

Applications of simulation-based burn probability modelling: a review

Marc-André Parisien^{A,D}, Denyse A. Dawe^A, Carol Miller^B,
Christopher A. Stockdale^A and O. Bradley Armitage^C

^ANatural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Edmonton, AB, T6H 3S5, Canada.

^BUSDA Forest Service, Rocky Mountain Research Station, Aldo Leopold Wilderness Research Institute, Missoula, MT, 59801, USA.

^CEmber Research Services Ltd, Eagle Bay, BC, V0E 1T0, Canada.

^DCorresponding author. Email: marc-andre.parisien@canada.ca

Abstract. Wildland fire scientists and land managers working in fire-prone areas require spatial estimates of wildfire potential. To fulfill this need, a simulation-modelling approach was developed whereby multiple individual wildfires are modelled in an iterative fashion across a landscape to obtain location-based measures of fire likelihood and fire behaviour (e.g. fire intensity, biomass consumption). This method, termed burn probability (BP) modelling, takes advantage of fire spread algorithms created for operational uses and the proliferation of available data representing wildfire patterns, fuels and weather. This review describes this approach and provides an overview of its applications in wildland fire research, risk analysis and land management. We broadly classify the application of BP models as (1) direct examination, (2) neighbourhood processes, (3) fire hazard and risk and (4) integration with secondary models. Direct examination analyses are those that require no further processing of model outputs; they range from a simple visual examination of outputs to an assessment of alternate states (i.e. scenarios). Neighbourhood process analyses examine patterns of fire ignitions and subsequent spread across land designations. Fire hazard combines fire probability and a quantitative assessment of fire behaviour, whereas risk is the product of fire likelihood and potential impacts of wildfire. The integration with secondary models represents situations where BP model outputs are integrated into, or used in conjunction with, other models or modelling platforms.

Additional keywords: fire behaviour, fire simulation models, landscape analysis, wildland fire risk.

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Introduction

Management of fire-prone landscapes is complex. Large fires can affect a host of highly valued resources and assets (HVRAs), including human communities, recreational opportunities, industrial infrastructure, timber, wildlife habitat and ecosystem services, such as the provision of clean water (Thompson *et al.* 2011), among others. These HVRAs might have different responses to fire, with some benefiting from the natural, restorative aspects of wildfire, while others could suffer unacceptable harm. In many parts of North America, there is a general desire to let wildfires fulfil their ecological role, insofar as they do not compromise the safety of people and critical infrastructure (Stephens *et al.* 2016). The inherent spatio-temporal variability of wildfire further complicates matters, challenging managers' ability to prepare for wildfire events. Knowing in advance the likelihood of burning at each point on the landscape and the potential fire behaviour and impacts of wildfires thus provides basic – and necessary – information for improving planning, mitigation and adaptation in fire-prone landscapes (Miller and Ager 2013). This generalised need for

a quantitative spatial estimate of fire probability was the impetus for the development of a modelling framework known as burn probability (BP) modelling, a 'brute force' approach to modelling in which fire likelihood is computed by simulating the ignition and spread of a large number of fires on a static (i.e. without vegetation succession) landscape (Finney 2005).

Although initially designed for strategic (i.e., long-term) planning purposes, BP modelling uses tools originally developed to support operational decision making. This modelling approach was made possible by the advent of deterministic fire growth models such as FARSITE in the USA (Finney 1998) and Prometheus in Canada (Tymstra *et al.* 2010). Prior to fire growth models, fire behaviour analysts working on campaign fires manually estimated fire spread, drawing out their predictions (i.e. fire perimeter) on topographic maps to support firefighting efforts (Andrews *et al.* 2007). Computerised fire-spread algorithms automated this process, thus providing expedited predictions of near-term fire behaviour using real-time and forecasted fire weather. Users of these systems eventually broadened their application to more experimental purposes. The earliest

adaptations often focused on strategic placement of fuel treatments, using a limited handful of simulation runs to test their effectiveness in mitigating undesirable fire behaviour (van Wagtenonk 1996; Stephens 1998). Over time, increased computing power and availability of geospatial data have supported more elaborate uses (Miller and Ager 2013). Newer applications directly included day-to-day variation in weather and randomness in the location of ignitions; this ‘batching’ of multiple fires under observed landscape-level variability became the embryonic BP model. In an example of ‘convergent evolution’, several wildland fire scientists, mainly in the USA and Canada, concomitantly developed this fledgling idea into several conceptually similar models (Davis and Miller 2004; Parisien *et al.* 2005; Finney 2006; Yang *et al.* 2008). The motivation for extending the use of fire-growth models was obvious: if an algorithm could adequately and efficiently estimate the spread and behaviour of a single fire, modelling thousands of wildfires across a landscape could depict the likelihood of fire at any given point and reveal landscape-scale patterns of fire occurrence that could otherwise not be gleaned.

Obtaining a quantitative estimate of fire likelihood and potential fire behaviour at any point on the landscape proved to be eminently useful to land managers and fire scientists alike. By accounting for the nearly infinite possible ignition start points and subsequent spread and likelihood of reaching a specific place of interest, BP models not only provide robust estimates of fire likelihood (assuming proper parameterisation), but also an estimate of the spatio-temporal variability of events. Ongoing improvements in performance and model processes have allowed for the expansion of the application and scope of BP models, as synthesised in Fig. 1. The most fundamental use of these models has been to compute BP and fire-behaviour maps to obtain some measure of likelihood or hazard to HVRAs through predefined combinations and interpretations of model outputs (Scott *et al.* 2013). This can be done for a baseline scenario of inputs or, alternatively, in combination with multiple scenarios of interest. Whereas baseline scenarios provide insight into potential fire behaviour on the landscape for a snapshot of time, performing multiple scenarios allow managers to assess the effects of alternative management decisions, retrospectively examine past landscapes or assess potential future conditions. Beyond the simple examination of BP or fire-behaviour maps, the analysis of BP model outputs can take advantage of rich information yielded from the numerous simulated wildfires. These analyses open the door to applications that consider ‘neighbourhood processes’ or, in other words, the idea that wildfires igniting in various parts of the landscape – sometimes remarkably far, in areas where very large fires may occur – may affect a given HVRA of interest (Scott *et al.* 2012a). In more elaborate risk-based uses, BP can quantify the expectation of loss (or in some cases, benefit) by combining fire likelihood with the impacts to HVRAs from fires. Table 1 provides illustrative examples of how these BP analyses can, and have been, applied to address management questions across diverse landscapes.

Burn probability models are designed to incorporate a degree of sophistication, but also flexibility, to answer complex ecological or management questions. To date, they have been used to investigate fuel treatment effectiveness, wildland–urban interface (WUI) exposure, habitat suitability for numerous

species, forestry planning, risk transmission and carbon budget analyses, to name only a few. Investigating the implications of climate change projections will undoubtedly become one of the main uses of BP models, as climate change is expected to lengthen the fire season and greatly increase the potential for large and intense wildfires (Flannigan *et al.* 2013; Riley and Loehman 2016). This heightened flammability, combined with an expanding WUI (Theobald and Romme 2007) and increasingly fragile ecosystems (McCarty 2001; Johnstone *et al.* 2016), creates a landscape in which unsuppressed fire can have severe consequences. In contrast, there are circumstances in which managers might wish to allow fires to burn so as to capitalise on the natural and restorative aspect of fire (Moritz *et al.* 2014), depending on the weather, timing and proximity to HVRAs (Black *et al.* 2008). Virtually all planning for fire and fuels management requires an understanding of where and when fires may occur – BP models provide managers with a powerful tool to examine where large and intense wildfires and HVRAs are most likely to co-occur.

The wide scope and flexibility of potential applications for BP modelling highlight its importance as a decision-support tool in land management and as a well understood framework for scientific investigation. The rapid expansion in applications of these models, however, might make it difficult for new users to understand all of the potential uses of the approach and, consequently, how to apply models for their specific needs. It should be noted that there are approaches for modelling the potential probabilistic outcomes of a particular known fire ignition that are used to support operational decision making during an ongoing event (Anderson 2010; Finney *et al.* 2011a). Although these approaches might share some of the concepts and inputs (e.g. weather) with the BP techniques described herein, they will not be considered in this review. The central goal is to demonstrate the range of potential and realised applications of BP models for use in decision making by managers and wildland fire scientists alike. Specifically, our objectives are to: (1) describe the inputs and outputs of BP models; (2) provide an overview of applications for which BP models have been used; (3) demonstrate common applications through case studies performed on an illustrative landscape; and (4) develop a comprehensive list of published studies using the BP method and categorise them by application type. In doing so, we aim to provide a resource to guide both new and experienced users of these models. Furthermore, we hope this synthesis will foster discussions regarding creative new uses of the approach and will encourage the future evolution and development of BP modelling.

Purpose

As with any tool, the first step when initiating a project using BP models is to ascertain that this approach is appropriate for the question at hand. The strength of BP models lies in their simulation of ignition and spread processes, which is often simplified in dynamic vegetation models (Abatzoglou and Williams 2016). Burn probability modelling is ideal for representing how wildfires ignite and spread across a complex (i.e. heterogeneous) landscape, and it offers maximum flexibility for exploring alternative scenarios. Regardless of the intention for BP modelling, a user must create ‘baseline’ outputs; that is, outputs based on the most basic

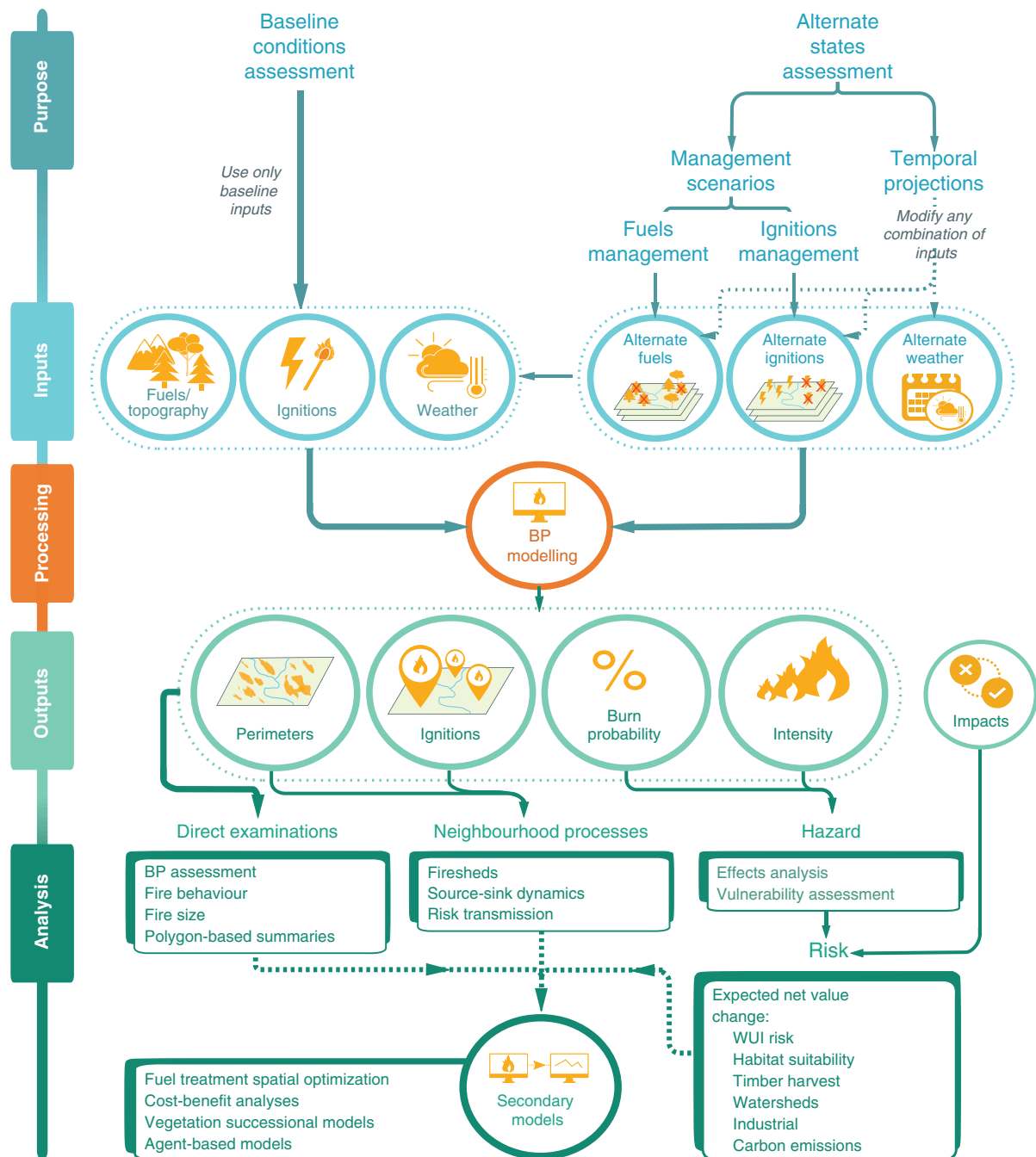


Fig. 1. Process of using burn probability models. BP, burn probability; WUI, wildland–urban interface.

(and unmanipulated) inputs. This baseline is useful in itself if the purpose of the BP analysis is to obtain a single set of outputs for which no alternate state (i.e. scenario) is to be compared (Calkin *et al.* 2010). For instance, many studies use BP or fire intensity maps to examine the spatial variability of wildfire in relation to landscape characteristics (Carmel *et al.* 2009) or HVRAs, such as communities (Alcasena *et al.* 2016). Baseline outputs are not necessarily simplistic: they can be used to derive complex landscape metrics or to undertake various analyses (as detailed in the sections below). A robust baseline is also required when using BP

models to conduct alternate state assessments wherein the baseline provides a reference state against which to assess change (Calkin *et al.* 2010).

An advantage offered by simulation models is the ability to examine several scenarios through thoughtful manipulation of inputs. These alternate state assessments generally stem from specific questions that pertain to land-management needs. For instance, shortly after the creation of the first BP models, several studies investigated aspects of vegetation modification (i.e. fuel treatments) on potential fire likelihood and fire behaviour, such as

Table 1. Selected examples of burn probability (BP) analyses with descriptions of implemented applications
Refer to Supplementary Material for a more thorough list of applications of BP models

Analysis type	Study	Location	Purpose
Direct BP/fire behaviour assessment	Salis <i>et al.</i> (2014)	Sardinia, Italy	Examined how land use, policy and weather changes within two time periods produced variation in simulated BP, fire size and fire intensity.
Polygon-based comparisons	Thompson <i>et al.</i> (2013)	Rocky Mountain region, USA	Summarised wildfire characteristics for 10 watersheds to facilitate prioritisation for fuel treatments.
Firesheds	Alcasena <i>et al.</i> (2017)	Northern Spain	Delineated the area in which fires could ignite and subsequently spread to communities (i.e. firesheds). Each fireshed pixel was classified by the number of structures affected by ignitions from that pixel, providing insight to where fire threats originate.
Source–sink	Ager <i>et al.</i> (2012)	Oregon, USA	Quantified areas as net sources or sinks of fire (based on their propensity to export large fires to other areas versus import fires that originate elsewhere) to inform conservation planning and fire-mitigation activities.
Risk transmission	Oliveira <i>et al.</i> (2016)	Southern Portugal	Investigated the effectiveness of fuel breaks in reducing wildfire spread between municipalities.
Hazard	Stockdale <i>et al.</i> (2019b)	Alberta, Canada	Quantified spatial patterns in wildfire hazard as the product of fire likelihood and fire intensity to evaluate different fire mitigation strategies on woodland caribou (<i>Rangifer tarandus caribou</i>) habitat.
Risk	Ager <i>et al.</i> (2007)	Oregon, USA	Calculated reductions in expected wildfire-caused habitat loss for northern spotted owl (<i>Strix occidentalis caurina</i>) under proposed fuel treatment scenarios.

maximising fuel-treatment placement (Finney 2007; Parisien *et al.* 2007) or conserving specific features (e.g. old-growth stands, endangered species habitat) for wildlife conservation purposes (Ager *et al.* 2010a). Scenario building has not been limited to fuels, however; it has also examined the effect of the other aspects of the fire environment, namely the number and spatial patterns of ignitions and changes in fire-conductive weather. These types of manipulations allow for temporal projections of fire activity and fire behaviour. Riley and Loehman (2016), for example, evaluated the potential increase in large-fire occurrence in northern Idaho, USA, by inputting climate projections to a BP model. Wang *et al.* (2016) assessed the future change in BP in south-central British Columbia (BC), Canada, in a similar fashion, but also incorporated explicit changes in the number of ignitions (using a regression model) and fuels (with a bioclimatic model) into future projections. Results of these studies showed that warmer and drier conditions would promote a greater potential for fire ignition and spread, but in south-central BC these same conditions are also likely to deplete the flammable biomass and lead to an overall decrease in fire likelihood.

Inputs

After defining the purpose of the project, the next step in BP modelling is the careful preparation of the inputs; that is, to ensure they are appropriate for the spatial and temporal extent of the analysis (Scott *et al.* 2013). In BP parlance, inputs represent fuels (i.e. land cover, including flammable biomass and unburnable areas), topography (where relevant), spatio-temporal patterns of ignitions and daily fire weather (Fig. 1). Most models originating in the USA or Canada are based on operational fire behaviour prediction systems that include a characterisation of fuels (often called ‘fuel types’ or ‘fuel models’). These fuels are associated with equations defining fire-behaviour components (e.g. rate of spread, fire intensity) as a function of topography, daily fire weather and time of year to account for changes in phenology (Anderson 1982; Forestry Canada Fire Danger Group 1992; Scott

and Burgan 2005). The vegetation of a study area must, therefore, be classified into pre-existing fuel types in order to use these BP models. Similarly, topography and weather must conform to the requirements of these systems; for example, the Canadian system uses daily noon Local Standard Time observations of temperature, relative humidity, wind speed, wind direction and 24-h rainfall. Burn probability models also incorporate the spatio-temporal variability in ignitions, often as spatial probability distributions that vary by season and by cause (i.e. human or lightning) (Scott *et al.* 2012a). In fire regimes where wildfires might burn for multiple days, it is necessary to incorporate realistic day-to-day variability in weather; this has been done in several ways, such as modelling the temporal structure of weather (Finney *et al.* 2011b) or drawing sequential fire-conductive conditions from historical databases (Parisien *et al.* 2013). In addition, it is possible to account for the spatial effect of topographic relief on wind speed and wind direction (Forthofer *et al.* 2014) by incorporating WindNinja grids to some BP models (e.g. Burn-P3, FlamMap).

Reliable and high-quality data are needed to develop inputs for BP modelling. Because this modelling approach – often considered ‘bottom up’ – explicitly uses the factors that control the ignition and spread to simulate wildfires, it is particularly responsive to data quality. Stratton (2006, 2009) provides guidance for modellers in terms of data assessment, appropriateness and evaluation. Fortunately, high-quality data is increasingly available to BP modellers. Relatively comprehensive and quality-controlled datasets of historical fires that include the presumed point of ignition, mapped perimeters and various attributes (e.g. ignition cause, reporting date) have been compiled and are continually updated (e.g. Short 2014; Canadian Forest Service 2019). The quality (and quantity) of daily weather data is also improving for both weather station observations and modelled datasets, as are fuels data, owing to the rapidly growing availability of remotely sensed information. It must be emphasised, however, that no data source is flawless; for example, to mitigate shortcomings in land-cover data, Parisien *et al.* (2013) had to use four sources of geospatial data to develop a fuels grid for BP

Box 1. Calibration and validation of burn probability (BP) outputs

Model calibration is a necessary aspect of every BP project (Scott *et al.* 2013). Calibration of BP outputs is typically done in a heuristic and iterative manner by adjusting the inputs of the model and assessing its outputs through comparison of actual and simulated fires (cf. Salis *et al.* 2013; Alcasena *et al.* 2016). A common model output used for calibration is the size of fires, whereby the fire size distribution of the simulated wildfires is compared with the historical (i.e. observed) distribution. Other factors that may be considered include the shape of wildfires, where they occur or their fire behaviour. While some users try to create a perfect match between the simulated and historical distributions, this presumes that the data used to generate fire parameter inputs (size, number, location) accurately reflect what we expect the near-term future fire environment to be. What is most important is that model inputs reflect realistic expectations of future fire activity. Calibration is easiest where a large number of historical wildfires have been recorded, but this may not be the case in areas with little fire activity or where historical fire data are sparse (Parisien *et al.* 2013; Short 2015), or where fire-regime parameters have shifted markedly owing to climate change or other factors. Model outputs for data-sparse areas, therefore, rely on expert assessment or any other relevant information – quantitative or not – about potential ignitions and fire spread. In short, there is no standard recipe for BP model calibration: the type and degree of calibration will vary according to the purpose of the project, as well as the specific aspects of the study area.

Whereas the calibration of BP model outputs is fairly straightforward, validation or measuring of predictive accuracy can be challenging, if not impossible in some cases. Simply put, there is no infallible way to assess BP model accuracy. While it is tempting to compare a BP map with recent patterns of wildfire occurrence as a way to evaluate the BP map's accuracy (cf. Parisien *et al.* 2005; Paz *et al.* 2011; Wu *et al.* 2013), this approach is somewhat misguided. This is especially true if: (1) poor data quality limits the reliability of the outputs; (2) data quantity (i.e. the number of years) is insufficient for a proper evaluation; (3) the BP estimates vary through time because of land-cover changes (i.e. owing to natural or anthropogenic disturbance); and (4) if subsequent real-world fire activity has occurred under conditions unrepresentative of the modelled environment (e.g. comparing real-world wildfires under heavy fire suppression with BP estimates produced for free-burning wildfires). Users should not dismiss the importance of presenting their BP modelling projects and outputs to local fire behaviour analysts and land managers who have an in-depth knowledge of the area; this may, in fact, be one of the best forms of validation, albeit a qualitative one.

modelling. Despite improvements in data availability and quality, it remains the responsibility of the modeller to assess potential data biases and consider how these may affect BP outputs (Scott *et al.* 2013; Short 2015) (Box 1).

Input building is typically the most time-consuming aspect of a BP project, and its importance cannot be overemphasised given the sensitivity of BP outputs to the model inputs (Parisien *et al.* 2010; Parisien *et al.* 2011; Parks *et al.* 2011). Although BP models are data heavy, a wealth of data are usually available to users, although some might require substantial manipulation (e.g. converting vegetation characteristics to fuel types). Whereas obtaining all of the aforementioned input data is ideal, some inputs can be simplified and still yield informative outputs, insofar as these abstractions are sensible and their limitations are recognised (Parisien *et al.* 2013). Where the proper data do exist, the readiness with which inputs can be manipulated makes the BP approach particularly well equipped for scenario building. The user can modify almost any factor driving the ignition and spread of wildfires (Erni *et al.* 2018). Although some scenarios are fairly straightforward to develop – the effects of fuel treatments can be assessed by reclassifying some patches of fuels to different fuel types – others are based on several assumptions and data modifications, as is often the case in retrospective analyses (Stockdale *et al.* 2019a) or future projections (Thompson and Calkin 2011).

Processing

Multiple platforms have been developed for BP modelling, such as the commonly used FlamMap (Finney 2006) and FSim (Finney *et al.* 2011b) in the USA, and Burn-P3 in Canada (Parisien *et al.*

2005). Other approaches, such as BurnPro (Davis and Miller 2004), a modified use of Landis (Yang *et al.* 2008) and batch processes of deterministic fire growth models (e.g. Carmel *et al.* 2009) have also been used to compute BP. Despite some relatively minor differences among the different models, they share a conceptually similar approach: they produce estimates of fire likelihood and potential fire behaviour for a snapshot in time (e.g. a particular fire year) rather than across a temporally varying horizon. This simplification means that BP models do not 'grow' vegetation, nor does vegetation respond to the fires that occur. Instead, the complexity of BP models lies in the degree of detail used to model fire ignitions and spread processes (Finney 2005). Specifically, BP models use deterministic fire spread to model spatially explicit fire growth, incorporating both effects of topography and heterogeneous fuels, and the spatial and temporal stochasticity in ignitions and weather. Although the different modelling platforms adopt various methods for calculating fire spread (by virtue of using their respective country's fire behaviour prediction systems), all incorporate stochasticity to derive location-based estimates of fire likelihood and behaviour.

Outputs

There are four categories of outputs from BP models: (1) ignition points; (2) the associated fire perimeters; (3) BP maps; and (4) fire behaviour maps. The first one, ignition points, is fundamentally simple, yet might exhibit spatial patterns surprisingly different from the corresponding inputs. For example, ignitions are typically simulated using frequency probability grids, and yet the spatio-temporal output patterns will almost certainly differ from the inputs because some fuels

are more 'ignitable' than others. Individual simulated fire perimeters are used in calculations of fire size, whereas the collection of perimeters are compiled to produce BP maps and fire behaviour maps. Burn probability maps are computed pixel-wise as the number of times each pixel burned divided by the total number of iterations. Fire behaviour maps summarise the values of fire-behaviour variables, such as the rate of spread, fire intensity and fuel consumption, in each pixel (e.g. mean, median, 90th percentile) (Scott *et al.* 2013). Fire behaviour calculated in this fashion might yield highly variable values among fires as a result of the variability in weather, landscape position and direction of spread; for example, a given location on the shore of a large lake will burn much more intensely by a frontal fire heading towards the lake than by a flanking fire that wraps around the lake. Although the most commonly used metric of fire behaviour is fire intensity or a transformation of this measure that approximates flame length or scorch height (Byram 1959; Alexander 1982), other available metrics will likely be more frequently used in the future. The forest crown fraction burned could, for instance, be mapped around communities to provide an indication of potential exposure to spotting from adjacent fuels. Also, measures of fuel consumption (surface and crown) from simulated fires could be used for potential fire emissions calculations (cf. Amiro *et al.* 2001).

Burn probability models differ with respect to their inputs and modelling processes, and these differences greatly affect the interpretation of outputs. Models like FSim or Burn-P3, which use Monte Carlo methods to simulate the ignition and spread of a large number of wildfires under variable daily weather conditions, produce a wide range of wildfire sizes and shapes that can occur on the landscape (including the largest possible wildfires), from which an annual BP can be calculated. In contrast, approaches like FlamMap and its command-line version, Randig, use a single constant condition of weather and fuel moistures to produce 'conditional' BP and fire-behaviour estimates (Finney 2005); that is, estimates are conditional upon wildfires occurring under these constant weather conditions. Whereas the first set of models may be used for a greater range of applications and offers more control on processes driving ignition and spread, the latter (FlamMap) is simpler and therefore less prone to uncertainty, and is less computationally intensive. The diverse uses and the limitations of different approaches to BP modelling are discussed in Scott *et al.* (2013). The examples provided in the analysis section below are produced using Burn-P3. In this case, BP denotes an annual probability; however, many studies use FlamMap to produce conditional BP and fire behaviour (e.g. Ager *et al.* 2007, 2010a; Mallinis *et al.* 2016).

Analysis

Analysis, in the context of this paper, describes the specific application of BP outputs and, as such, is directly linked to the purpose and goal of the user (Fig. 1). We categorised the numerous potential uses of BP outputs into three broad classes: (1) direct examination; (2) neighbourhood processes; and (3) hazard and risk. Additionally, a conceptually different class was considered to describe situations where BP model outputs were integrated into, or used in conjunction with, other models or modelling platforms (i.e. 'secondary models'). To

illustrate several applications of BP models for a real landscape, we performed a suite of analyses using the Burn-P3 model (Parisien *et al.* 2005) on the landscape surrounding Fort Good Hope, Northwest Territories, Canada. This small town (population 570) is located in the northern boreal forest (66°15'31"N 128°37'43"W), in a landscape composed of a mix of coniferous forest (high flammability), deciduous forests (low flammability) and grassland-shrubland (high flammability in the springtime (April and May), low in the summer). The area has a typical boreal fire regime, which is dominated (in terms of area burned) by large and intense wildfires and can be largely considered as 'natural', given the low (<5%) proportion of human ignitions and minimal human alteration of the vegetation cover. The modelling was performed over a 50-km radius around the town (in addition to a 20-km buffer area), and broadly followed the methods used by Parisien *et al.* (2011) for Wood Buffalo National Park, located south of Fort Good Hope. Given the illustrative purpose of this modelling exercise, we made some simplifications to the modelling; for instance, ignitions were spatially random. Other inputs retain some degree of realism, however, by being derived from historical wildfire data, fuels and weather. In addition, model outputs were calibrated by comparing the size and shape of simulated wildfires with those of the historical database. Below, we discuss each of our broad categories of analyses and describe how they could be applied to the landscape surrounding Fort Good Hope.

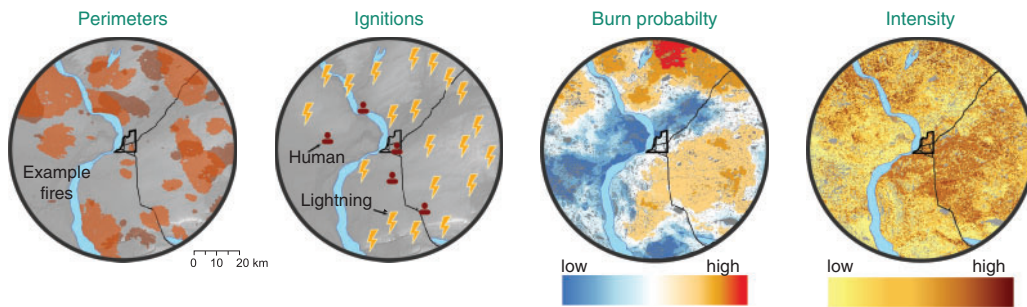
Direct examination

Direct examination is the most straightforward type of analysis of BP outputs, given that it requires minimal or no further processing. These analyses can be as elementary as visual assessment of outputs to determine which areas are most prone to fire, or they can be somewhat more involved, requiring calculations to compare BP or fire-behaviour patterns. For instance, simple calculations can be used to summarise BP outputs within polygons to provide 'polygon-based' metrics that describe and facilitate comparison of fire behaviour across land designations or other spatially explicit areas of interest (Thompson *et al.* 2013). Polygon-based summaries of BP, fire intensity and other metrics derived from simulated fire perimeters have mostly been used to assess watershed fire exposure, examining how these metrics differ among watersheds to prioritise mitigation efforts (Scott *et al.* 2012b). Direct examination of outputs is also used in alternate states analyses, in which BP model inputs are manipulated so that the effect or sensitivity on model outputs can be evaluated. Outputs resulting from these alternate model inputs are either directly compared using side-by-side maps (Furlaud *et al.* 2018; Salis *et al.* 2018), or evaluated by way of a 'difference' map that highlights the degree of change in BP or fire behaviour between the baseline and an alternate state (Ager *et al.* 2010b; Lozano *et al.* 2017).

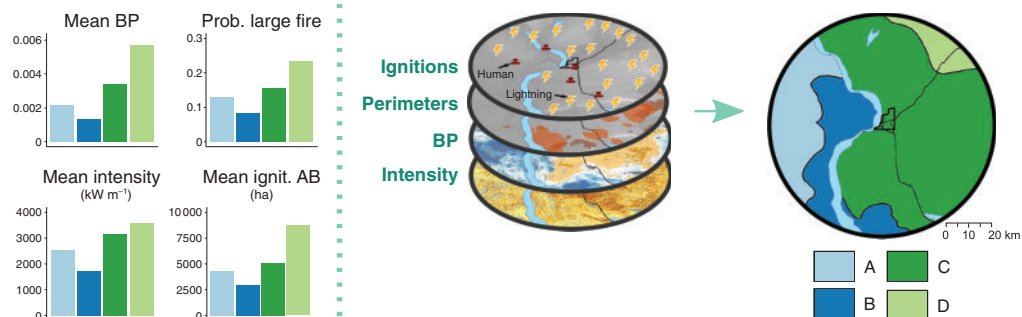
We demonstrate direct examination of BP outputs, looking first at a subset of fire perimeters, ignition points and maps of BP and fire intensity in the context of the town of Fort Good Hope (Fig. 2a). The immediate vicinity of the town is subject to moderate-to-high BP and intensity, in comparison with the rest of the landscape. A subset of BP model outputs summarised by polygons is then displayed for ecoregions (modified slightly for illustrative purposes) within the study area (Fig. 2b), with

Direct examinations

(a) Outputs



(b) Polygon-based summaries



(c) BP ratio following fuel treatments



Fig. 2. Illustrations of different analyses within the direct examination classification. Users can (a) look at outputs alone or (b) use polygon-based summaries, as defined in Table 2, to compare these outputs between regions of interest. Users can also modify the baseline fuel grid with fuel treatments (c), and represent the resulting change to burn probability as the ratio of baseline scenario outputs over fuel treatment scenario outputs. High ratios represent a large decrease in fire probability as a result of the treatment. BP, burn probability; AB, area burned.

descriptions of each metric provided in Table 2. Using these polygon-based summaries, we can quickly identify ecoregional differences in fire likelihood and behaviour; for instance, despite its small size, Region D has the highest BP, intensity and likelihood of producing large fires (Fig. 2b). We then illustrate an alternate states assessment involving a fuel

management scenario (Fig. 2c). In this example, baseline fuels receive fuel treatments of different types (i.e. thinning, prescribed burns, harvest) in close proximity to the townsite. The ratio of baseline to treated BP values shows that the fuel treatments did effectively decrease the likelihood of burning in the vicinity of the town (Fig. 2c).

Table 2. Description of polygon-based burn probability (BP) summarisation metrics used in Fig. 2b as defined in Thompson et al. (2013) and Scott and Thompson (2015)

Metric	Description
Mean burn probability	Average BP value of all pixels within the ecoregion.
Mean fire intensity	Average fire intensity (in kW m ⁻¹) of all pixels within the ecoregion.
Probability of large fires	Percentage of fire iterations igniting within each ecoregion that grow larger than a given threshold (10 000 ha).
Mean ignition area burned	Average area burned within each ecoregion by fires igniting within that ecoregion; calculated by dividing the total area burned by the number of ignitions. Describes the size that fires igniting within any ecoregion are likely to grow.

Neighbourhood processes

Neighbourhood process analyses tell us about where fires are coming from relative to a given location of concern. These analyses help to examine patterns of fire ignitions and subsequent spread to or between given locations or other relevant land designations or jurisdictional boundaries. Managers might be interested in delineating the spatial extent of a ‘fireshed’ – the area within which ignitions can start and fires could burn into a particular location. This analysis can be accomplished by identifying ignition points and fire perimeter extents of all fires that make contact with that given location (Thompson et al. 2013). Firesheds can provide important insights for guiding policy decisions, such as quantifying the risk to WUI communities if fires igniting in designated areas are allowed to burn unsuppressed (Scott et al. 2012a). The ‘source–sink’ ratio is a metric developed by Ager et al. (2012) that describes each pixel’s propensity for producing or receiving fire, and is the ratio of a pixel’s wildfire contribution to the surrounding landscape (i.e. fires produced by ignitions from within that pixel, or within a specified neighbourhood of the pixel) relative to the frequency with which it is burned by fires that originated elsewhere. ‘Risk transmission’ quantifies the amount of fire, or in some applications the expected loss, in a given area (e.g. ecoregion, jurisdiction) caused by fires that spread from ignitions in another (often neighbouring) area (Ager et al. 2014). Comparing the magnitude of incoming with outgoing fire can identify where suppression resources or fire mitigation activities are best allocated, what agencies are responsible for initiating those activities (based on which has jurisdiction in areas where fires are originating) and the characteristics that make certain designations more prone to fire than others (Haas et al. 2015; Ager et al. 2016).

Using the Fort Good Hope area as an example, we illustrate how BP model outputs can be used to analyse firesheds, source–sink ratios and risk transmission metrics (Fig. 3). First, we delineate a fireshed (Fig. 3a) by identifying all simulated fires with perimeters intersecting the town boundary, and by mapping the spatial extent of these fire perimeters (or alternatively the extent of their associated ignition points). Note that no wildfires reaching the townsite originated from the other side of the river. Although this river, the McKenzie, is one of the largest in the world, there have been instances when wildfire has crossed the river due to spotting. We then calculate source–sink ratios across the study landscape (Fig. 3b) by creating a raster of fire size (FS), which represents the area burned from each ignition point. Given that not all pixels contain ignitions and some pixels contain many, a moving-window analysis is used to create a

smooth FS surface. The source–sink ratio (SSR; Ager et al. 2012) is then calculated as:

$$SSR = \log(FS/BP) \tag{1}$$

In this example, the area surrounding the townsite appears to be a net ‘sink’ for fires, meaning the area does not generate many large fires but does have relatively high BP, chiefly as a result of large fires burning into the area from the ‘sources’ to the south-west (Fig. 3b). We then assess how fires spread between the modified ecoregions introduced in Fig. 2 by calculating risk transmission (Fig. 3c). In this example, we determine the average area burned in one region owing to fires that originate from ignition points in another region. Fires igniting within and burning out of Region B into Regions A and C are shown to illustrate the concept. The magnitude of risk transmission between regions, as represented by the ratio of arrow sizes in Fig. 3c, provides insights into where fires affecting a region originate. For example, despite its small size, Region D transmits the largest average area burned per ignition to Region C; if managers wished to mitigate risk transmission to Region C, fuel treatments near the border between these two regions would likely be effective (Oliveira et al. 2016).

Hazard and risk

Fire hazard and wildland fire risk, although considered together here, are distinct. Fire hazard, as traditionally used in BP modelling analyses, combines fire probability and a quantitative assessment of fire behaviour, such as fire intensity (Scott et al. 2013), which has been related to both fire-suppression capabilities (Hirsch et al. 1998) and fire severity (de Groot et al. 2007). Wildland fire risk is the product of fire likelihood (or BP) and the potential impacts of wildfire (negative or positive) (Finney 2005). The ‘impacts’ part of the equation depends on the user’s purpose and the nature of the values at risk; ‘risk’ can take on a variety of incarnations (Hardy 2005). Impacts to HVRAs might be highly variable or difficult to measure, which, as such, often means that expert judgement is required to estimate the response of each HVRA to fire (Thompson and Calkin 2011). Change to HVRAs, as described by the impact component of the risk equation, can be measured according to any valuation system, and have proven useful when assessing wildfire impacts such as expected financial losses (Alcasena et al. 2017), ecological habitat change (Ager et al. 2007) or carbon emissions (Chiono et al. 2017). Because impacts can vary according to the magnitude of the fire behaviour, risk is often

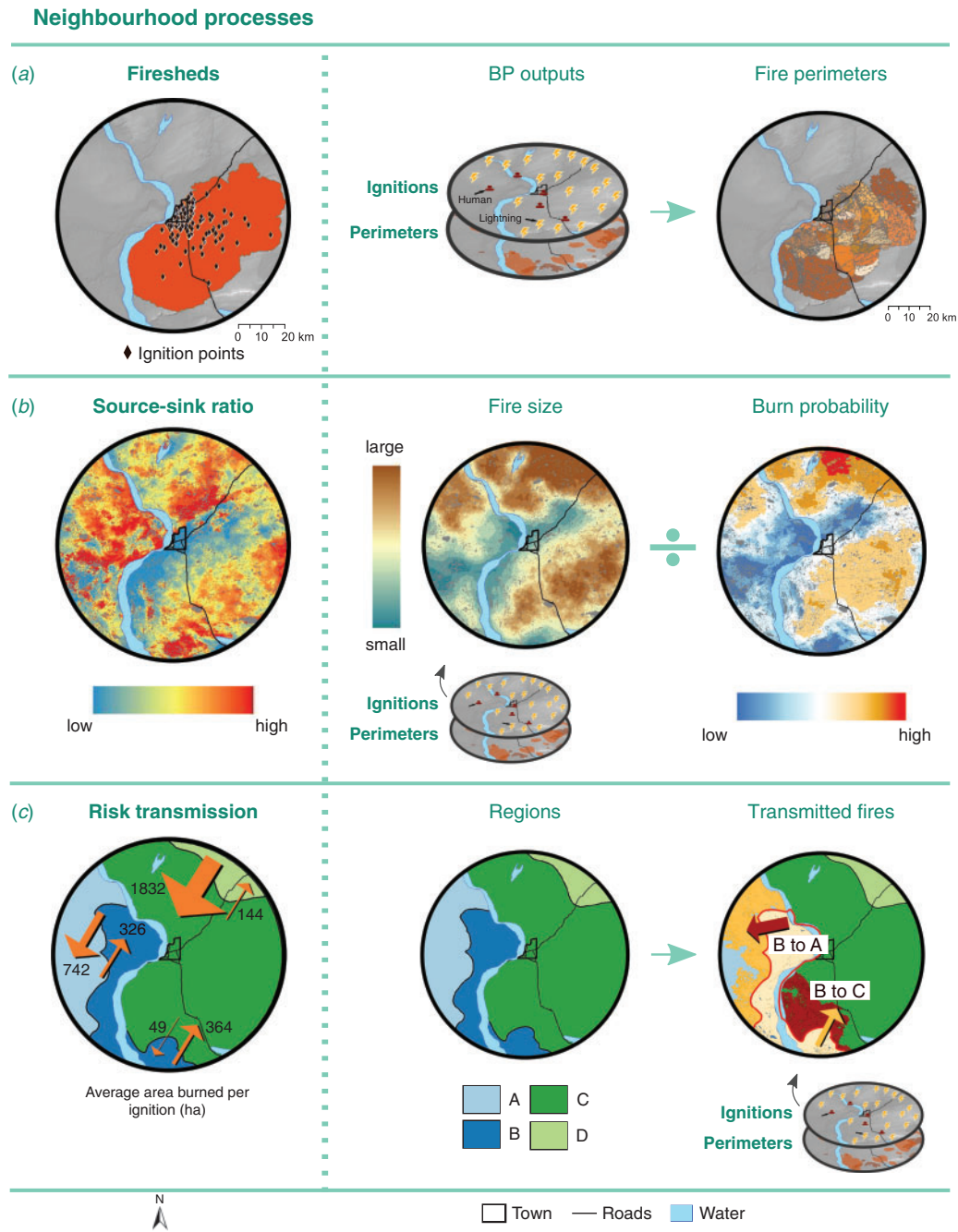


Fig. 3. Different applications of burn probability modelling for neighbourhood process analyses. (a) Firesheds are calculated from all fire perimeters intersecting Fort Good Hope and can be combined with ignition locations or dissolved to show the fireshed extent. (b) Source–sink ratios are the ratios of fire size produced by ignitions from within a pixel to burn probability. High source–sink ratios describe locations from which large fires are more likely to be transmitted, as compared with the likelihood of their burning from fires igniting elsewhere. (c) Risk transmission quantifies how fire is transmitted between regions. Fires igniting within and burning out of Region B into Regions A and C are shown to illustrate the concept. The average area burned per ignition in each region is calculated for transmitted fires and can be used to illustrate the scale of risk transmission between regions. The size of arrows between regions is proportional to the average area burned by fires transmitted between them.

framed as being conditional on a specific value or classification of fire behaviour (e.g. low, moderate or high fire intensity) (Finney 2005).

To demonstrate how fire hazard can be applied in Fort Good Hope, we mapped integrated values of fire likelihood and intensity following the method of Stockdale *et al.* (2019b), who

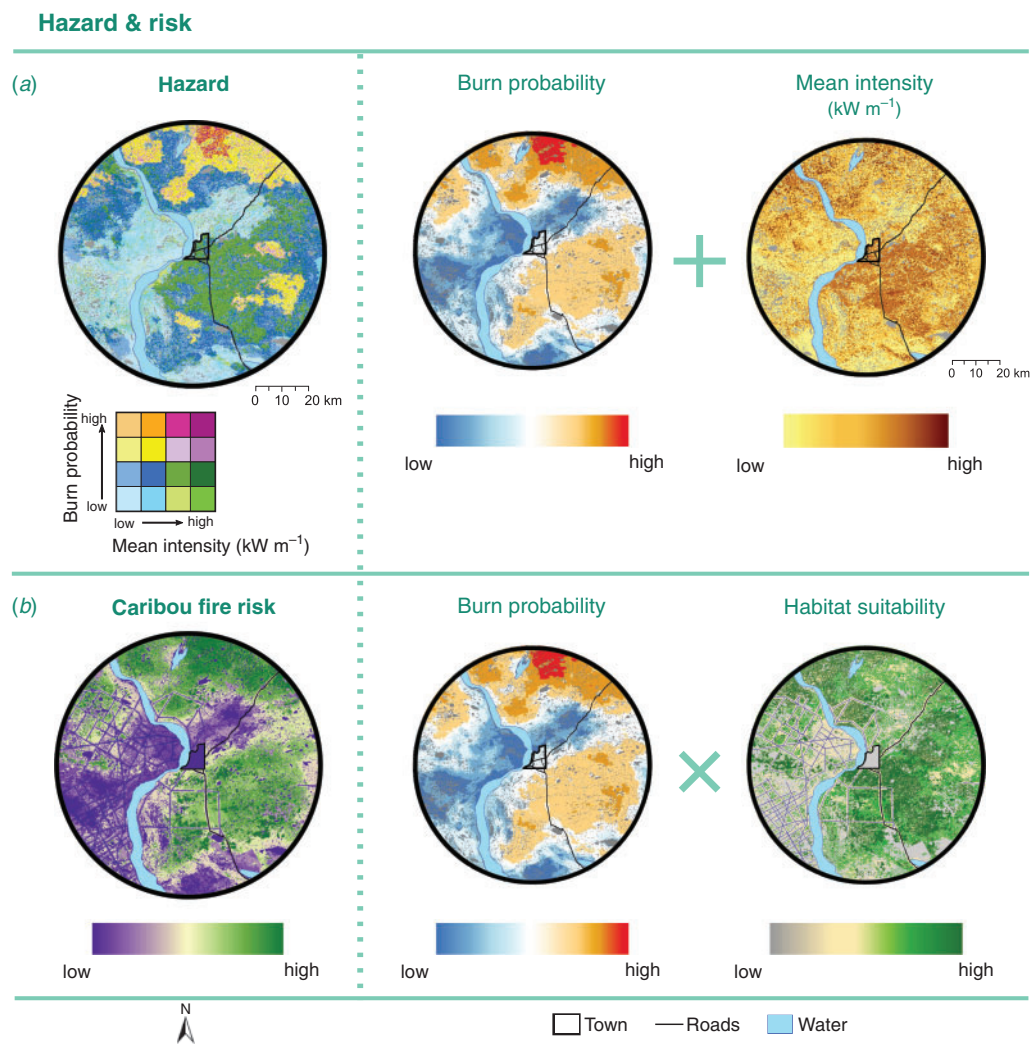


Fig. 4. Examples of how hazard and risk can be calculated. (a) Hazard combines the likelihood of burning with intensity and is here represented in a map that categorises hazard by the contributions of each of these sub-components. (b) Risk is demonstrated simplistically as a caribou management scenario, in which burn probability is combined with the potential for impact on caribou, on the basis of habitat suitability. Calculations of habitat suitability are based on Whitman *et al.* (2017); habitat suitability was reduced within a 500-m proximity to linear features to account for higher predation likelihood. Areas of higher risk represent both higher fire likelihood and potential impacts to caribou.

partitioned BP and intensity into four categories and mapped hazard as the composite of those classes (Fig. 4a). The area surrounding the townsites exhibits a low-to-moderate BP, but if a wildfire were to occur, it would likely burn at a high intensity (Fig. 4a). This information can be used by managers to gauge their tolerance to wildfire events and to guide mitigation efforts. With respect to wildland fire risk, we developed an illustrative example of risk to the habitat of a species of conservation concern in Canada: the boreal woodland caribou (*Rangifer tarandus caribou*) (Fig. 4b). We first define the potential impacts of wildfire on caribou by creating a habitat suitability model, based broadly on the framework devised by Whitman *et al.* (2017), where habitat suitability consists of the combination of availability of nutritional resources and potential for predation loss based on vegetation types and stand age. In this case, habitat suitability within a 500-m buffer of linear features was reduced to account

for increased risk of predation by the main predator of the caribou, the grey wolf (*Canis lupus*) (James and Stuart-Smith 2000). We then multiplied habitat suitability and BP to arrive at a simplified expression of risk to caribou. In our example, areas of higher habitat quality were typically found in continuous conifer forests and lichen woodlands. In our landscape, these vegetation types also tend to be prone to wildfire, suggesting that higher-quality caribou habitat within the Fort Good hope study region is generally at greater risk of impact from wildfire than areas less suitable to caribou.

Integration with secondary models

As a result of their inherent flexibility, BP model outputs have been integrated into other modelling frameworks and combined with those of other models. For instance, Lozano *et al.* (2017) used general circulation model data of projected climate as the

weather input to a BP model to study how fire behaviour (i.e. intensity, size) and BP might change in the future. Combining external models with BP models is not limited to a single-model coupling; [Stralberg *et al.* \(2018\)](#) merged statistical models of future fire potential and future vegetation with BP models to examine how wildfire might catalyse vegetation transitions under future climates. A similar framework was used in a wildlife management application to assess temporal projections of climate and wildfire-mediated changes to caribou habitat quality ([Barber *et al.* 2018](#)). The scope of the problems to which BP and coupled secondary models have been applied is broad, encompassing numerous practical forest management applications such as the spatial optimisation of fuel treatments to protect WUI communities ([Bar Massada *et al.* 2011](#)), the appraisal of the financial consequences of alternate fire management decisions ([Thompson *et al.* 2015](#); [Thompson *et al.* 2017](#)) and the integration of timber harvest planning with fire mitigation activities ([Acuna *et al.* 2010](#)).

Future directions

An area of potential improvement to BP modelling is to increase the computational efficiency of the models. In spite of the increased availability of high-performance computers, simulations can still take days or weeks to run. In Canada, the Burn-P3 model is primarily run on personal computers because it has not yet been adapted for cloud-based or supercomputing resources. Other models, such as FlamMap, have 'internally' enhanced computation capabilities based upon a modified fire-spread algorithm, but are still not optimised for distributed (e.g. cloud) computing ([Finney 2002](#)). Perhaps a more daunting challenge for BP models are the limitations of the fire behaviour prediction models upon which they are based. The Canadian system, for instance, is known to perform well where vegetation corresponds with a fuel type from the Fire Behaviour Prediction System, but there are many vegetation types that are poorly, if at all, represented ([Parisien *et al.* 2013](#)). The current operational system in the USA is limited in that it considers only surface fire spread ([Rothermel 1972](#)); however, modifications have been made to incorporate crown-fire modelling from models created for Canadian forests and other sources in two distinct methods ([Finney 1998](#); [Scott and Reinhardt 2001](#)). Another limitation to BP models is the lack of long-range spotting and breaching of non-fuels in some modelling platforms. Many US models (e.g. FlamMap, FSim) incorporate spotting, although this feature has not been thoroughly tested in the field. In Canada, this feature does not exist. The omission of spotting undoubtedly leads to underestimates in fire probability, for example, on the lee side of large fuelbreaks (e.g. rivers, lakes). Although there are creative ways to circumvent such issues, such as making fuelbreaks partially flammable, shortcomings persist.

Because the technology for improving BP model performance is becoming more available and more affordable, many of the BP models may soon be revamped. The ability to access a BP model online and run it as a 'software as a service', rather than installing it on personal computers, represents an attractive and readily attainable avenue for BP models. In addition to modernising the look and feel of BP model interfaces, optimising processes by using cloud resources would greatly reduce run

times and relieve the computing burden on local workstations. Maximising BP models' resources would inevitably open new doors in terms of applications. For example, it would be possible to produce BP and fire-behaviour maps for time periods other than the usual annual (once a season) period, such as weekly, or even daily. The next generation of BP model would still be used in its classic context to inform long-term problems, but also provide a finer temporal resolution of likelihood of burning as it changes throughout the season. This information would complement the existing suite of products that currently support fire-management operations, like FSPro (USA) and PFAS (Canada), methods which were developed for assessing the spread potential of single fires as they are burning ([Anderson 2010](#); [Finney *et al.* 2011a](#)). By considering a large number of potential ignition locations, a daily BP model output could, for instance, assess the fire likelihood in areas where ignitions are yet to be detected. Numerous other possibilities exist for redeveloping BP models and integrating them with other dynamic models, such as vegetation growth, insect epidemic spread and forest harvesting, among others.

List of published studies using the burn probability method

To demonstrate further the wide range of potential applications of BP models, we compiled a list of published literature on the topic of BP modelling (as defined in this paper) and categorised it by application types (see Supplementary Material available online). The list includes only those articles and reports from the published literature that were indexed in reference databases, and was developed through an online reference search and by cross-referencing citations of articles. Because some studies included multiple analyses, a single reference may appear in multiple categories. The list is meant to be a useful reference for users seeking more detailed information on BP applications and methodology.

Conclusion

Although the BP approach has remained largely unchanged (at least in concept) since its inception two decades ago, the number of ways in which it has been used has greatly increased. Indeed, an array of applications has contributed to our enhanced knowledge of wildland fire science and has added rigour to wildland fire management and planning. Concomitant improvements in our understanding of wildland fire and technological advances have caused BP models to be used for far more purposes than their initial single-use aim of mapping wildfire likelihood. Furthermore, the flexible nature of BP modelling allows the user to investigate innumerable scenarios to determine what their effect would be on wildfire risk, which can assist land managers and wildland fire risk analysts in making real-world decisions that can potentially reduce the impact of wildfires. The BP approach does remain fairly specialised in scope; for example, these models are not designed or intended for the explicit evaluation of fire-vegetation feedbacks. The strength of BP models lies in their ability to model many fire ignitions and fire spread in great detail. Due to the approach's intrinsic modularity, the manner in which inputs are integrated and processed (e.g. seasonal patterns of ignitions, how weather drives spread) can continually be refined. Moreover, BP models

can welcome outputs from other models as inputs and, conversely, its own outputs can be readily integrated or combined with other modelling platforms. The functionality and uses of the BP approach will continue to evolve and expand due to advances in computing power, thereby offering new possibilities by eliminating past computation constraints.

Conflicts of interest

The authors declare no conflicts of interest.

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References

- Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences of the United States of America* **113**, 11770–11775. doi:10.1073/PNAS.1607171113
- Acuna MA, Palma CD, Cui W, Martell DL, Weintraub A (2010) Integrated spatial fire and forest management planning. *Canadian Journal of Forest Research* **40**, 2370–2383. doi:10.1139/X10-151
- Ager AA, Finney MA, Kerns BK, Maffei H (2007) Modeling wildfire risk to northern spotted owl (*Strix occidentalis caurina*) habitat in Central Oregon, USA. *Forest Ecology and Management* **246**, 45–56. doi:10.1016/J.FORECO.2007.03.070
- Ager AA, Vaillant NM, Finney MA (2010a) A comparison of landscape fuel treatment strategies to mitigate wildland fire risk in the urban interface and preserve old forest structure. *Forest Ecology and Management* **259**, 1556–1570. doi:10.1016/J.FORECO.2010.01.032
- Ager AA, Finney MA, McMahan A, Cathcart J (2010b) Measuring the effect of fuel treatments on forest carbon using landscape risk analysis. *Natural Hazards and Earth System Sciences* **10**, 2515–2526. doi:10.5194/NHESS-10-2515-2010
- Ager AA, Vaillant NM, Finney MA, Preisler HK (2012) Analyzing wildfire exposure and source–sink relationships on a fire prone forest landscape. *Forest Ecology and Management* **267**, 271–283. doi:10.1016/J.FORECO.2011.11.021
- Ager AA, Day MA, Finney MA, Vance-Borland K, Vaillant NM (2014) Analyzing the transmission of wildfire exposure on a fire-prone landscape in Oregon, USA. *Forest Ecology and Management* **334**, 377–390. doi:10.1016/J.FORECO.2014.09.017
- Ager AA, Day MA, Short KC, Evers CR (2016) Assessing the impacts of federal forest planning on wildfire risk mitigation in the Pacific Northwest, USA. *Landscape and Urban Planning* **147**, 1–17. doi:10.1016/J.LANDURBPLAN.2015.11.007
- Alcasena FJ, Salis M, Vega-García C (2016) A fire modeling approach to assess wildfire exposure of valued resources in central Navarra, Spain. *European Journal of Forest Research* **135**, 87–107. doi:10.1007/S10342-015-0919-6
- Alcasena FJ, Salis M, Ager AA, Castell R, Vega-García C (2017) Assessing wildland fire risk transmission to communities in Northern Spain. *Forests* **8**, 30. doi:10.3390/F8020030
- Alexander ME (1982) Calculating and interpreting forest fire intensities. *Canadian Journal of Botany* **60**, 349–357. doi:10.1139/B82-048
- Amiro BD, Todd JB, Wotton BM, Logan KA, Flannigan MD, Stocks BJ, Mason JA, Martell DL, Hirsch KG (2001) Direct carbon emissions from Canadian forest fires, 1959–1999. *Canadian Journal of Forest Research* **31**, 512–525. doi:10.1139/X00-197
- Anderson HE (1982) Aids to determining fuel models for estimating fire behavior. USDA Forest Service, Intermountain Forest and Range Experiment Station Technical Report INT-122 (Ogden, UT). doi:10.2737/INT-GTR-122
- Anderson KR (2010) A climatologically based long-range fire growth model. *International Journal of Wildland Fire* **19**, 879–894. doi:10.1071/WF09053
- Andrews PL, Finney MA, Fischetti M (2007) Predicting wildfires. *Scientific American* **297**, 46–55. doi:10.1038/SCIENTIFICAMERICAN0807-46
- Bar Massada A, Syphard AD, Hawbaker TJ, Stewart SI, Radeloff VC (2011) Effects of ignition location models on the burn patterns of simulated wildfires. *Environmental Modelling & Software* **26**, 583–592. doi:10.1016/J.ENVSOFT.2010.11.016
- Barber QE, Parisien M-A, Whitman E, Stralberg D, Johnson CJ, St-Laurent M-H, DeLancey ER, Price DT, Arseneault D, Wang X, Flannigan MD (2018) Potential impacts of climate change on the habitat of boreal woodland caribou. *Ecosphere* **9**, e02472. doi:10.1002/ECS2.2472
- Black AE, Williamson M, Doane D (2008) Wildland fire use barriers and facilitators. *Fire Management Today* **68**, 10–14.
- Byram GM (1959) Combustion of forest fuels. In ‘Forest fire control and use’. (Ed. KP Davis.) pp. 61–89. (McGraw-Hill Book Co.: New York)
- Calkin DE, Ager AA, Gilbertson-Day J (2010) Wildfire risk and hazard: procedures for the first approximation. USDA Forest Service, Rocky Mountain Research Paper RMRS-GTR-235 (Fort Collins, CO). doi:10.2737/RMRS-GTR-235
- Canadian Forest Service (2019) Canadian National Fire Database – agency fire data. (Natural Resources Canada, Ottawa, ON). Available at <http://cwfis.cfs.nrcan.gc.ca/ha/nfdb>
- Carmel Y, Paz S, Jahashan F, Shoshany M (2009) Assessing fire risk using Monte Carlo simulations of fire spread. *Forest Ecology and Management* **257**, 370–377. doi:10.1016/J.FORECO.2008.09.039
- Chiono LA, Fry DL, Collins BM, Chatfield AH, Stephens SL (2017) Landscape-scale fuel treatment and wildfire impacts on carbon stocks and fire hazard in California spotted owl habitat. *Ecosphere* **8**, e01648. doi:10.1002/ECS2.1648
- Davis B, Miller C (2004) Modelling wildfire probability using a GIS. In ‘Proceedings of the 2004 Annual ASPRS Conference’, 23–28 May 2004, Denver, CO. American Society for Photogrammetry and Remote Sensing, Denver, CO, USA.
- de Groot WJ, Field RD, Brady MA, Roswintarti O, Mohamad M (2007) Development of the Indonesian and Malaysian fire danger rating systems. *Mitigation and Adaptation Strategies for Global Change* **12**, 165–180. doi:10.1007/S11027-006-9043-8
- Erni S, Arseneault D, Parisien M-A (2018) Stand age influence on potential wildfire ignition and spread in the boreal forest of northeastern Canada. *Ecosystems* **21**, 1471–1486. doi:10.1007/S10021-018-0235-3
- Finney MA (1998) FARSITE: Fire area simulator – model development and evaluation. USDA Forest Service, Rocky Mountain Research Station Research Paper RMRS-RP-4 (Ogden, UT). doi:RMRS-RP-4
- Finney MA (2002) Fire growth using minimum travel time methods. *Canadian Journal of Forest Research* **32**, 1420–1424. doi:10.1139/X02-068
- Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management* **211**, 97–108. doi:10.1016/J.FORECO.2005.02.010
- Finney MA (2006) An overview of FlamMap fire modeling capabilities. In ‘Fuels management – how to measure success: conference proceedings’, 28–30 March 2006, Portland, OR. (Eds PL Andrews, BW Butler) USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-41, pp. 213–220. (Fort Collins, CO)
- Finney MA (2007) A computational method for optimising fuel treatment locations. *International Journal of Wildland Fire* **16**, 702–711. doi:10.1071/WF06063
- Finney MA, Grenfell IC, McHugh CW, Seli RC, Trethewey D, Stratton RD, Brittain S (2011a) A method for ensemble wildland fire simulation. *Environmental Modeling and Assessment* **16**, 153–167. doi:10.1007/S10666-010-9241-3

- Finney MA, McHugh CW, Grenfell IC, Riley KL, Short KC (2011b) A simulation of probabilistic wildfire risk components for the continental United States. *Stochastic Environmental Research and Risk Assessment* **25**, 973–1000. doi:10.1007/S00477-011-0462-Z
- Flannigan M, Cantin AS, de Groot WJ, Wotton M, Newbery A, Gowman LM (2013) Global wildland fire season severity in the 21st century. *Forest Ecology and Management* **294**, 54–61. doi:10.1016/J.FORECO.2012.10.022
- Forestry Canada Fire Danger Group (1992) Development and structure of the Canadian Forest Fire Behavior Prediction System. Forestry Canada, Headquarters, Fire Danger Group and Science and Sustainable Development Directorate, Information Report ST-X-3 (Ottawa, ON). Available at <http://cfs.nrcan.gc.ca/pubwarehouse/pdfs/10068.pdf>
- Forthofer JM, Butler BW, Wagenbrenner NS (2014) A comparison of three approaches for simulating fine-scale surface winds in support of wildland fire management: Part I. Model formulation and comparison against measurements. *International Journal of Wildland Fire* **23**, 969–981. doi:10.1071/WF12089
- Furlaud JM, Williamson GJ, Bowman DMJS (2018) Simulating the effectiveness of prescribed burning at altering wildfire behaviour in Tasmania, Australia. *International Journal of Wildland Fire* **27**, 15–28. doi:10.1071/WF17061
- Haas JR, Calkin DE, Thompson MP (2015) Wildfire risk transmission in the Colorado Front Range, USA. *Risk Analysis* **35**, 226–240. doi:10.1111/RISA.12270
- Hardy CC (2005) Wildland fire hazard and risk: Problems, definitions, and context. *Forest Ecology and Management* **211**, 73–82. doi:10.1016/J.FORECO.2005.01.029
- Hirsch KG, Corey PN, Martell DL (1998) Using expert judgement to model initial attack fire crew effectiveness. *Forest Science* **44**, 539–549. doi:10.1093/FORRESTSCIENCE/44.4.539
- James ARC, Stuart-Smith AK (2000) Distribution of caribou and wolves in relation to linear corridors. *The Journal of Wildlife Management* **64**, 154–159. doi:10.2307/3802985
- Johnstone JF, Allen CD, Franklin JF, Frelich LE, Harvey BJ, Higuera PE, Mack MC, Meentemeyer RK, Metz MR, Perry GLW, Schoennagel T, Turner MG (2016) Changing disturbance regimes, ecological memory, and forest resilience. *Frontiers in Ecology and the Environment* **14**, 369–378. doi:10.1002/FEE.1311
- Lozano OM, Salis M, Ager AA, Arca B, Alcasena FJ, Monteiro AT, Finney MA, Del Giudice L, Scoccimarro E, Spano D (2017) Assessing climate change impacts on wildfire exposure in Mediterranean areas. *Risk Analysis* **37**, 1898–1916. doi:10.1111/RISA.12739
- Mallinis G, Mitsopoulos I, Beltran E, Goldammer JG (2016) Assessing wildfire risk in cultural heritage properties using high spatial and temporal resolution satellite imagery and spatially explicit fire simulations: The case of Holy Mount Athos, Greece. *Forests* **7**, 46. doi:10.3390/F7020046
- McCarty JJP (2001) Ecological consequences of recent climate change. *Conservation Biology* **15**, 320–331. doi:10.1046/J.1523-1739.2001.015002320.X
- Miller C, Ager AA (2013) A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire* **22**, 1–14. doi:10.1071/WF11114
- Moritz MA, Batllori E, Bradstock RA, Gill AM, Handmer J, Hessburg PF, Leonard J, McCaffrey S, Odion DC, Schoennagel T, Syphard AD (2014) Learning to coexist with wildfire. *Nature* **515**, 58–66. doi:10.1038/NATURE13946
- Oliveira TM, Barros AMG, Ager AA, Fernandes PM (2016) Assessing the effect of a fuel break network to reduce burnt area and wildfire risk transmission. *International Journal of Wildland Fire* **25**, 619–632. doi:10.1071/WF15146
- Parisien M-A, Kafka VG, Hirsch KG, Todd JB, Lavoie SG, Maczek PD (2005) Mapping wildfire susceptibility with the Burn-P3 simulation model. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre, Information report NOR-X-405 (Edmonton, AB)
- Parisien M-A, Junor DR, Kafka VG (2007) Comparing landscape-based decision rules for placement of fuel treatments in the boreal mixedwood of western Canada. *International Journal of Wildland Fire* **16**, 664–672. doi:10.1071/WF06060
- Parisien M-A, Miller C, Ager AA, Finney MA (2010) Use of artificial landscapes to isolate controls on burn probability. *Landscape Ecology* **25**, 79–93. doi:10.1007/S10980-009-9398-9
- Parisien M-A, Parks SA, Miller C, Krawchuk MA, Heathcott M, Moritz MA (2011) Contributions of ignitions, fuels, and weather to the spatial patterns of burn probability of a boreal landscape. *Ecosystems* **14**, 1141–1155. doi:10.1007/S10021-011-9474-2
- Parisien M-A, Walker GR, Little JM, Simpson BN, Wang X, Perrakis DDB (2013) Considerations for modeling burn probability across landscapes with steep environmental gradients: an example from the Columbia Mountains, Canada. *Natural Hazards* **66**, 439–462. doi:10.1007/S11069-012-0495-8
- Parks SA, Parisien M-A, Miller C (2011) Multi-scale evaluation of the environmental controls on burn probability in a southern Sierra Nevada landscape. *International Journal of Wildland Fire* **20**, 815–828. doi:10.1071/WF10051
- Paz S, Carmel Y, Jahshan F, Shoshany M (2011) Post-fire analysis of pre-fire mapping of fire-risk: A recent case study from Mt. Carmel (Israel). *Forest Ecology and Management* **262**, 1184–1188. doi:10.1016/J.FORECO.2011.06.011
- Riley KL, Loehman RA (2016) Mid-21st-century climate changes increase predicted fire occurrence and fire season length, Northern Rocky Mountains, United States. *Ecosphere* **7**, e01543. doi:10.1002/ECS2.1543
- Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service Research Paper INT-115 (Odgen, UT)
- Salis M, Ager AA, Arca B, Finney MA, Bacciu V, Duce P, Spano D (2013) Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. *International Journal of Wildland Fire* **22**, 549–565. doi:10.1071/WF11060
- Salis M, Ager AA, Finney MA, Arca B, Spano D (2014) Analyzing spatiotemporal changes in wildfire regime and exposure across a Mediterranean fire-prone area. *Natural Hazards* **71**, 1389–1418. doi:10.1007/S11069-013-0951-0
- Salis M, Del Giudice L, Arca B, Ager AA, Alcasena-Urdiroz F, Lozano O, Bacciu V, Spano D, Duce P (2018) Modeling the effects of different fuel treatment mosaics on wildfire spread and behavior in a Mediterranean agro-pastoral area. *Journal of Environmental Management* **212**, 490–505. doi:10.1016/J.JENVMAN.2018.02.020
- Scott JH, Burgan RE (2005) Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model. USDA Forest Service, Rocky Mountain Research Paper RMRS-GTR-153 (Fort Collins, CO). doi:10.2737/RMRS-GTR-153
- Scott JH, Reinhardt ED (2001) Assessing crown fire potential by linking models of surface and crown fire behavior. USDA Forest Service, Rocky Mountain Research Paper RMRS-RP-29 (Fort Collins, CO). doi:10.2737/RMRS-RP-29
- Scott JH, Thompson MP (2015) Emerging concepts in wildfire risk assessment and management. In 'Proceedings of the large wildland fires conference', 19–23 May 2014, Missoula, MT. (Eds RE Keane, M Jolly, R Parsons, K Riley) USDA Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-73, pp. 196–206. (Fort Collins, CO)
- Scott JH, Helmbrecht DJ, Parks SA, Miller C (2012a) Quantifying the threat of unsuppressed wildfires reaching the adjacent wildland–urban interface on the Bridger–Teton National Forest, Wyoming, USA. *Fire Ecology* **8**, 125–142. doi:10.4996/FIREECOLOGY.0802125
- Scott JH, Helmbrecht DJ, Thompson MP, Calkin DE, Marcille K (2012b) Probabilistic assessment of wildfire hazard and municipal watershed

- exposure. *Natural Hazards* **64**, 707–728. doi:10.1007/S11069-012-0265-7
- Scott JH, Thompson MP, Calkin DE (2013) A wildfire risk assessment framework for land and resource management. USDA Forest Service, Rocky Mountain Research Paper RMRS-GTR-315. (Fort Collins, CO)
- Short KC (2014) A spatial database of wildfires in the United States, 1992–2011. *Earth System Science Data* **6**, 1–27. doi:10.5194/ESSD-6-1-2014
- Short KC (2015) Sources and implications of bias and uncertainty in a century of US wildfire activity data. *International Journal of Wildland Fire* **24**, 883–891. doi:10.1071/WF14190
- Stephens SL (1998) Evaluation of the effects of silvicultural and fuels treatments on potential fire behaviour in Sierra Nevada mixed-conifer forests. *Forest Ecology and Management* **105**, 21–35. doi:10.1016/S0378-1127(97)00293-4
- Stephens SL, Collins BM, Biber E, Fulé PZ (2016) U.S. federal fire and forest policy: emphasizing resilience in dry forests. *Ecosphere* **7**, e01584. doi:10.1002/ECS2.1584
- Stockdale CA, McLoughlin N, Flannigan M, Macdonald SE (2019a) Could restoration of a landscape to a pre-European historical vegetation condition reduce burn probability? *Ecosphere* **10**, e02584. doi:10.1002/ECS2.2584
- Stockdale CA, Barber Q, Saxena A, Parisien M-A (2019b) Examining management scenarios to mitigate wildfire hazard to caribou conservation projects using burn probability modeling. *Journal of Environmental Management* **233**, 238–248. doi:10.1016/J.JENVMAN.2018.12.035
- Stralberg D, Wang X, Parisien M-A, Robinne F-N, Solyomos P, Mahon CL, Nielsen SE, Bayne EM (2018) Wildfire-mediated vegetation change in boreal forests of Alberta, Canada. *Ecosphere* **9**, e02156. doi:10.1002/ECS2.2156
- Stratton RD (2006) Guidance on spatial wildland fire analysis: models, tools, and techniques. USDA Forest Service, Rocky Mountain Research Paper RMRS-GTR-183. (Fort Collins, CO). doi:10.2737/RMRS-GTR-183
- Stratton RD (2009) Guidebook on LANDFIRE fuels data acquisition, critique, modification, maintenance, and model calibration. USDA Forest Service, Rocky Mountain General Technical Report RMRS-GTR-220. (Fort Collins, CO)
- Theobald DM, Romme WH (2007) Expansion of the US wildland–urban interface. *Landscape and Urban Planning* **83**, 340–354. doi:10.1016/J.LANDURBPLAN.2007.06.002
- Thompson MP, Calkin DE (2011) Uncertainty and risk in wildland fire management: a review. *Journal of Environmental Management* **92**, 1895–1909. doi:10.1016/J.JENVMAN.2011.03.015
- Thompson MP, Calkin DE, Finney MA, Ager AA, Gilbertson-Day JW (2011) Integrated national-scale assessment of wildfire risk to human and ecological values. *Stochastic Environmental Research and Risk Assessment* **25**, 761–780. doi:10.1007/S00477-011-0461-0
- Thompson MP, Scott J, Kaiden JD, Gilbertson-Day JW (2013) A polygon-based modeling approach to assess exposure of resources and assets to wildfire. *Natural Hazards* **67**, 627–644. doi:10.1007/S11069-013-0593-2
- Thompson MP, Haas JR, Finney MA, Calkin DE, Hand MS, Browne MJ, Halek M, Short KC, Grenfell IC (2015) Development and application of a probabilistic method for wildfire suppression cost modeling. *Forest Policy and Economics* **50**, 249–258. doi:10.1016/J.FORPOL.2014.10.001
- Thompson MP, Riley KL, Loeffler D, Haas JR (2017) Modeling fuel treatment leverage: encounter rates, risk reduction, and suppression cost impacts. *Forests* **8**, 469. doi:10.3390/F8120469
- Tymstra C, Bryce RW, Wotton BM, Taylor SW, Armitage OB (2010) Development and structure of Prometheus: the Canadian Wildland Fire Growth Simulation Model. Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre Information Report NOR-X-417. (Edmonton, AB)
- van Wageningen JW (1996) Use of a deterministic fire growth model to test fuel treatments. In ‘Sierra Nevada Ecosystem Project: final report to congress’. Vol. II, Ch. 43, University of California – Davis, Wildland Resources Center Report 37. (Davis, CA)
- Wang X, Parisien M-A, Taylor SW, Perrakis DDB, Little J, Flannigan MD (2016) Future burn probability in south-central British Columbia. *International Journal of Wildland Fire* **25**, 200–212. doi:10.1071/WF15091
- Whitman E, Parisien M-A, Price DT, St-Laurent M-H, Johnson CJ, DeLancey ER, Arseneault D, Flannigan MD (2017) A framework for modeling habitat quality in disturbance-prone areas demonstrated with woodland caribou and wildfire. *Ecosphere* **8**, e01787. doi:10.1002/ECS2.1787
- Wu Z, He HS, Liu ZH, Liang Y (2013) Comparing fuel reduction treatments for reducing wildfire size and intensity in a boreal forest landscape of northeastern China. *The Science of the Total Environment* **454–455**, 30–39. doi:10.1016/J.SCITOTENV.2013.02.058
- Yang J, He HS, Shifley SR (2008) Spatial controls of occurrence and spread of wildfires in the Missouri Ozark Highlands. *Ecological Applications* **18**, 1212–1225. doi:10.1890/07-0825.1