THESIS

COMPARING CROWN FIRE PREDICTIONS IN PONDEROSA PINE STANDS AMONG FOUR FIRE BEHAVIOR MODELS

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ABSTRACT

COMPARING CROWN FIRE PREDICTIONS IN PONDEROSA PINE STANDS AMONG FOUR FIRE BEHAVIOR MODELS

Fire and land managers commonly use fire behavior modeling systems to support their planning and decision-making process. Fire modeling systems have been increasingly used across the western United States to plan fuel treatments that reduce hazard fuels, especially as a drier climate has resulted in more frequent high severity wildfire. Given differences in model types, approaches, assumptions, and sensitivity to various input parameters, modeling systems can produce different predictions and lead to different management decisions. Variability arising from model selection results in increased uncertainty within the decision-making framework. Multi-model comparisons help identify areas of model agreement and disagreement, reduce uncertainty associated with management decisions, and identify directions for future experimentation. Here, I compare predictions of fire type and crown fire rate of spread (ROS) among four modeling systems that represent a range of model types and complexities—Wildland-urban interface Fire Dynamics Simulator (WFDS), QUIC-Fire, a Rothermel-based modeling framework, and Crown Fire Initiation and Spread (CFIS).

Comparisons (n = 297) were made based on a range of forest structure and environmental conditions representative of treated and untreated ponderosa pine forest stands in the southern Rocky Mountains. All four models predicted crown fire occurrence for 71% of simulations in total. WFDS, QUIC-Fire, and CFIS agreed on fire type more than 65% of the time. Rothermel predicted crown fire for 41% of simulations with ROS predictions 45% lower than the other models. Models tended to agree on crown fire occurrence in scenarios with a low canopy base height and greater surface and canopy fuel loading, indicating lower uncertainty in predicted fire behavior among models when fuel hazard is greatest. Differences among model predictions were more evident in scenarios with greater canopy base heights, moderate surface and canopy fuel levels, and at lower windspeeds. These results suggest that uncertainty introduced by model selection is likely greatest for designing and evaluation of fuel treatments, and that further research on fire behavior in treated forests stands is needed.

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1.1 INTRODUCTION

Fire behavior modeling has historically focused on providing estimates of key fire metrics including rate of spread (ROS), fire type (e.g., surface vs. crown), energy released, and flame length and depth to support fire operations (Sullivan, 2007b). In recent years, the use of wildland fire modeling has expanded beyond support for fire operations into all phases of fire and land management. One area where fire behavior model use has become critically important is in the design and evaluation of fuel treatments aimed at minimizing the negative impacts of future fires on ecosystems and society (Ex et al., 2019; Ott et al., 2023). This application space has been especially important in ecosystems across the western US where federal land management agencies have committed significant resources to reducing fuel loading and potential for large stand replacing crown fires through active management (USDA Forest Service, 2022). In this context, wildland fire behavior models play a critical role in assessing how changes in the surface and canopy fuel loadings influence the potential for surface and crown fire occurrence and fire behavior including the spread rate.

The development of wildland fire models has been ongoing since the 1920s, producing a large quantity of different models and modeling systems ranging from relatively simple and easy to use empirical models to complex three-dimensional physical models (Sullivan, 2007a, 2007b, 2007c). Empirical and quasi-empirical modeling systems are developed by relating observed fire behavior metrics such as head fire ROS to often easily measurable predictor variables such as wind speed. These models traditionally have been developed to provide fire behavior predictions for use by fire managers when suppression decisions are needed during an ongoing wildfire (Sullivan, 2007b). Examples of empirical and quasi-empirical modeling systems include Crown Fire Initiation and Spread (CFIS) (Alexander et al., 2006) and modeling systems based on the Rothermel surface fire ROS model (1972), active crown fire ROS model (Rothermel, 1991), and crown fire initiation model (Van Wagner, 1977), such as BehavePlus (Andrews et al., 2008), the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) (Reinhardt & Crookston, 2003), and FARSITE (Finney et al., 1998). While many empirical models were primarily developed to support fire operations, they are also often the primary tools used by land managers to support decision making and by scientists to provide insights into a range of questions including fuel treatment effectiveness (Fulé et al., 2012).

Physical and quasi-physical fire behavior models differ in that they attempt to explicitly represent the underlying chemical and physical processes and their interactions believed to drive fire behavior. Physical and quasi-physical models are often of greater complexity (Sullivan, 2007a), requiring more detailed inputs and more computational requirements to perform a simulation (Sullivan, 2007c). Although they demand more resources, physical and quasi-physical models can provide insights into the potential mechanisms driving fire behavior across a large range of fire management questions (Papadopoulos & Pavlidou, 2011; Hoffman et al., 2018). Examples of physical and quasi-physical models include Wildland urban interface Fire Dynamics Simulator (WFDS) (Mell et al., 2007), QUIC-Fire (Linn et al., 2020), and FIRETEC (Linn et al., 2002). Given the high computational demands of these models they are not commonly used in land and fire management decision making. However, they have been used by the scientific community to assess questions including assessing disturbance interactions

(Hoffman et al., 2012; Sieg et al., 2017), and the effectiveness of various silvicultural approaches for reducing fire rate of spread and severity (e.g., Ziegler et al., 2017; Ritter et al., 2022).

As the application of fire behavior modeling systems has increased, so have calls for evaluation that leads to a more complete understanding of the limitations and uncertainties inherent in model predictions (Cruz et al., 2003; Alexander & Cruz, 2013; Hoffman et al., 2018). In scientific computing this understanding is assessed through the verification, validation, and uncertainty quantification process, referred to as VVUQ. Within the VVUQ framework, verification involves activities to ensure that the model solves the underlying equations correctly, validation has conventionally focused on substantiating that the model predictions are within a specified range of accuracy for a given application, and uncertainty quantification is the process of understanding how various sources of error and uncertainty impact model predictions (National Research Council, 2012). Fire behavior model validation has traditionally been viewed through the lens of accuracy whereby predictions are compared to empirical observations and standard measures such as mean error are estimated and reported (e.g., Cruz et al., 2003; Alexander & Cruz, 2006). Ideally model validation efforts rely on well quantified physical experiments that span a range of conditions and scales for a given question of interest. However, given the wide range of questions, scales and ecosystems for which fire models are applied there is often a lack of experimental data available for model evaluation. This is especially true when attempting to evaluate models for crown fire initiation and spread, as the risk and expense required to conduct experiments and gather wildfire data has led to a paucity of high-quality datasets available for model evaluation (Alexander & Quintillo, 1990; Filkov et al., 2018), especially for physical models which require spatially explicit tree data (Ziegler et al., 2019).

Given the numerous models available and the insufficient evaluation data to inform model selection, many mangers rely on the most accessible or familiar modeling system (Shea et al., 2020; Wade-Malone et al., 2024). However, given differences in model types, approaches, assumptions, and sensitivity to various input parameters, modeling systems can result in different predictions and lead to different management decisions (Boon et al., 2019; Shea et al., 2020; Reich et al., 2022). Variability arising from model selection results in increased uncertainty within the decision-making framework. One approach to help reduce this uncertainty is to utilize multi-model comparisons to identify where agreement and disagreement in predictions from a wide range of model types, assumptions and approaches occur. It is important to recognize that model agreement is not evidence of model accuracy and does not ensure an error free decision-making process. However, agreement among many models is indicative that model choice is not important and thus reduces the overall uncertainty associated with decision making (Wade-Malone et al., 2024). On the other hand, differing model predictions indicate that the model selection process is influential and increases uncertainty.

Multi model approaches are commonly used in other scientific disciplines such as epidemiology (Boon et al., 2019; Shea et al., 2020; Wade-Malone et al., 2024), and climate science (Duan et al., 2019) to inform management actions, however, the use of multi-model comparisons in wildland fire science has been limited. Scott (2006) utilized five intensely sampled conifer stands to assess three semi-empirical models including CFIS and two Rothermel (1972) based modeling systems, FlamMap (Finney, 2006) and NEXUS (Scott, 1999). The results of this comparison indicated that CFIS predicted greater occurrence of crown fire and larger rates of spread than the Rothermel-based systems. Using a larger (n = 57) dataset of American and Canadian wildfires, Alexander & Cruz (2006) found that active crown fire rate of spread predictions from CFIS were not only greater but also more accurate than those from the Rothermel (1991) crown fire spread model. Physical models have been compared across a range of simulated conditions. Comparing models developed by Los Alamos National Laboratory (LANL), QUIC-Fire produced similar ROS estimates to FIRETEC in stand scale, prescribed burn scenarios (Linn et al., 2020) and similar burn shapes and ROS when implemented with topography (Robinson et al., 2023). One of the limitations of the multiple-model comparisons made to data in fire science is that they often have only used models of similar types and assumptions. The lack of a more comprehensive set of model-comparisons is likely in part due to challenges with data harmonization, and the computational resources required for running physics based modeling systems, thus limiting the potential usefulness of multi-model comparisons.

In this manuscript I assess agreement and disagreement by comparing fire type (surface and crown) and crown fire ROS predictions among four commonly used wildland fire behavior models and across a wide range of ponderosa pine forest fuel complexes and environmental conditions. The four systems included in this multi-model comparison were chosen to represent a range of model types, structures, and complexities including WFDS (Mell et al., 2007), QUIC-Fire (Linn et al., 2020), a Rothermel-based modeling framework (Scott & Reinhardt, 2001), and CFIS (Alexander et al., 2006). I summarize overall model agreement by assessing scenarios where all or most models agree, followed by an evaluation of model-to-model comparisons. To better understand the potential factors driving model relationships, I determined how forest structure and environmental variables influenced model agreement. I identified areas of model agreement that reduce the uncertainty that different management decisions would be reached, as well as areas of disagreement that should be prioritized for future experimentation.

1.2 MATERIALS AND METHODS

To support multi-model comparison of crown fire initiation and spread I utilized a dataset of 297 unique scenarios that spanned a range of forest structures and burning conditions representative of ponderosa pine (*Pinus ponderosa)* forests across the southern Rocky Mountains (Table 1). The scenarios utilized were based on those used by Ziegler et al. (2017) (n = 56) and Ziegler (2022) (n = 241) to assess the effectiveness and evaluate tradeoffs among various fuel treatment options.

Table 1: The range of forest structure and environmental conditions as simulated in WFDS and applied to QUIC-Fire, Rothermel, and CFIS.

Simulated Conditions	**Characteristic**	**Abbreviation (units)**	**Minimum**	**Maximum**
Environmental Conditions	Windspeed at 20 m	U_{20} (m s^{-1})	2	15
	Surface Fuel Moisture Content	FMC (%)	5	12
Canopy Fuel Characteristics	Canopy Base Height	CBH (m)	1.9	12.4
	Canopy Bulk Density	CBD (kg m^{-3})	0.01	0.15
	Canopy Fuel Loading	CFL (kg m^{-2})	0.14	2.65
Surface Fuel Characteristics	Surface Fuel Loading	SFL (kg m^{-2})	0.22	1.27
	Surface Fuel Height	(cm)	3	11
Stand Characteristics	Trees Per Hectare	TPH (trees ha^{-1})	11	942
	Quadratic Mean Diameter	QMD (cm)	16	76
	Stand Height	(m)	9.8	35.1
	Crown Length	CL (m)	6.2	23.5
	Canopy Cover	CC (%)	7	55
	Basal Area	BA (m^2)	5.0	30.8

All 297 scenarios were developed using stem mapped tree data from eight 200 m by 200 m plots in recently treated ponderosa pine dominated stands across the Southern Rocky

Mountains (Figure 1). All live trees at least 1.4 m tall had their location, species, diameter at breast height, crown base height, crown radius and tree height measured while stumps had their location, species, and diameter at stump height recorded (Ziegler et al., 2017). Surface fuel estimates on each site post treatment were made using a combination of planar intercept and destructive sampling (Brown, 1974). To reconstruct the initial forest structure, linear regressions equations based on the diameter at stump height were used to estimate the DBH, crown radius, height and crown base height for all cut trees and this data was combined with the post-treatment data and surface fuel estimates from neighboring areas. Ziegler et al. (2017) developed 56 unique fire scenarios consisting of 14 different forest structures and four unique burning environments. For more information on the collection of stem-mapped datasets and the development of the scenarios see Ziegler (2014) and Ziegler et al. (2017, 2019).

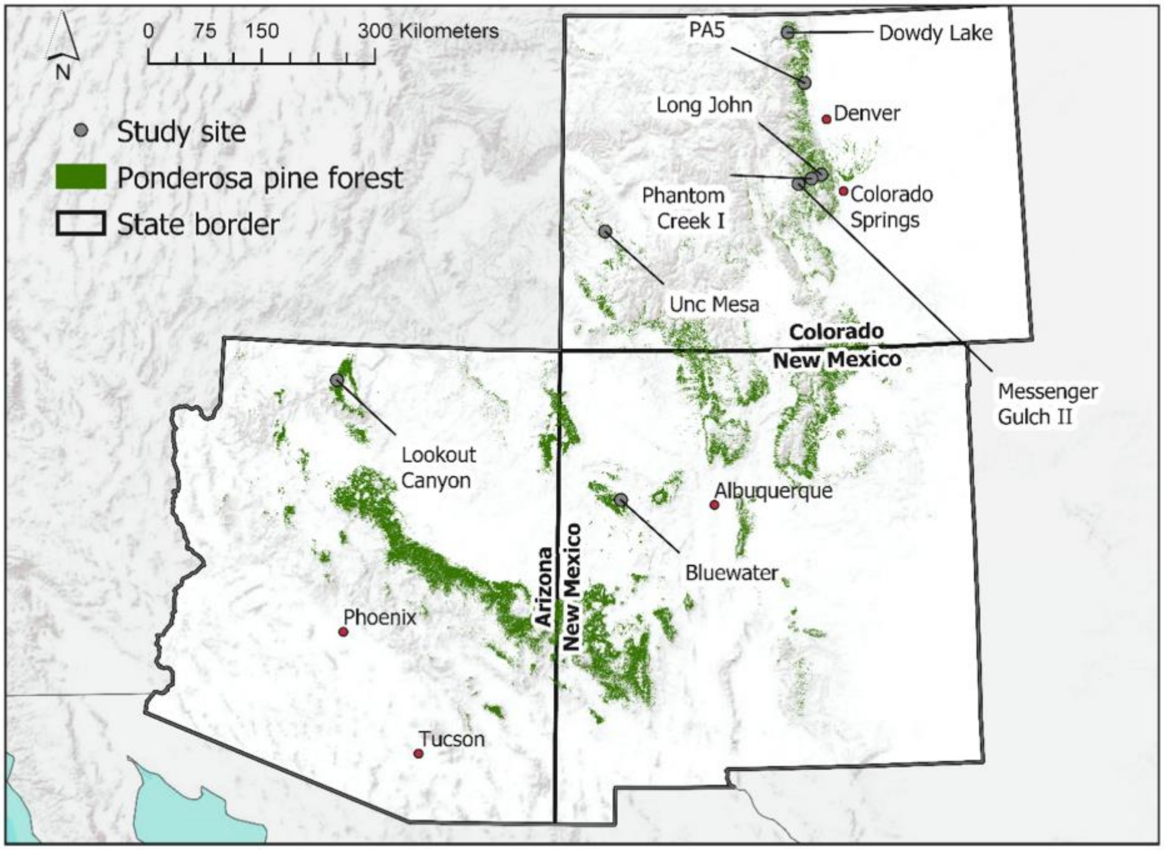

Figure 1: Figure originally published by Ziegler et al. (2019) as "Figure 3. Geographic locations of stem-mapped study sites in southwestern USA; extents of ponderosa pine forests are added for context (Gap Analysis Project http://www.usgs.gov/core-science-systems/science-analystics-and-synthesis/gap/, accessed 04/07/2019)."

Using five of the same stem-mapped data sets, Ziegler (2022) developed a set of 241 scenarios to examine tradeoffs in potential fire behavior across five sites for pretreatment, six unique-cutting methods, three residual basal areas, and three levels each of open wind speed, surface fuel load, and surface fuel moisture. Ziegler (2022) utilized the C-Optimized Fedorov's exchange algorithm (Atkinson et al., 1992) to select a subset of all possible simulations to be included in the final 241 scenarios. Using the pre-treatment scenarios as a starting point the effect of various silvicultural treatments were simulated through geo-statistical algorithms developed to represent random, distance based and variable retention harvests. Unlike the 56 scenarios developed in Ziegler et al. (2017), these scenarios used a process that ensured that differing cutting methods or residual basal areas had identical median fuel loads but allowed their spatial distributions to differ.

Using this dataset, we compared the fire type and crown fire ROS predictions among four fire behavior modeling systems that represent a range of types and complexities. WFDS represents a traditional physical simulator that utilizes CFD and requires more computational resources (Mell et al., 2007). QUIC-Fire represents a newer physical simulation system with reduced resource requirements, but that requires the same spatially explicit inputs (Linn et al., 2020). "Rothermel" represents a well-established quasi-empirical modeling system implemented in the fire management applications used by most fire and land managers in the United States (Scott & Reinhardt, 2001). CFIS represents a modeling system based heavily on empirical crown fire observations in boreal forests (Alexander et al., 2006). Each modeling system will be introduced in further detail, and methods used to implement the dataset will be presented.

1.2.1 WFDS

The Wildland-urban interface Fire Dynamics Simulator (WFDS) employs a computational fluid dynamics (CFD) approach in a spatially explicit, three-dimensional numerical grid to simulate interactions among the fuels, atmosphere, and fire through space and time (Mell et al., 2007, 2009). WFDS uses a low Mach-number approximation and either a direct numerical simulation or large-eddy approximation for the solution of conservation equations (Mcgrattan et al., 2013). WFDS is an extension of the Fire Dynamics Simulator (FDS) (Mcgrattan et al., 2013) which was developed by the National Institute of Standards and Technology (NIST) and US Forest Service Pacific Northwest Research Station. Mell et al.

applied FDS to the wildland urban interface by testing it first with surface fuels (2007) and then with individual tree crowns (2009). Evaluation of WFDS for crown fire behavior at the stand scale can be found in Mueller et al. (2015) Hoffman et al. (2016), and Ritter et al. (2020).

All 297 simulations were implemented in WFDS version 9977. Domains were flat and designed with lateral sides at y = 0 and y = 400 m (Figure 2). Winds entered the domain at x = 0 m following a power log scale dictated by the open windspeed 20 m above ground level. Ziegler et al. (2017) had a domain length of x = 1000 m, height of z = 100 m, and was comprised of square meter (x, y) cells ranging in height from z = 0.5 m at the ground to 2.0 m at the top of the domain. Ziegler (2022) had a domain comprised of cubic meter cells with a length of x = 900 m and height of z = 90 m.

For all domains, a four-hectare area of interest (AOI) representing the forested stand resided x = 100 m from the end of the domain with a y = 100 m buffer on the top and bottom and a x = 700 m (Ziegler et al., 2017) or 600 m (Ziegler, 2022) buffer for wind development before the AOI. Trees were created in their respective locations within the AOI as right cones defined by their unique heights, crown base heights, and crown radii. All crowns were assigned a foliar moisture content of 100%, a surface area to volume (SAV) ratio of 4000 m^2 m^{-3}, and a bulk density of 1.2 kg m^{-3} (Ziegler et al., 2017) or 0.5 kg m^{-3} (Ziegler, 2022). Trees outside the AOI were created to mimic the characteristics and arrangement of those inside. Fine surface fuels were assigned differently for Ziegler et al. (2017) and Zigler (2022). Zigler et al. (2017) created a homogenous layer of surface fuels across the domain defined by mean loading, height, and a 5% FMC. Ziegler (2022) created heterogenous fuel beds, with the loading and height of fuels in each location dependent upon whether they were beneath trees or in a canopy opening.

For each simulation, the average windspeed throughout the AOI was output at 2, 6, 10, and 20 m above ground level 300 (Ziegler, 2022) and 1300 seconds (Ziegler et al., 2017) after the simulation started. Fire was ignited as a 300 m long line fire 50 m upwind of the AOI. ROS was estimated as the fire crossed the AOI by calculating the fire time of arrival (TOA) difference. Ziegler (2022) calculated the TOA difference in one location to that 10 m downstream along the x-axis and averaged to calculated ROS. Ziegler et al. (2017) spaced 10 belt transects along the x-axis 20 m apart across the y-axis and estimated ROS by calculating the distance traveled along the x-axis every second averaged across all time steps and transects. Canopy fraction burned (CFB) was calculated at the end of each simulation as the ratio of canopy fuel consumed to the amount that was originally there. To assign a fire type to WFDS simulations, I used a 25% CFB threshold as the transition from surface to crown fire following Hoffman et al. (2016).

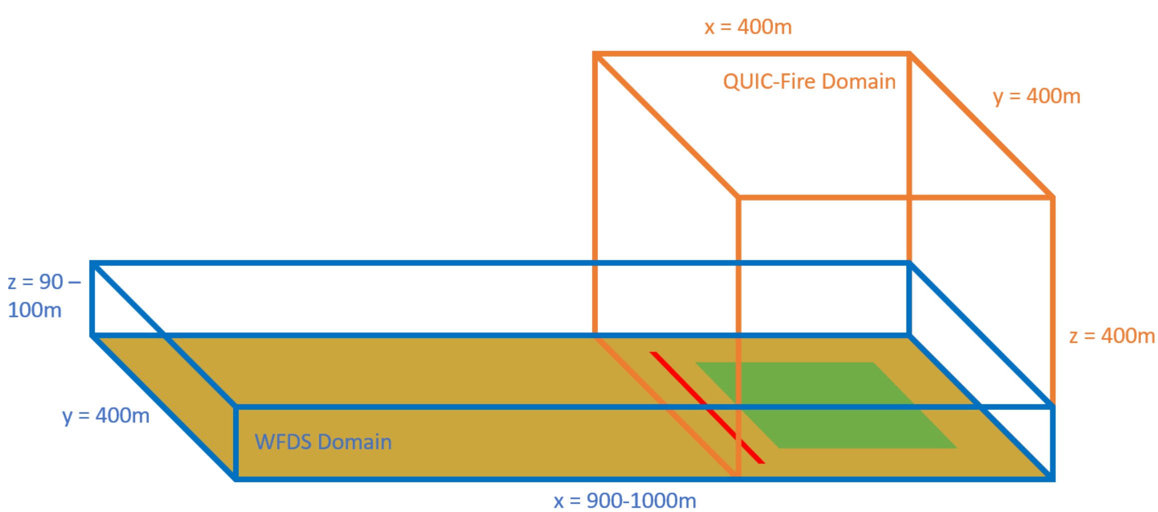

Figure 2: The domain shape and setup for WFDS (blue) and QUIC-Fire (orange) including the Area of Interest (green) and ignition line (red).

1.2.2 QUIC-Fire

QUIC-Fire is a quasi-physical model that couples interactions among the fuels, atmosphere, and fire without CFD approaches, reducing its computational costs relative to other physical simulators. QUIC-Fire was primarily developed for prescribed fire planning by allowing managers to test different firing patterns, but it can also be used to simulate free spreading surface and crown fires (Linn et al., 2020). QUIC-Fire was developed by linking cellular automata fire spread model FIRE-CA (Achtemeier et al., 2012; Achtemeier, 2013) with QUIC-URB, a wind solver that uses empirical algorithms and mass conservation to compute flow fields (Pardyjak & Brown, 2003; Singh et al., 2008). Given that QUIC-Fire is a relatively newer model it has had limited validation to date, however, QUIC-Fire predicted a similar overall burned area compared to the 2019 Spring Hill wildfire in the New Jersey Pinelands (Gallagher et al., 2021).

QUIC-Fire simulations were developed and run using version 6.0.0. Domains were 400 m x 400 m in the (x, y) dimensions with the 4 ha AOI in the middle and surrounded by 100 m on all sides (Figure 2). Differences in the overall domain size between QUIC-Fire and WFDS reflect differences in the flow solver of the two models. Wind entered the domain along the x = 0 m boundary using a logarithmic profile defined by the windspeed at z = 20 m. Domain cells measured 2 m x 2 m in the (x, y) dimensions. The wind grid was 400 m high, composed of 30 cells measuring from z = 1.0 m tall at the surface to 38.9 m at the top. The fire and fuels grid was composed of z = 1 m tall cells and measured 1 m taller than the tallest tree in each simulation. Vegetative fuels were generated using the TREES program developed by Los Alamos National Laboratory (LANL, 2023) by inputting individual tree crown properties including location, height, crown width, crown base height, a foliar moisture content of 100%, and a fuel radius sizescale of 0.0005 m. The crown bulk density value differed from WFDS to ensure that the total canopy fuel loading in QUIC-Fire matched that of WFDS within 10%. This difference in crown bulk density stems from differences in the sub-grid scale fuel distribution assumptions between QUIC-Fire and WFDS. Surface fuels matched those in WFDS simulations.

Simulations began with ignition of a 4 m wide and 300 m long line fire 50 m upwind of the AOI. To ensure the simulation ran until the flaming front had crossed the entire AOI, I confirmed > 95% of the surface fuels were consumed by the end of the simulation. ROS was calculated along the center of the x axis as the fire crossed the AOI, and fire type was defined using a 25% CFB threshold as the transition from surface fire to crown fire. I output the average windspeed at z = 2, 6, 10, and 20 m throughout the AOI every 100 seconds throughout the simulation.

1.2.3 Rothermel

Scott and Reinhardt (2001) describe a quasi-empirical modeling system, referred to hereafter as “Rothermel”, that predicts fire type and a point-source prediction for ROS in the direction of the wind. This modeling system relies on linking a series of empirical and quasi-empirical models including a surface fire ROS model (Rothermel, 1972), crown fire rate of spread model (Rothermel, 1991), and a crown fire initiation model (Van Wagner, 1977). Unlike WFDS and QUIC-Firem, Rothermel-based modeling systems are based on a fuel cell concept where surface fuel characteristics that influence fire behavior, such as the loading and surface area to volume ratios of each fuel class, are homogenized over a given area of interest (Rothermel, 1972). To aid managers in selecting which fuel model to use as an input to a Rothermel-based modeling system, systems such as FFE-FVS implement a logic process to assign standard fuel models (Rebain et al., 2010). An extensive evaluation of Rothermel-based systems (n = 1278 fire observations) found a ROS underprediction bias present in more than three-quarters of the simulations (Cruz & Alexander, 2013), including in the coniferous forests of western North America (Cruz & Alexander, 2010). Because they are widely recognized, standardized, and accessible, these Rothermel based fire behavior modeling systems are nonetheless the common model choice of many fire managers (Scott, 2006).

I used the firebehavioR R package (Ziegler, 2019; Ziegler et al., 2019; R Core Team, 2022) to mimic the Scott & Reinhardt (2001) Rothermel-based modeling system. Environmental inputs for wind speed were the open wind speed at 10 m (U_{10}), and a wind adjustment factor (WAF) using the 'waf' function in firebehaviorR based on mean surface fuel height, mean tree height, mean crown ratio, and an estimation for canopy cover following Crookston & Stage (1999). FMC was used to define a moisture regime for all six fuel classes except for live woody, which was entered as 60%. I followed procedures outlined for FFE-FVS (Rebain et al., 2010) to assign fuel models to each simulation and estimate CBH, CBD, and CFL. A complete description of this process can be found in Appendix A. I ran the Rothermel function and output ROS and fire type as surface, passive, active, or conditional. To simplify fire type outputs and reduce uncertainty in defining fire type I defined crown fire as a combination of passive and active fire types.

1.2.4 CFIS

CFIS is a quasi-empirical fire behavior modeling system that predicts fire type and point-source predictions of passive and active crown fire ROS (Alexander et al., 2006). CFIS first predicts the probability of crown fire occurrence using the open windspeed at 10 meters (U_{10}), estimated fine fuel moisture (EFFM), fuel stratum gap (FSG), and surface fuel consumption

(SFC). The crown fire occurrence component was based on logistic models created using 71 observations of experimental fires at the transition between surface and crown fire behavior (Cruz et al., 2004). If crown fire is more likely to occur than surface fire, values for EFFM, U_{10}, and canopy bulk density (CBD) are used to predict whether active crown fire or passive crown fire is more likely. Thirteen passive and 24 active crown fires observations were used to develop separate ROS formulas for each fire type (Cruz et al., 2005). Alexander & Cruz (2006) compiled a relatively large (n = 57) empirical dataset of Canadian and American wildfires in boreal forests and found that CFIS predicted crown fire ROS with an error of ±25% for 42% of the data.

CFIS was implemented using the 'cfis' function of the firebehavioR R package (Ziegler et al., 2019). The same U_{10} value described for Rothermel was used for CFIS. To best represent fine surface fuels, FMC was used for estimated fine fuel moisture (EFFM) and I assumed complete consumption of the available SFL to estimate SFC. The fuel stratum gap (FSG) was calculated by subtracting the mean surface fuel height from the median crown base height. Canopy bulk density was calculated using a loading over depth method and followed the equation (1):

$$CBD = \frac{\left(\frac{initial\ dry\ mass\ of\ stand\ canopy\ fuels\ in\ WFDS}{stand\ area}\right)}{90th\ percentile\ for\ tree\ height - median\ crown\ base\ height}$$

The ignition delay input was entered as zero as this output was inconsequential for ROS and fire type results. CFIS output fire type as surface, passive, or active. As with Rothermel, I combined passive and active fire type predictions into a crown fire class.

1.2.5 Multi-Model Comparison

To identify areas of agreement and disagreement among model predictions of fire type and crown fire ROS, I made comparisons among all four models and among each model pairing. First, I reported the proportion of surface fire and crown fire predicted by each model. Next, I reported the proportion of simulations where all four models agreed on fire type, where three models agreed on fire type, and where two models predicted crown fire and two models predicted surface fire. Then, I calculated the proportion of simulations where models agreed on fire type and used Cohen's Kappa to account for agreement reliability using the unweighted kappa2 function of the irr package (Gamer & Lemon, 2019). To better understand the fuel and environmental conditions under which all models agreed on crown fire or surface fire, and each model pairing agreed on either fire type, I used binary logistic regression to determine the multiplicative change in the log-odds ratio of model agreement for a one-unit increase in five predictor variables of interest that strongly influence crown fire initiation and ROS—U_{20}, FMC, CBH, CBD, and SFL. This was implemented using the generalized linear model function of the R stats package (R Core Team, 2022) and an alpha (α) level of 0.05 (this was standard practice for all statistical tests unless otherwise noted) and followed the equation (2):

$$glm(model\ pairing \sim CBH + CBD + U_{20} + SFL + EFFM,\ family = binomial)$$

I then used the predict function to predict the probability of all four models agreeing on crown fire or surface fire across the range of simulated conditions for each predictor variable. I also predicted the probability of each model pairing agreeing for the predictor variables which were significant for it.

To compare crown fire ROS predictions, I first reported statistics related to the range of crown fire ROS predictions for each model. Then, I narrowed to simulations where both models predicted crown fire for each model pairing and calculated mean difference (m min^{-1}) and mean percent difference (%). Next, I used a multinomial regression model to examine how the relationship between U_{20} and CBD caused differences in ROS for each model pairing. This was implemented using the linear model function and for each model pairing followed the equation (3):

$$lm(ROS\ difference \sim CBD + U_{20})$$

I then used the predict function to predict the percentage difference between model ROS predictions across the range of simulated U_{20} and CBD conditions.

1.3 RESULTS

1.3.1 Fire Type Comparisons

Crown fire was predicted to occur in 86%, 79%, 78%, and 41% of simulations for WFDS, QUIC-Fire, CFIS, and Rothermel, respectively. All four models predicted the same fire type for 32% of the simulations, unanimously agreeing on crown fire for 29% and surface fire for 3%. Three models predicted the same fire type for 46% of simulations, with all but one model agreeing on crown fire for 39% and surface fire for 7%. For the remaining 22% of simulations, two models predicted crown fire and two models predicted surface fire.

Fire type agreement ranged among individual model pairings from 87 - 42% (Table 2). The greatest agreement occurred among WFDS and QUIC-Fire (WQ) which agreed on fire type for 87% of simulations (K = 0.54). Pairings with Rothermel consistently had the lowest proportion agreeing, and kappa values for pairings with WFDS (WR) and QUIC-Fire (QR) were near zero, indicating fire type agreement may have occurred by chance. When disagreement among paired models occurred, it was always because WFDS predicted more crown fire than the other model in the pairing, or Rothermel predicted more surface fire than the other model in the pairing (Figure 3).

Table 2: The proportion of simulations agreed upon by each model pairing, as well as the kappa statistic indicating likelihood of model agreement. A kappa value of 1 indicates that models would reliably agree constantly, 0 indicates that model agreement occurs entirely by chance, and -1 indicates that models would reliably disagree constantly.

Models Paired	Pairing Abbreviation	Agreement Proportion	Kappa (K) value
WFDS : QUIC-Fire	WQ	87	0.54*
WFDS : Rothermel	WR	48	0.07
WFDS : CFIS	WC	75	0.15*
QUIC-Fire : Rothermel	QR	42	-0.05
QUIC-Fire : CFIS	QC	65	-0.05
CFIS : Rothermel	CR	58	0.23*

* Indicates statistical significance at alpha = 0.05

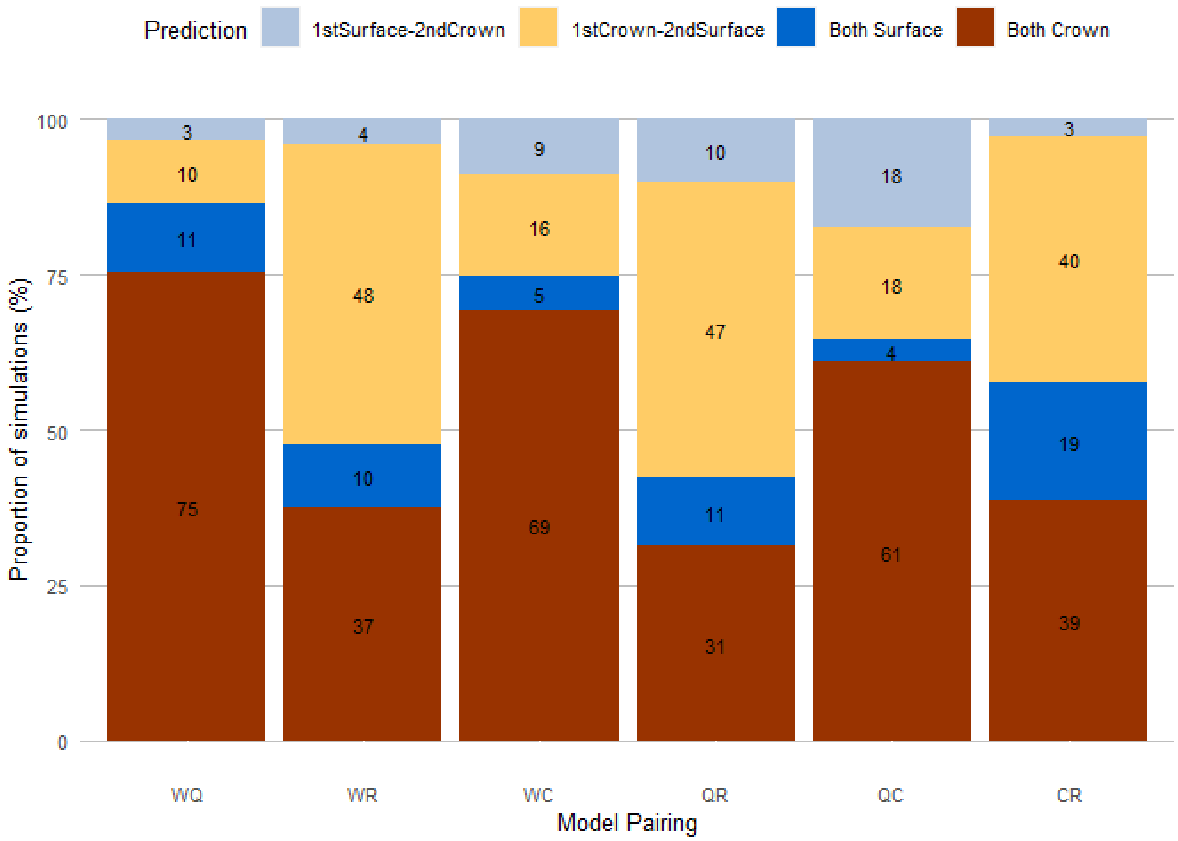

Figure 3: Stacked bar charts displaying the proportion of simulations (in the numbered bars) where each model pairing agreed and disagreed on each fire type combination. Brown indicates both models agreed on crown fire, dark blue indicates both models agreed on surface fire, yellow indicates the first model in the pairing predicted crown fire while the other predicted surface fire, and light blue indicates the first model in a pairing predicted surface fire while the second model in the pairing predicted crown fire.

Model agreement on fire type depended upon a combination of forest structural variables including CBH, CBD, and SFL, as well as U_{20} (Table 3). U_{20} and SFL significantly predicted all four models agreeing on both crown fire and surface fire, while CBH only significantly predicted all four models agreeing on crown fire. For all model pairings, the odds ratios of model agreement significantly decreased as CBH increased. CBD significantly predicted fire type agreement among all model pairings except for WFDS and CFIS (WC) even though it was not a significant predictor for all models agreeing on either fire type. FMC was not an important explanatory variable for identifying agreement among models (except WC).

Table 3: Odds ratios from binary logistic regression that indicate the multiplicative change in the odds of fire type agreement for each one unit increase in the predictor variable. The first section is the odds ratios of all four models agreeing on fire type, while the second section is the odds ratios for agreement among each model pairing.

		CBH	**CBD**	**U_{20}**	**SFL**	**FMC**
	One unit increase	1 m	0.01 kg m^{-3}	1 m s^{-1}	0.1 kg m^{-2}	1 %
Full Agreement	Crown	0.43*	1.06	1.17*	1.14*	0.98
	Surface	1.44	0.85	0.12*	0.38*	0.00
Model Pairing	WQ	0.69*	0.87*	0.72*	0.98	1.05
	WR	0.87*	1.19*	1.15*	1.01	0.95
	WC	0.77*	0.93	1.24*	1.26*	0.85*
	QR	0.86*	1.12*	1.11*	1.00	0.93
	QC	0.64*	0.87*	1.05	1.14*	0.93
	CR	0.85*	1.20*	0.96	0.96	0.97

* Indicates statistical significance at alpha = 0.05

Binary regression trends show that model agreement tended to occur under the more extreme fuel and burning scenarios on either end of the simulated range of conditions. All four models were generally more likely to agree on crown fire than surface fire. All models were more likely to predict surface fire at the lowest U_{20} and SFL values, and all models were more likely to agree on crown fire at the lowest CBH and as U_{20} and SFL increased. The probability of agreement decreased with CBH across all model pairings, supporting the trend that all models may agree on crown fire occurrence at the lowest CBH but that they are less likely to agree on fire type as CBH increases. Model pairings were generally more likely to agree on fire type as U_{20}, SFL, and CBD increased. While WFDS and QUIC-Fire (WQ) were very likely to agree on fire type at low windspeeds, they became less likely to agree at higher windspeeds (Figure 4).

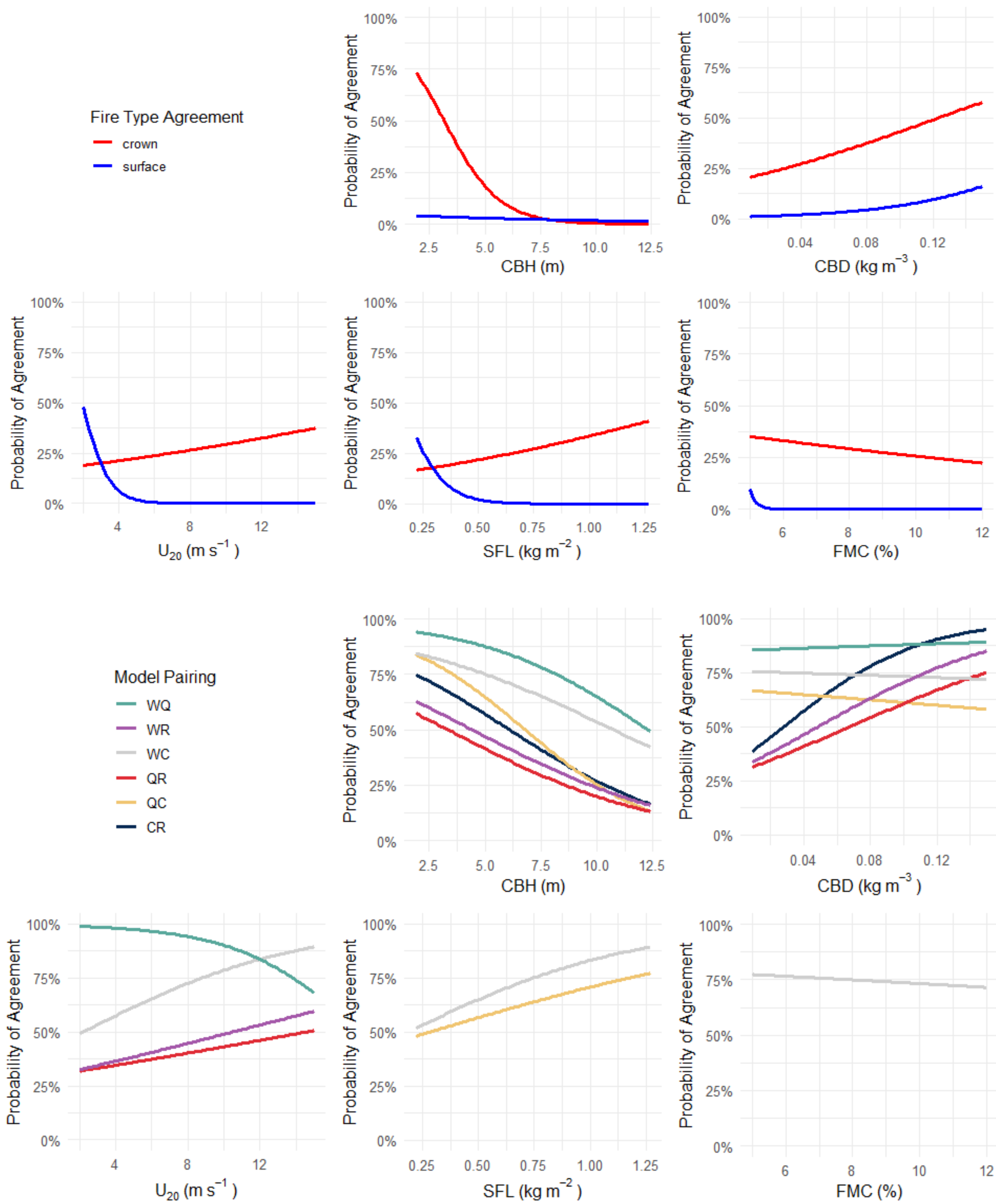

Figure 4: Top—Binary logistic regression plots displaying the predicted probability of all four models agreeing on fire type across the range of each predictor variable's simulated conditions. Bottom—Binary logistic regression plots displaying the predicted probability of agreement for model pairings across the range of each predictor variable's simulated conditions. Only those model pairings that were deemed statistically significant for each predictor variable were included in the bottom figure.

1.3.2 Crown Fire Rate of Spread Comparisons

WFDS had the greatest median crown fire ROS predictions followed by QUIC-Fire, Rothermel, and CFIS. QUIC-Fire had the greatest variability in ROS predictions followed by WFDS, CFIS, and Rothermel. Rothermel's greatest ROS prediction was 52 m min^{-1}, CFIS' greatest ROS prediction was 87 m min^{-1}, and WFDS and QUIC-Fire both had ROS predictions > 100 m min^{-1} (Figure 5).

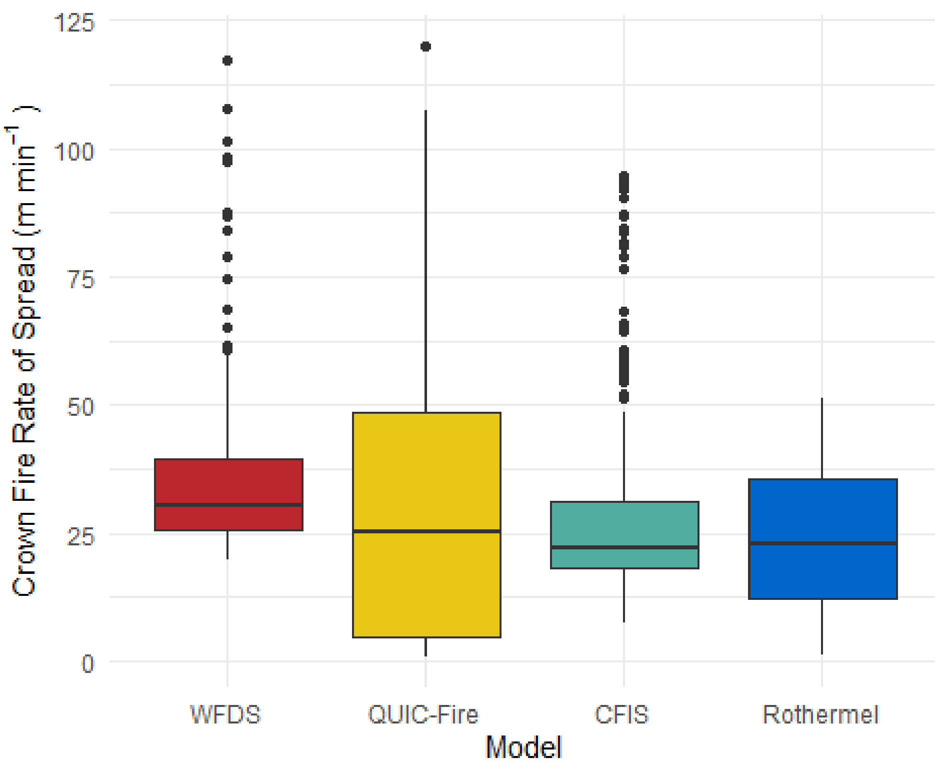

Figure 5: Boxplots displaying the range of crown fire ROS predictions per model.

WFDS and Rothermel (WR) had the greatest mean difference, with the average ROS prediction from WFDS 18.84 m min^{-1} greater than Rothermel (Table 4). WFDS and QUIC-Fire (WQ) had the least mean difference (6.11 m min^{-1}) but the greatest mean percent difference, indicating that while the difference in their means may have been smaller, differences between paired predictions overall may have been larger. WFDS and CFIS (WC) had the least mean percent difference (42%) and a mean difference of 9.81 m min^{-1}.

Table 4- Statistics calculated from paired ROS predictions for each model pairing. For each model pairing, the first model listed had higher ROS predictions overall. Mean difference measures the average ROS difference among models. Mean Percent Difference reflects the average magnitude of differences between models relative to their average values.

	WQ	**WR**	**WC**	**QR**	**QC**	**CR**
Predictions (n)	224	111	206	93	181	115
Mean difference (m min^{-1})	6.11	18.84	9.81	12.33	9.55	11.4
Mean Percent Difference (%)	84	63	43	50	72	57

Predicted percentage differences in crown fire ROS related to CBD and U_{20} varied by model pairing (Figure 6). For all model pairings involving WFDS (WQ, WR, and WC), WFDS tended to predict a faster ROS at lower windspeeds across all CBD values. For all model pairings involving QUIC-Fire, QUIC-Fire tended to predict faster ROS at the greatest wind speeds and when CBD was lower. For all model pairings involving Rothermel, Rothermel tended to predict a faster ROS when CBD and U_{20} were greater. CFIS tended to predict a faster ROS than WFDS and QUIC-Fire when CBD and U_{20} were greater, but a faster ROS than Rothermel when CBD and U_{20} were lower.

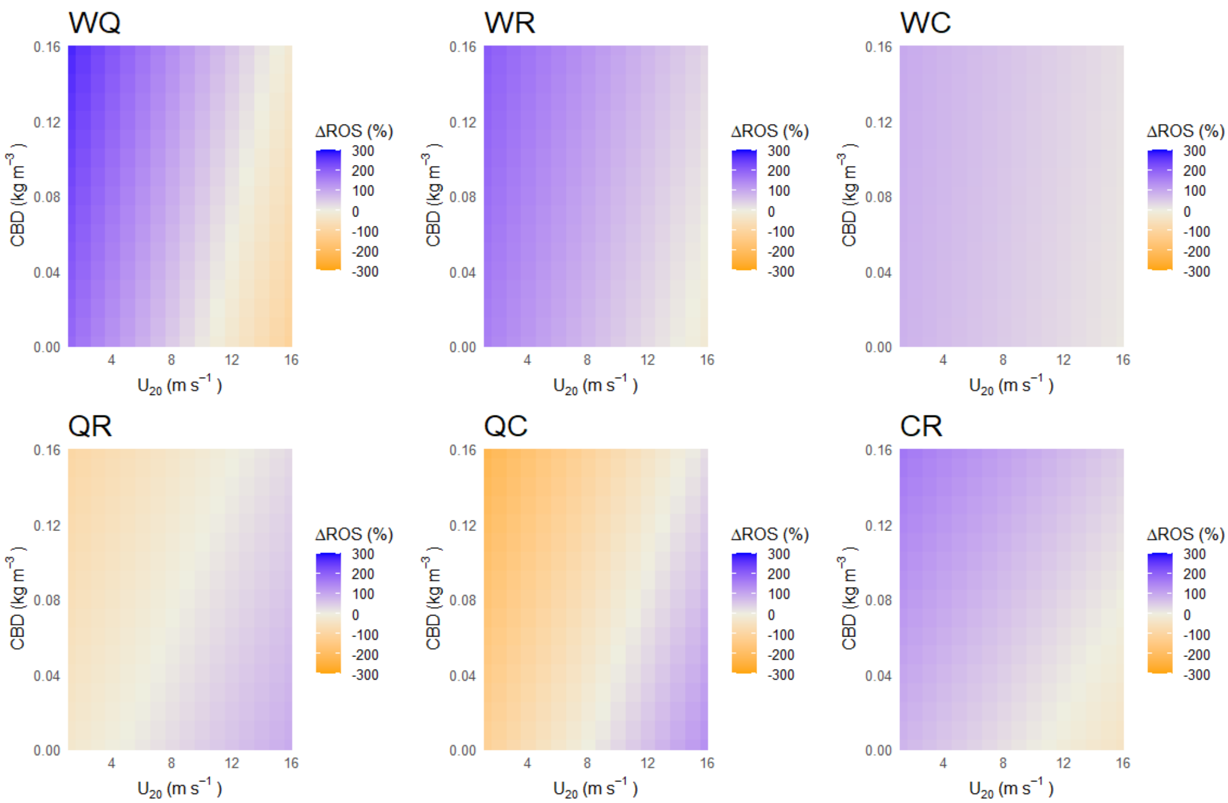

Figure 6: Scatterplots displaying the predicted percent difference in ROS as a function of CBD and U20 for each model pairing. Blue values indicate the first model is more likely to overpredict ROS in those conditions, while orange values indicate the second model is more likely to overpredict ROS.

1.4 DISCUSSION

Multi-model comparison of WFDS, QUIC-Fire, Rothermel, and CFIS identified scenarios where models were most likely to reach similar, as well as different, fire type predictions. Models were more likely to agree on crown fire occurrence at the lowest CBH, and less likely to agree on either fire type as CBH increased. Regardless of model type, assumptions, and input requirements, this suggests that there is a CBH threshold low enough for any of the four models to predict crown fire. In stands with a very low CBH, managers are likely to recognize that crown fire is likely, and that a fuel treatment is necessary to reduce crown fire behavior. In these scenarios, there is reduced uncertainty that managers would reach a different management decision, and so any model's prediction may be sufficient to properly inform their decision. As forest structure changed to better represented stands with a variety of fuel treatments, fire type predictions become more variable among the models. Models were more likely to disagree on fire type in the middle of the spectrum for CBH and U_{20}, and when CBD and SFL were slightly reduced. These areas of disagreement suggest that using a multi-model ensemble with models of different types would better support decision making in these scenarios. As fuel treatments may modify forest fuel structure in a variety of ways, multi-model comparisons are essential to identify uncertainty related to which to implement, and so using information from a multi-model comparison may lead to a more informed decision.

Differences in crown fire occurrence and rate of spread predictions were evident among fire models. WFDS generally predicted more crown fire and higher ROS' than the other models. WFDS and QUIC-Fire agreed on the most crown fire using a 25% CFB threshold, but they had different ROS estimates. While these models had similar wind profiles overall, drag in QUIC-Fire seemed to be less evident than in WFDS, resulting in within stand windspeeds that seemed more closely influenced by U_{20} in QUIC-Fire than in WFDS. These differences, or other physical development differences, could have resulted in the differing ROS predictions between these models. WFDS agreed on fire type with QUIC-Fire and CFIS ≥ 65% of the time, with mean ROS differences ≤ 10 m min^{-1}. Rothermel was about as likely to predict a different fire type than the other models as it was to predict the same fire type, while its ROS estimates were ≥ 10 m min^{-1} lower. These results are supported by previous model evaluation that suggests that WFDS may overpredict crown fire ROS (Hoffman et al., 2016) and that Rothermel is likely to underpredict ROS (Cruz & Alexander, 2010, 2013). When validating fire models with empirical results, underprediction in a model could have drastic consequences for wildfire response (Alexander & Cruz, 2006). Over and under prediction relationships for this research represent comparisons among models, and even when models have similar predictions, a real-world truth may not be reflected (Boon et al., 2019).

There are further limitations to this research that are worth noting. We choose fire models to represent different model types, though other modeling systems could be applied to this dataset. Choices made to harmonize model inputs and outputs created additional uncertainty. While variables such as FMC were maintained as near constants across all four fire models, variables such as SFL and CBD were more unique to each system. By lumping passive and active simulations as crown fire for Rothermel and CFIS, I also influenced how crown fire ROS was calculated. How we defined fire type and measured ROS in WFDS and QUIC-Fire also influenced results, and the nature of physical models means different results could be produced following different methods.

As managers use models to inform their decision making for a variety of applications, their perception of a system and trust in its predictions can dynamically evolve and influence how they perceive its credibility (Yilmaz & Liu, 2020). It is important to continually evaluate fire behavior modeling systems as they are applied to fire management and to identify which conditions are especially worth pursuing for future experimentation (Mell et al., 2010; Alexander & Cruz, 2013a; Hoffman et al., 2018). Collaborative hubs, as used in predictive epidemic modeling, should be fostered within the fire science community to encourage communication between modelers and managers, sharing of datasets, and further model evaluation efforts (Reich et al., 2022). Model validation can be furthered by gathering empirical crown fire datasets from prescribed fires and wildfires (Filkov et al., 2018; Hiers et al., 2020). Datasets with sufficient information to evaluate physical modeling systems are especially needed. Especially regarding fuel treatment planning, multi-model comparison can reduce the uncertainty associated with model choice and its influence on management decisions.

1.5 CONCLUSION

I performed a multi-model comparison of fire type and crown fire ROS across 297 simulations encompassing treated and untreated ponderosa pine stands and a range of environmental conditions. Model agreement on crown fire occurrence at low CBH strongly suggests to land managers that a treatment should be implemented regardless of which model they use. WFDS, QUIC-Fire, Rothermel, and CFIS were less likely to agree on fire type in treated stands and under more moderate conditions, suggesting that future multi-model comparisons should focus on these scenarios, and that using ensemble methods and multiple models is especially useful for fuel treatment planning. Although collecting high quality empirical crown fire observations will remain an important goal for model validation, evaluation may continue through multi-model comparisons, and comparing fire behavior modeling systems of varying types continues to present a unique opportunity for managers and scientists alike to weigh their potential applications. These systems must provide utility and encourage managers to confidently apply fuel treatments that reduce the potential for undesirable crown fire behavior.

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APPENDIX A

As Rothermel based modeling systems make unique assumptions, I mimicked the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) (Rebain et al., 2010) to assign crown fuel characteristics for CBD, CFL, and CBH to each stand. I used the species, DBH, height, and crown ratio of each tree to calculate these characteristics. Unknown species were assigned as ponderosa pines and unknown DBH was assigned as 12in. When compared with mean values for each stand, open stands with fewer TPH typically had lower heights and higher CBHs, while the reverse often proved true for denser stands. Following the fuel model (FM) selection process outlined for the Central Rockies within FFE-FVS (Rebain et al., 2010), I assigned fuel models to each simulation. First, I assigned simulations (n = 297) into a forest cover type based on their species composition as originally published by Ziegler and others (Ziegler, Hoffman, Battaglia, et al., 2019).

The ponderosa pine cover type was used to determine FM for simulations (n = 188) where the stand's species composition was > 60% ponderosa pine. First, I determined canopy cover as used in Rothermel—by calculating the area of a circle for each tree in the stand using its radius, summing these to calculate total area without overlap, solving for crown cover considering overlap disregarding exact tree location (Crookston & Stage, 1999), and calculating this number as a ratio to the maximum potential stand area. Canopy cover for all simulations fell below the 60% threshold. Next, I was directed to determine if tree and snag biomass was absent from the understory to assign FM 2—grass in the understory of a timber stand. I narrowed to simulations (n = 47) with low SFL (<= 0.4 kg/m^2) and high surface fuel heights (> 13 cm)—values producing a bulk density indicative of grassy fuels. Next, to find mid-flame windspeed, I multiplied the WAF I calculated for the enviro input in Rothermel with the U_{10} to assign simulations (n = 97) with mid-flame windspeeds less than seven miles per hour to FM 5. The remaining simulations (n = 44) were also assigned FM 5 by following the model selection logic to the oak brush cover type.

The mixed conifer cover type selection logic was used to assign FMs to the remaining simulations (n = 109) where ponderosa pines represented less than 60% of trees within the stand. These forests may still have many ponderosa pines (PIPO), but subdominant species include Douglas fir (PSME), quaking aspen (POTR5), gamble oak (QUGA), and a variety of other species (JUSC2-Rocky Mountain Juniper, PIED- Pinyon Pine, PIEN-Engelmann Spruce, PIFL2-Limber Pine, PIPU-Blue spruce, and PICO-Lodgepole pine) (Reynolds et al., 2013). Uncompahgre Mesa had a variety of species besides ponderosa pine, but the basal area of ponderosa pine remained greater than that of any other species, so these simulations (n = 56) were assigned FM 9. Phantom Creek was dominated by Douglas fir, and I assumed this site had a structural class 3 or higher and so assigned these simulations (n = 53) FM 10. All simulations (n = 297) were assigned to fuel model 2, 5, 9, or 10. Certain elements made each of these fuel models unique, which would have affected fire behavior (Table 1).

Table 1: Unique elements of each of the selected fuel models. Asterisk indicates a fuel class is not present within that fuel model.*

		FM 2	**FM 5**	**FM 9**	**FM 10**
General Info	Simulations	47	141	56	53
	Description	Timber-grass understory	Brush	Hardwood-long-needle pine litter	Timber-litter understory
	Depth (cm)	30.48	61.00	6.00	30.48
	Mx Dead	15	20	25	25
Fuel loading (Mg ha^{-1})	1hr	4.48	2.25	6.54	6.73
	10hr	2.25	1.12	0.93	4.48
	100hr	1.12	*	0.34	11.23
	Live Herb	1.12	*	*	*
	Live Woody	*	4.48	*	4.48
SAV Ratio	1hr	9843.00	6561.68	8202.00	6561.68
	Live Herb	4921.26	*	*	*
	Live Woody	*	4921.26	*	4921.26

LIST OF ABBREVIATIONS

AOI: Area of Interest

BA: Basal Area

CBD: Canopy Bulk Density

CBH: Canopy Base Height

CFB: Canopy Fraction Burned

CFD: Computational Fluid Dynamics

CFIS: Crown Fire Initiation and Spread

CFL: Canopy Fuel Loading

DBH: Diameter at Breast Height

EFFM: Estimated fine fuel moisture

FMC: Fuel Moisture Content

FFE-FVS: Fire and Fuels Extension - Forest Vegetation Simulator

FM: Fuel Model

FSG: Fuel Stratum Gap

HT: Stand height

QMD: Quadratic Mean Diameter

ROS: Rate of Spread

SAV: Surface Area to Volume Ratio

SFC: Surface Fuel Consumed

SFL: Surface Fuel Loading

TPH: Trees Per Hectare

U_{20}: open windspeed 20m above ground level (open windspeed input for WFDS and QF)

U_{10}: open windspeed 10m above ground level (a common model input)

WAF: Wind Adjustment Factor

WFDS: Wildland-urban interface Fire Dynamics Simulator

Units

M: meters

S: seconds

Km: kilometers

Kg: kilograms

Mg: megagrams

Ha: hectares

Min: Minutes

Hr: Hours

Agreement

WQ, WR, WC, QR, QC, CR

W- WFDS

Q- QUIC-Fire

R- Rothermel

C- CFIS