes. Given extreme stochasticity in fire occurrence patterns, low-BP areas should not be expected to be fire-free in any given year, further emphasizing that comparisons of observed area burned and predicted BP are inappropriate.

2. Interpretation and relevance of model outputs

B & M refer to manager "expectations" to question the relevance of BP model outputs. As we have established, no one—and no model—could ever exactly predict individual wildfires, particularly given the stochastic nature of wildland fires and the coarseness of fire spread models currently used. In our experience, managers do not expect BP models to provide this information. In fact, managers typically understand that BP models are one of many tools they can use and do not consider any model as a panacea. For instance, within the BP modeling approach, model outputs other than BP can be mined to provide a wide range of insights into the scale of risk, risk transmission, and effect of landscape fragmentation on fire-management activities (Haas et al., 2014). Perhaps most important, fire models are a key tool to design and evaluate strategic fuel treatment programs. In this context, absolute values of BP are less important than the relative change in BP and other fire behavior metrics relevant to forest and fuel management programs. A similar appraoch has recently been used to measure the effectiveness of fire-suppression policies (Reimer et al., 2019). Also, in an era where climate change is increasingly driving large fire events, fire simulation models are providing valuable insights into "surprise" fires that are not part of the historical record (Hulse et al., 2016).

We, therefore, submit that, if the fire-prediction systems and spread algorithms on which BP models are based are largely accurate, BP outputs are very useful, especially when combined with other equally important metrics that collectively inform fire management strategies. Properly parameterized BP models and their multitude of derived products can be interpreted as the landscape-level potential of a given location to experience a large wildfire of a certain intensity. Fire simulation modeling such as Burn-P3, FSim, and FlamMap are meant to inform strategic (i.e., long-term) fuel management programs as part of larger, multifaceted forest restoration programs (Ager et al., 2011) and not to predict where individual fires will occur in a given year (Scott et al., 2013). Though it is extremely difficult (if not impossible) to know where and when fire ignitions will occur, and which ones will "escape" initial attack and become large, knowledge of where the landscape is inherently more flammable is useful for whoever is living and working in fire-prone areas. Annual BP values, which are low in B & M's areas, may not appear useful for a specific year, but they do reveal a non-negligible likelihood for burning across the longer time horizons associated with forest management planning (usually 10–20 years in Alberta). For example, if one assumes a simple Poisson process for discrete events (which we know to be over-simplistic) and no major landscape change, the range of annualized BP values reported by B & M

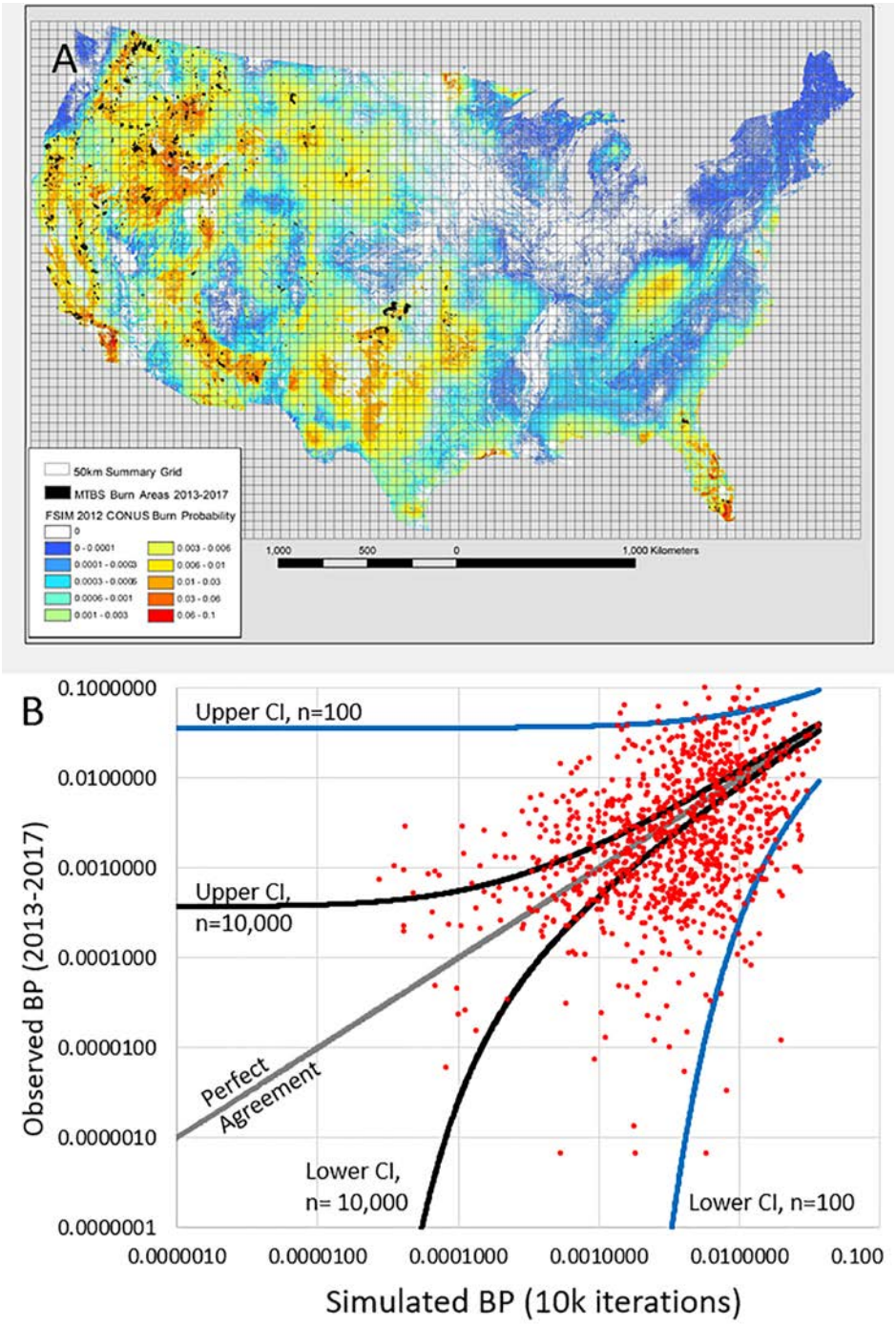

Fig. 3. Comparison of burn probability (BP) simulated using FSim for the 2012-vintage LANDFIRE data (Short et al., 2016) with (A) burned areas observed (2013–2017) from MTBS (black), and (B) BP calculated as proportions of 50-km grid cells burned by the wildfires shown in (A) plotted against simulated BP. Plot B also shows 95% binomial confidence intervals calculated for different sample sizes (number of simulated or observed years). Simulations have samples of n = 10,000 iterations and relatively narrow confidence limits, whereas samples of n = 100 years are wide enough to encompass most of the estimated probabilities estimated from five years of wildfire activity (2013–2017). Upper and lower confidence limits for n = 5 years are not displayed because they are roughly constant at 0.5 and 0.0, respectively, and encompass all observations.

(BP = 0.018 to 0.0616) translates to 20-year burn probabilities that range up to 70.8%; certainly a value worthy of attention.

Any evaluation of model performance requires an in-depth understanding of what the model products are telling us. B & M seem to imply that BP models should predict the occurrence of a selected set of individual wildfires occurring over a short window of time— yet Burn-P3 and other BP models were not designed nor meant to be used for this purpose. The inability of Burn-P3 to predict a limited and select set of observed fires led B & M to conclude that "burn probability maps may not be useful for informing fine-scale activities in these landscapes." We dispute this claim. When high-quality data are used and inputs are thoughtfully prepared, BP models produce a spatially resolved quantitative estimate of fire likelihood that can inform strategic planning (e.g., focus fuel management and pre-suppression planning efforts) and, therefore, can complement fire-management tools that involve modelling active fires and support tactical (short-term) activities (Parisien et al., 2005; Scott et al., 2013). BP models tell us, for instance, that very large wildfires tend to converge where there are large tracts of high-flammability vegetation in spite of relatively few ignitions (Ager et al., 2012; Parisien et al., 2011), and that fire refugia (i.e., forests often spared by lethal wildfires) are often found in areas of low BP where vegetation is naturally fragmented or isolated, such as on the lee side of large lakes (Ager et al., 2012). Furthermore, likelihood mapping is but one of many possible outputs from BP models that provide useful insights for fire and risk management decision making (Parisien et al., 2019). For example, the models can take advantage of the simulation of individual wildfires to compute "firesheds", which consist of mapping all potential ignitions that may reach a feature of interest (e.g., the

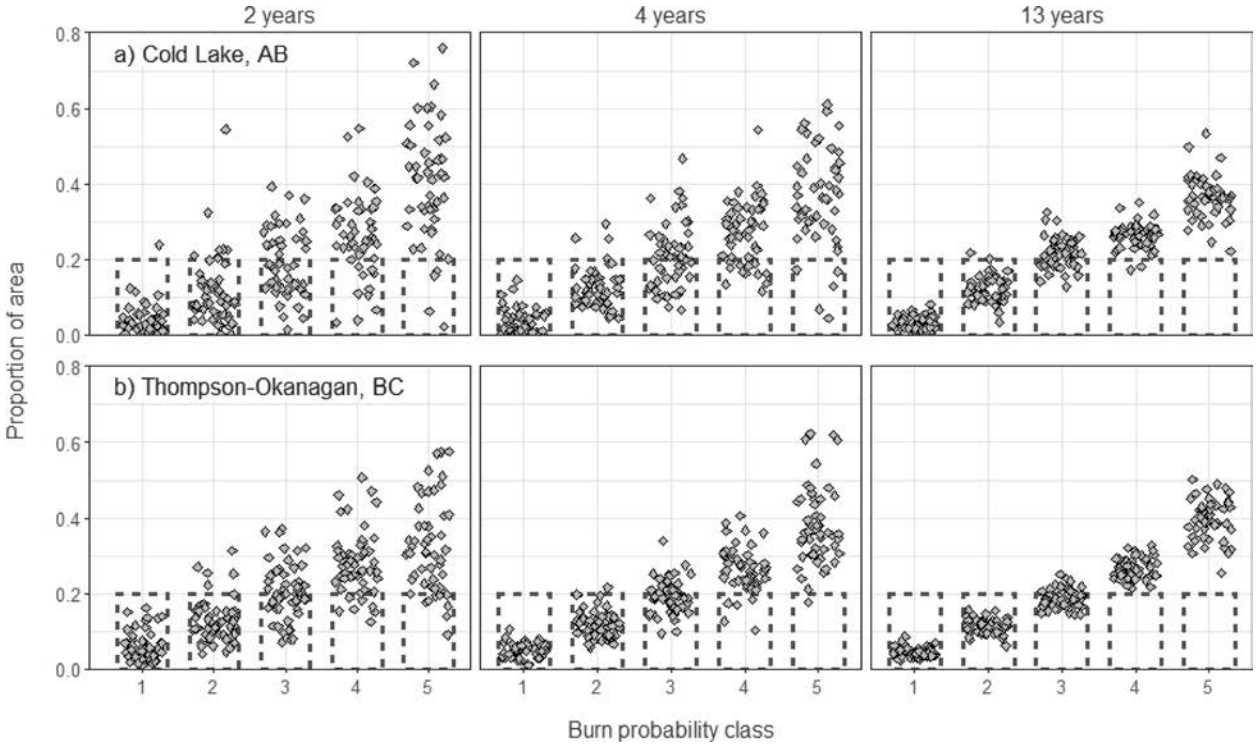

Fig. 4. The proportion of the sampled area burned by the quantile classification method (dashed boxes) used in Beverly and McLoughlin (2019) from two studies: one in Cold Lake, AB and one in the Thompson-Okanagan area of BC. Every point represents the proportion of the area burned by class (proportion for the five classes = 1) for 50 random samples of two (left column), four (middle), and 13 iterations (i.e. years) (right). The results are based on the samples of simulated fire perimeters that were used in the calculation of the BP maps.

wildland-urban interface) (Scott et al., 2012, Ager et al., 2019), and can be used to evaluate the relative effect of innumerable fuel-change or ignition-management scenarios compared to a baseline assessment (Thompson et al., 2017). Without BP models, these types of analyses would be exceptionally difficult to achieve.

3. Data quality considerations

Burn-P3 and related models such FSim and FlamMap are highly sensitive to the quality of input data, such as the number and spatio-temporal patterns of ignitions, the accuracy of mapped fuels, and the care with which ignition frequency and fire size distributions are calibrated (Parisien et al., 2010). In light of this, Stratton (2009) emphasized the importance of performing a thorough 'data critique' before embarking on any fire simulation project. Describing the source data, how the inputs were created, and what modeling decisions were made imparts some transparency to the modeling procedure and allows managers and scientists to better interpret the modeling outputs. In the B & M article, this important data-related information is only available for one of the five study areas (WC), through a previous publication (Beverly et al., 2009). Thus, it is impossible to know if problems or inaccuracies in the source data or in the creation of inputs have contributed to the model-performance metrics reported by B & M.

B & M mention that "observed burned areas were also 42–95 times greater than median annual burned area in our Boreal and Foothills study areas (WC, LLB, FTMC) and 26 to 1635 times greater in our Rocky Mountain study areas (CLGY and WW)." This directly acknowledges that the baseline against which they calibrated their models did not match the conditions within the more recent, and potentially changed, fire regime with which they attempt to validate their BP results. Such a discrepancy can be due to either a poor parameterization of the model, sheer luck (e.g., the occurrence of a very large fire within a two-year evaluation period), or a lack of stationarity due to changes in climate or human land use. Although current or future fire potential may greatly exceed that of the recent past (Riley and Loehman, 2016), such a drastic change from the simulation period to the evaluation period in B & M's article is surprising. We thus question the soundness of building inputs from a period up to 53 years prior to the evaluation period. Rather, it would have been preferable to build BP inputs to represent expected conditions rather than attempt to closely match historical ones (Parisien et al., 2013). Although B & M state that "core Burn-P3 modeling processes do not vary from user to user", a review of the literature suggests otherwise: there is no strict prescription for the Burn-P3 model and, in fact, this goes against the philosophy of the BP modelling approach, whereby inputs and assessments of outputs are adjusted to best suit the landscape under consideration and questions being asked (Parisien et al., 2019).

In BP models, the quality and representativeness of mapped fuels are critical to producing reliable outputs. In particular, updating fuels-related data after large-scale disturbances is an essential, yet challenging, aspect of this type of fire simulation modeling. Following a wildfire in a forested area, there is a short period of time during which fuel conditions can be regarded as non-fuel, as vegetation can recover and become flammable within a few years (albeit less flammable than mature forests) (Erni et al., 2017; Parks et al., 2018). Assumptions about the temporal progression of fuel conditions used in simulation for these disturbed areas can affect BP outputs. In Fig. 5, we highlight two of the instances where B & M incorrectly assumed that non-fuels mapped immediately after large wildfires remained largely unchanged up until the evaluation period, many years after the fire. Specifically, the fuels after two very large wildfires, the 1998 Virginia Hills fire (168,819 ha) in the WC study area and the 2002 House River fire (236,446 ha) in the LLB study area, were considered by B & M to be largely composed of non-fuel (and grass in case of the Virginia Hills fire, according to Beverly et al., 2009). The effect of this assumption on their BP maps is evident in their results (Beverly and McLoughlin, 2019, Fig. 3). However, in these two areas, the Enhanced Vegetation Index computed from Landsat (Fig. 5) shows that vegetation recovered fairly

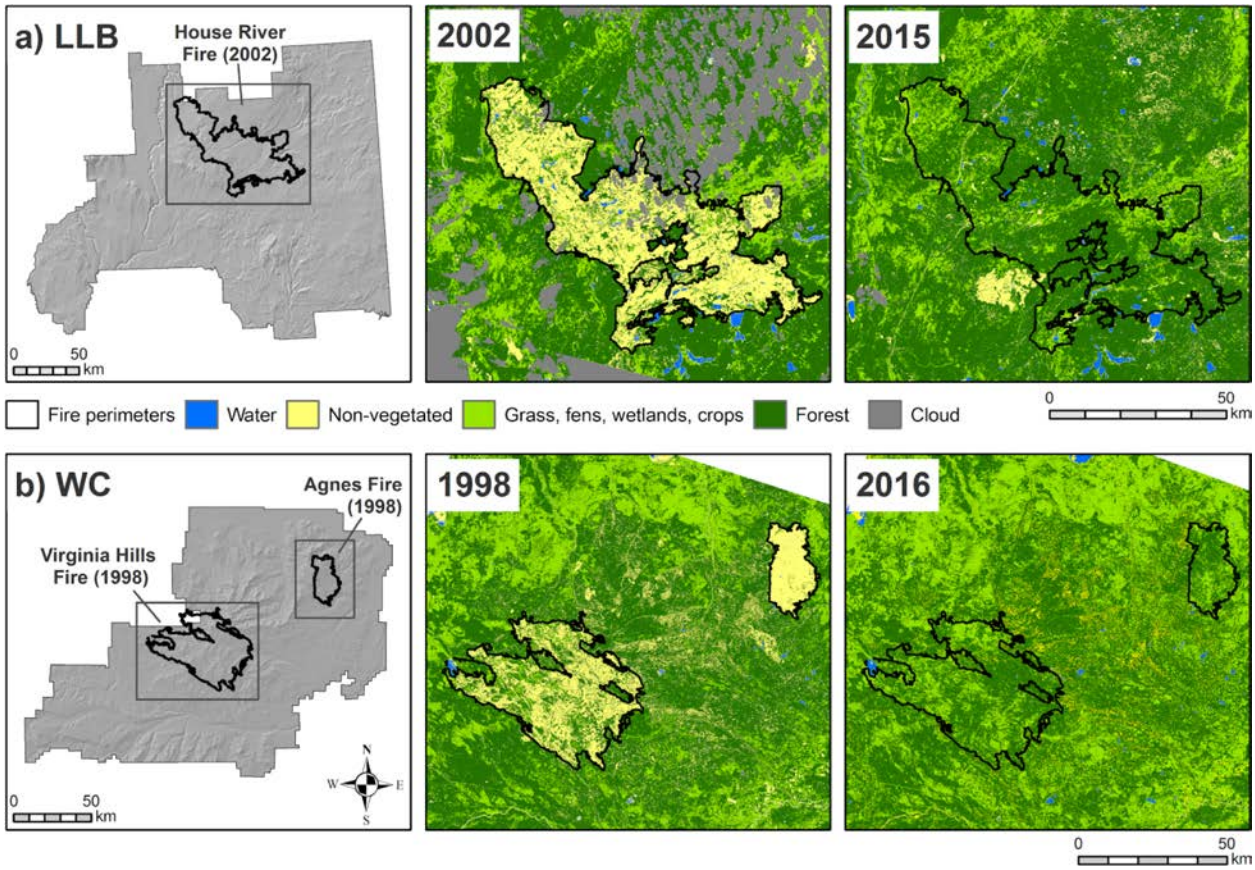

Fig. 5. Postfire vegetation recovery represented using a maximum likelihood classification of Enhanced Vegetation Index (EVI) for large wildfires of the LLB (a) and WC (b) study areas of Beverly and McLoughlin (2019). There is a clear progression from non-vegetation (yellow) immediately after a fire to widespread treed vegetation (dark green) after several years (right-hand panels). A map of the fuels used for modeling the WC study area (Beverly et al., 2009) shows that a large proportion of the Virginia Hills fire was classified as non-fuels, whereas the smaller Agnes fire was entirely classified as grass. The EVI indicates that these two burns were largely forested during the evaluation period.

rapidly after wildfire—naturally and through reforestation—and much of these two areas has become flammable from the perspective of the Canadian Fire Behavior Prediction System (Forestry Canada Fire Danger Group, 1992) before or during the evaluation period. In fact, one of the authors (M.-A. Parisien) sampled the vegetation of the House River fire in 2018 and observed average dominant tree heights of 8.1 m. The misclassification of fuels for such large areas will invariably affect BP patterns. Although B & M are mindful of changes in fuels affecting BP estimates ("[…] substantial land cover change over short time periods that would quickly erode the representativeness of burn probability maps."), in these instances we believe they have neglected to adequately update fuels, thus diminishing the reliability of their outputs and their subsequent ability to assess model skill.

4. Possible next steps

We agree with B & M that an evaluation of model skill is an important exercise for gauging predictive ability and for identifying ways in which a model can be improved. However, in light of the issues detailed here, we assert that B & M's evaluation does not effectively assess BP model (specifically, Burn-P3) performance. This said, we acknowledge the challenging nature of model assessment, which perhaps explains the dearth of examples in the published literature (e.g., Parisien et al., 2005; Paz et al., 2011). Moving forward, it would be ideal to explore robust methods to evaluate BP model skill. As shown in Figs. 2 and 3, comparing probability values with burned areas is problematic—in fact, it is a comparison between different entities having different units; a probability-to-probability comparison would be preferable. It could be useful, for instance, to compare statistically derived probability surfaces of wildfires for different years and time periods (e.g., year, month, week) with BP maps. Although outputs from statistical models will never be perfectly congruent to those of simulation models, they could be informative in assessing performance, given that both types of models use similar fire-environment information (e.g., vegetation, weather, topography, landscape and anthropogenic features).

In their concluding statements, B & M appear dismissive of the merits of BP modelling and claim that their results "could be used to inform new approaches to fire risk mapping in northern forests ecosystems". They hint at an alternative method for "approximating fire likelihood maps with readily known and easily mapped fire environment and fire regime factors known to influence burn probability values […]." We presume they are referring to statistical models of fire activity. Although these are useful and easy to compute, they are not designed to explicitly consider the landscape context in which fires ignite and spread and as such, cannot fully capture spatial effects such as "fire shadows" on the lee side of lakes and other landscape-scale properties of large fires. Statistical models are additionally limited with respect to testing "what-if" management scenarios (e.g., ignition prevention programs, fuels management), and do not produce outputs suitable for investigating the potential social and ecological effect of individual fires (e.g. Ager et al., 2007). As illustrated in Fig. 3b, the precision of observations in estimating likelihood of burning introduces huge uncertainty and will likely be less reliable than carefully conducted simulations.

A large number of authors seem to agree that commonly used BP

models such as Burn-P3, FSim, and FlamMap are quite useful, as Parisien et al. (2019) found 133 published articles and reports using BP models. At their most basic level, BP models "spatialize" the extreme variability of large-scale fire growth and behavior. While fire-behavior models have their shortcomings, striving to further their development will provide immediate benefits to BP models and other spatial tools on which they are based. This is not to say that the "exploration of alternative possible assessment methods", as B & M suggest, is without merit—it is—but rather than being dismissed, BP methods should be used to complement outputs of other types of models (e.g., Barros et al., 2019). The potential consequences of wildfires are such that no useful information for predicting or understanding their likelihood, occurrence, or effects should be overlooked.

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