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Reconstruction of the Spring Hill Wildfire and Exploration of Alternate Management Scenarios Using QUIC-Fire

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Abstract: New physics-based fire behavior models are poised to revolutionize wildland fire planning and training; however, model testing against field conditions remains limited. We tested the ability of QUIC-Fire, a fast-running and computationally inexpensive physics-based fire behavior model to numerically reconstruct a large wildfire that burned in a fire-excluded area within the New York–Philadelphia metropolitan area in 2019. We then used QUIC-Fire as a tool to explore how alternate hypothetical management scenarios, such as prescribed burning, could have affected fire behavior. The results of our reconstruction provide a strong demonstration of how QUIC-Fire can be used to simulate actual wildfire scenarios with the integration of local weather and fuel information, as well as to efficiently explore how fire management can influence fire behavior in specific burn units. Our results illustrate how both reductions of fuel load and specific modification of fuel structure associated with frequent prescribed fire are critical to reducing fire intensity and size. We discuss how simulations such as this can be important in planning and training tools for wildland firefighters, and for avenues of future research and fuel monitoring that can accelerate the incorporation of models like QUIC-Fire into fire management strategies.

Keywords: prescribed fire; wildfire; QUIC-Fire; coupled fire-atmospheric models; fuels

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1. Introduction

Over the years, wildland fire models have varied substantially in complexity and performance from simple 1D empirical models that can quickly estimate forward fire rates of spread to computationally intensive simulators that can simulate complex fire behavior and associated processes [1,2]. As wildland fire behavior is inherently a complex result of fuel, weather conditions, and physical processes that vary with the scale and spatial distribution of combusting material, there are strengths and weaknesses across this continuum of tools that often trade off the incorporation of relevant factors and scale of outputs for simplicity in computational requirements. In short, there is a time and place for a range of approaches, but where the refinement of computationally complex models and the equipment to run them have grown, there exists untapped potential for their use and testing as comprehensive tools to accomplish planning, training, and research. In accounting for spatial and temporal heterogeneity in conditions that drive fire behavior, these new complex modeling approaches can be used to comprehensively explore diverse management scenarios and elucidate options to achieve desired outcomes.

The class of three-dimensional, physics-based fire behavior simulation models integrate fine-scale (meters), spatially explicit fuel conditions and ignition patterns with weather and topography to simulate wildland fire behavior processes for planning or operational purposes [3]. Simulated fire behavior and effect outputs of these simulators are resolved in three-dimensional space and have been developed and expanded extensively compared to former models [4–7]. These coupled-fire atmospheric fire behavior models differ from previous approaches, in that they govern predictions based on physical processes of fire behavior rather than empirical correlations and are designed specifically to operate at high temporal resolutions in three-dimensional space. This difference is critical because it allows for the simulation of marginal burning conditions and spread types of fire (e.g., backing, flanking, and irregular or interacting fire lines), which are typical of prescribed burning and non-catastrophic wildfires, but are also sensitive to the three-dimensional heterogeneity of fuels [8]. Such tools offer a means to better understand potential fire behavior conditions and effects, so as to ultimately be able to "game the system" through rigorous sensitivity testing of conditions that drive fire behavior to estimate how contrasting management or weather scenarios may play out in specific management units or landscapes. Ultimately, this generation of spatially and temporally explicit fire behavior models will enable advances in planning, student learning, and fire behavior research.

While computational fluid dynamics models, including FIRETEC [9] and WFDS [6], have provided the most robust research on fire-scale fire behavior, they remain computationally expensive and have not found operational applications. New generation, 3D physics-based fire behavior simulators that simplify solutions but retain the physics-based coupling of the fire to the atmosphere have emerged in recent years (e.g., WFDS Level set [10], WRF-SFIRE [7], and QUIC-Fire [4]). Each of these models is a coupled atmosphere/fire behavior model, which account for spatially explicit flow patterns and convection with regard to fine-scale heterogeneity of fuel structure, condition, and topography. To this extent, these models can represent and predict the impacts of gradients in fuel conditions or shifting forest community types, fuel breaks of irregular sizes and shapes, shifting winds, fire-induced meteorology, and irregular or interacting fire lines [8].

Of the available physics-based fire behavior models, QUIC-Fire was designed for use in prescribed fire management and fuel treatment scenarios [4]. QUIC-Fire is a coupled fire–atmosphere model that links a diagnostic wind solver (QUIC-URB), with a cellular automata fire model (FIRE-CA) [4]. Meant as an operational alternative to HIGRAD/FIRETEC, QUIC-Fire is a fast-running model capable of near real-time prediction with very low system requirements and multiple modules for performing necessary tasks. QUIC-URB is a diagnostic model for computing mean flow fields that uses empirical algorithms and mass conservation to quickly compute 3D flow fields [11,12]. Initially developed for flow around building complexes, QUIC-URB has been extended to include the influence of forest canopies and fire plumes. FIRE-CA is the fire propagation module of QUIC-Fire, based on a previously successful cellular automata approach to coupling fire behavior to the atmosphere [13,14]. QUIC-Fire has been compared with both experimental results and a high-fidelity model for a variable length fire line, and for complex ignitions within a canopied domain [4]. QUIC-Fire and similar models represent a promising future for operational fire behavior use, with a faster-than-real-time runtime and the capability of running 3D vegetation and wind models in spatially explicit domains. This allows for ensemble runs to explore fire behavior predictions involving complex ignitions and heterogeneous fuels.

Testing and exploration of QUIC-Fire and other physics-based fire behavior models under complex prescribed fire and wildfire scenarios remains limited to numerical simulations, barring a limited number of field experiments [4,7,15,16]. This is largely due to the complexity in orchestrating fire experiments on prescribed fires [17,18], let alone wildfires [8]. Inherently, tracking fire spread progression at sufficient spatial resolutions is challenging and requires substantial planning and coordination, as does gathering sufficient information about fuels and weather conditions during burns. While many fuel conditions can be assessed ahead of prescribed burns (sometimes even years in advance in vegetation types that change slowly or predictably), there are a limited number of environments where sufficient research is available to facilitate this [19]. Still, comparisons between spatially explicit model predictions and field-observed fire progressions are needed to validate these models and for their continued refinement [20,21].

In response to this need for further field testing of QUIC-Fire and exploration of its potential to simulate management scenarios, we tested the ability of QUIC-Fire's ability to simulate a well-documented wildfire and explore how prior forest management or repeated previous fires, which can modify fuel structure and composition, may have impacted the outcome of this fire. The first objective was to reconstruct the 2019 Spring Hill Wildfire and benchmark the model predictions using field observations of fire spread rates and other metrics. Then, we used the model to evaluate how the fire may have behaved differently if repeated wildfires or prescribed burning had shaped fuel conditions rather than fire exclusion. We accomplished this by modifying the three-dimensional fuel inputs to represent a series of prescribed fire and wildfire scenarios within the footprint of the Spring Hill Wildfire. We also examined the influence of spatial positioning of fuel treatments on the landscape. Finally, we examined the influence of wind on the progression of the fire.

2. Materials and Methods

2.1. Site and Fire Description

The New Jersey Pinelands National Reserve (PNR) is a 440,000-ha forested area centered at approximately 39°40′ N latitude, 74°40′ W longitude, only a few kilometers east of the metropolitan continuum that connects the greater Philadelphia and New York areas. The PNR is a United Nations Educational, Scientific and Cultural Organization (UNESCO) world heritage site and international biosphere reserve, celebrated for its ecological importance and rarity as well as its cultural significance. For millennia the PNR has been a fire-prone landscape and continues as such [22–25]. This is primarily due to a combination of droughty soils, fire-adapted species which compete and regenerate remarkably well amidst frequent fires, and weather conditions which can quickly become conducive to burning.

This study focused on the Spring Hill Plains and West Plains areas of the PNR [26], where the Spring Hill Fire burned through roughly 4000 ha during a single operation period (e.g., 1300 on 29 March 2019–0300 on 30 March 2019). These areas reflect approximately half of the globally rare Pine Plains ecosystems in the PNR and are comprised of a unique genetic provenance of pitch pine (*Pinus rigida* Mill.) that exhibits short stature and strong expression of fire adaptations [27,28]. The compact form of this forest (often not exceeding 3 m in height), extremely droughty soils, and slight elevation of this area historically supported a fire return interval of 4–8 years [26,29,30]. Pitch pine is the dominant canopy species in the area of the fire, with a mid-story of blackjack oak (*Quercus marilandica* Muenchh.) and younger pitch pines, and an understory comprised primarily of ericaceous shrubs (*Vaccinium* and *Gaylussacia* species), scrub oaks (*Q. ilicifolia* Wangenh.), and laurels (*Kalmia latifolia* Kalm. and *K. angustifolia* L.) [25]. Contrary to the historic wildfire frequency, much of this portion of the PNR's Pine Plains remained fire-excluded through recent history, following a series of catastrophic wildfires that impacted the area in 1963 [24].

The Spring Hill Fire began on the edge of a former gravel pit as a result of an abandoned campfire near the southern portion of the Spring Hill Plains, within Penn State Forest in Burlington County, New Jersey. The fire was pushed by moderate south winds and spread extremely rapidly, quickly eliminating the potential for a direct attack on the fire in the long-unburned fuels. An indirect plan was initiated but required significant time to close roads and clear the public who had been recreating in the forest, allowing a classic, unimpeded, wind-driven progression to approximately 35 ha within the first hour of burning. The fuel domain around the area of the fire was set to the dimensions 2 km × 4 km × 16 m, while the wind domain was set to 2 km × 4 km × 80 m (Figure 1).

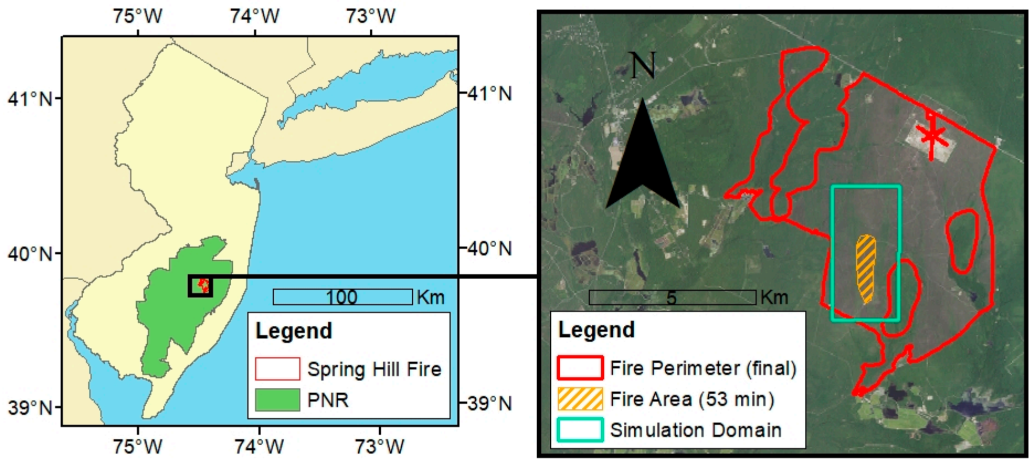

Figure 1. Spring Hill Fire location in the PNR (**left**). Spring fire perimeter at 53 min following ignition (estimated from time of detection), final fire perimeter, QUIC-Fire simulation domain (**right**).

In terms of wildfire reconstructions, the Spring Hill Fire represents a unique opportunity to test QUIC-Fire and explore hypothetical scenarios to understand how alternate proactive prior management scenarios could have impacted fire outcomes. Weather data from multiple weather stations both downwind and upwind of the fire at regular intervals were readily available. Extensive analyses of fuel loading and structure for the areas representative of the fire and contrasting prior management scenarios were also available [15,24,31,32]. Spatial data and fire behavior observations from the fire incident commander and suppression crews were also available to help guide the modeling effort.

2.2. Spring Hill Fire Reconstruction

2.2.1. Fuels Parameterization

For modeling purposes, the three-dimensional arrangement of the fuels was represented using a numerical domain consisting of a 1000 $\times$ 2000 $\times$ 16 array of 2 $\times$ 2 $\times$ 1 m voxels. The domain's fuels were represented as three primary components—litter fuels, shrub fuels, and tree fuels—based on data from previously published studies in this environment. Each voxel was given two attributes, bulk density of available fuel and fuel moisture content (FMC), to represent heterogeneity in fuel characteristics.

A numerical representation for surface fuel voxels was built based on field data collected from two heavily studied burn units in the East Plains area of the PNR [15,20,21]. These sites were similar in species composition and structure, fire history, and were geographically appropriate, being that they were <10 km from the Spring Hill Fire. Fuel composition, particle type, fuel layer depths, and fuel loading for these sites were acquired from the published dataset of these experiments, *New Jersey Fuel Treatment effects: Pre- and Post-burn biometric data* [32], and were used to inform a normal distribution of mass and bulk density for available litter and shrub fuels. Thus, surface fuel was distributed across the domain's 1 m tall surface cells, with an average bulk density of 1.286 $\pm$ 0.386 kg/m^3 for litter (mean $\pm$ 1 standard deviation) and 0.428 $\pm$ 0.213 kg/m^3 for shrubs. From analysis of the pre- and post-burn measurements, it was determined that not all shrub fuel would have been available for combustion and consumption (e.g., thicker live stems). To account for available fuel, an array of normally distributed available fuel values with an average of 69.5 $\pm$ 21.8 % was produced. The product of the shrub fuel times the percentage of available fuel was used to create the final shrub fuel estimates that were added to the surface voxels.

Stand and canopy characteristics of the simulation domain were simulated using the formulation presented in [16] and informed by stand data from the two burn sites referenced earlier [23]. Midstory and canopy fuels for the predominant dwarf pine areas were represented by randomly distributing 2750 stems/ha (1788 as pine as 962 oak) throughout the simulation domain. Where tall trees were present (Figure 2), 386 additional stems/ha of tall pitch pine trees were added. Canopy attributes for each tree type were based on the average characteristics of trees found on the domain (Table 1). Following the methodology described in [16], using height, height-to-live crown (HTLC), crown radius, and the CL factor (percentage of the canopy that is concave down), each tree was converted into a three-dimensional axisymmetric shape bound to the top and bottom by one concave down and one concave up paraboloids, to represent an idealized tree. Fine fuels were distributed within each tree shape, with fuel declining toward the center of the trunk and toward the bottom of the canopy. Fuel from the trees was subsequently split between voxels based on how it overlapped with the three-dimensional voxel array. Dwarf and tall pine canopy fuels were distributed across the domain based on canopy height model data (CHM) of the burned area that was derived from airborne laser scanner data (ALS) described in [33], following the methods of [34]. Areas of the domain where ALS data indicated that canopy height exceeded 10 m were modeled as having tall trees, while the remainder of the domain reflected short-statured dwarf pitch pine forest conditions (Figure 2).

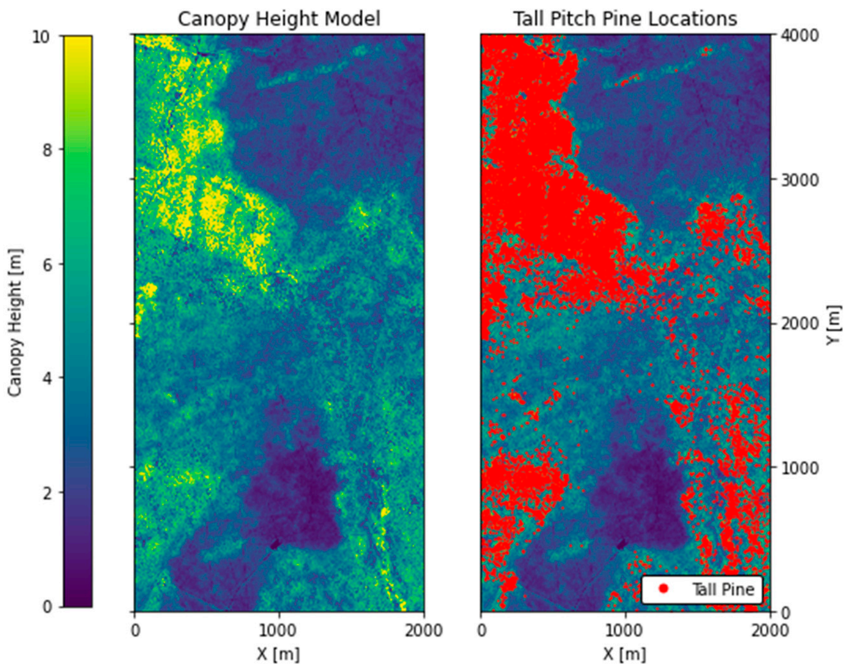

Figure 2. Canopy height and distribution of tall trees across the Spring Hill Fire domain.

Table 1. Attributes for dwarf pitch pine, typical pitch pine, and oak used in the Spring Hill Fire reconstruction.

Tree Type	Height (m)	HTLC (m)	Crown Radius (m)	CL Factor
Pitch Pine (dwarf)	5.50	3.50	2.00	0.80
Pitch Pine (typical)	11.00	7.00	2.50	0.80
Oak	3.50	1.15	1.00	0.99

The fuel moisture content (FMC) of surface fuels was estimated from data collected during prescribed fire experiments and sampling at the same time of year and under similar weather and fuel conditions [20,21,35]. FMC values collected during previous nearby fire experiments in very similar fuels have typically had fuel moisture contents of approximately 25–31%. Since the Spring Hill Fire began in the afternoon, morning dew would have evaporated and additional drying would have occurred, so the simulations used an FMC of 10% for litter fuels [36]. Shrub FMC was set to 60.2 ± 039%. For the final surface fuel voxel values, the estimated litter and shrub bulk density values were summed, and the FMC was calculated with a weighted average. FMC of canopy fuels was set to 100%.

Sand roads were delineated as 5 m-wide fuel breaks in the simulation domain based on data from the New Jersey Department of Environmental Protection Bureau of GIS (https://www.nj.gov/dep/gis/, accessed on 8 January 2021) and the authors' knowledge of the area (Figure 3).

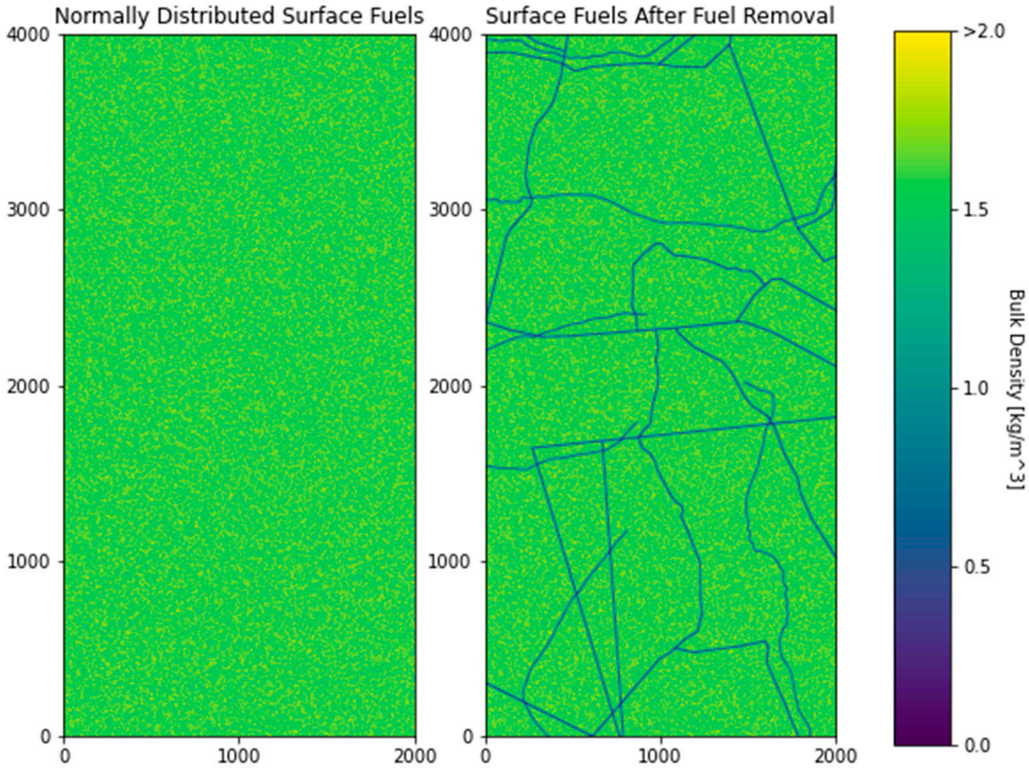

Figure 3. Bulk density of 1 m-tall surface fuel cells before and after fuel break removal.

2.2.2. Weather

Meteorological data collected at 4 weather stations located within $\leq$ 8 km of the Spring Hill Fire were evaluated for use in the fire reconstruction. Towers at Cedar Bridge (39.839720 N, −74.380447 W) and Oswego Lake (39.715417 N, −74.514210 W) collected 5 min average wind speed and direction data, while a station at Coyle Field (39.816775 N, −74.425620 W) collected half hourly data. A research weather tower also at the Cedar Bridge site independently collected wind data with a 1 min resolution. Important differences in the observations at each of these stations and lack of congruity with fire manager observations during the burn challenged the use of these data and required further data exploration (Figure 4a,b). Thirty-minute data from the Coyle weather station was unusable due to having a temporal resolution too low to relate to the fire. Data from both towers at Cedar Bridge were unusable due to initial windspeeds that were far slower than those reported during the beginning of the burn, and containing large wind shifts that contradicted reported fire behavior. Oswego Lake was selected for simulation purposes due to most closely aligning with weather reported by fire managers, but also had two issues that needed to be reconciled: First, directional data was recorded only as a cardinal direction, and this low-resolution directionality resulted in exaggerated wind shifts. We addressed this by data smoothing, using the average of the preceding and succeeding directions at each 5 min time step, and additionally made a 12° correction with the assumption that the windvane at this station was aligned to magnetic north, rather than true north, since the raw smoothed data appeared to be about 12° off—which equaled the offset between true and magnetic north for this region (Figure 4c). Wind speed of the revised Owego Lake averaged 5.04 m/s and peaked at 10.73 m/s (Figure 4b). Winds were generally from the south, with a slight westerly component for the first 20 min of the fire, followed by a slight easterly shift for the next 20 min of the fire, and then consistently south for the remaining 20 min of the simulation period (Figure 4c).

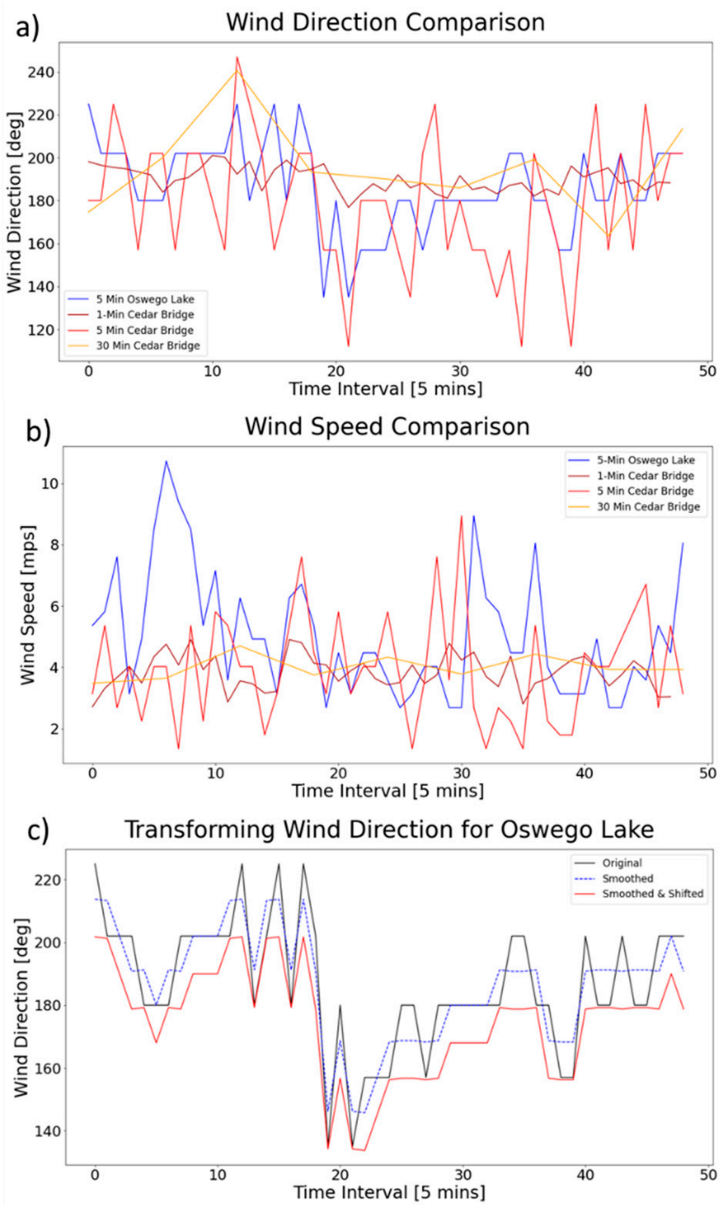

Figure 4. (**a**) Comparison of wind direction data collected at Oswego Lake and Cedar Bridge during the initial four hours of the Spring Hill Fire, (**b**) comparison of wind speed data collected at Oswego Lake and Cedar Bridge during the initial four hours of the Spring Hill Fire, and (**c**) transformations of Oswego Lake's wind direction data. Original data was smoothed to reduce the dramatic fluctuations in direction due to low reporting precision of direction in the raw data.

2.3. Simulation Validation

The Spring Hill Fire reconstruction simulation was evaluated using a "threat score" approach [37], which is a simple spatial metric that represents the overlap between the predicted and observed burned area. The threat score is comprised from the following evaluation of predicted fire extent pixels: true positives (TP), false positives (FP), and false negatives (FN). For this study, TP represents the burned area in the simulation that was also burned in the actual fire, FP represents the burned area in the simulation that did not burn in the fire, and FN represents the area that did not burn in the simulation but did burn in the actual Spring Hill Fire. The final threat score is calculated as:

$$\text{Threat score} = \text{TP} / (\text{TP} + \text{FP} + \text{FN}), \quad (1)$$

A simulation with a fire footprint that perfectly overlaps with the observed burnt area would have a threat score of one, while a threat score that approaches zero would indicate that the simulation's burnt area predictions did not overlap with the observed fire footprint. However, although the location of the fire's head was certain at 1 h into the burn, flank locations were less certain. To establish flank locations of the fire, we traced the crown streets visible in Google Earth images that were continuous with the location of the head fire. These corresponded to the general shape of the perimeter observed from the ground and air at that time by fire response personnel. We also estimated the rate of spread from these paths for both the actual fire and the predicted fire and compared them (Figure 5).

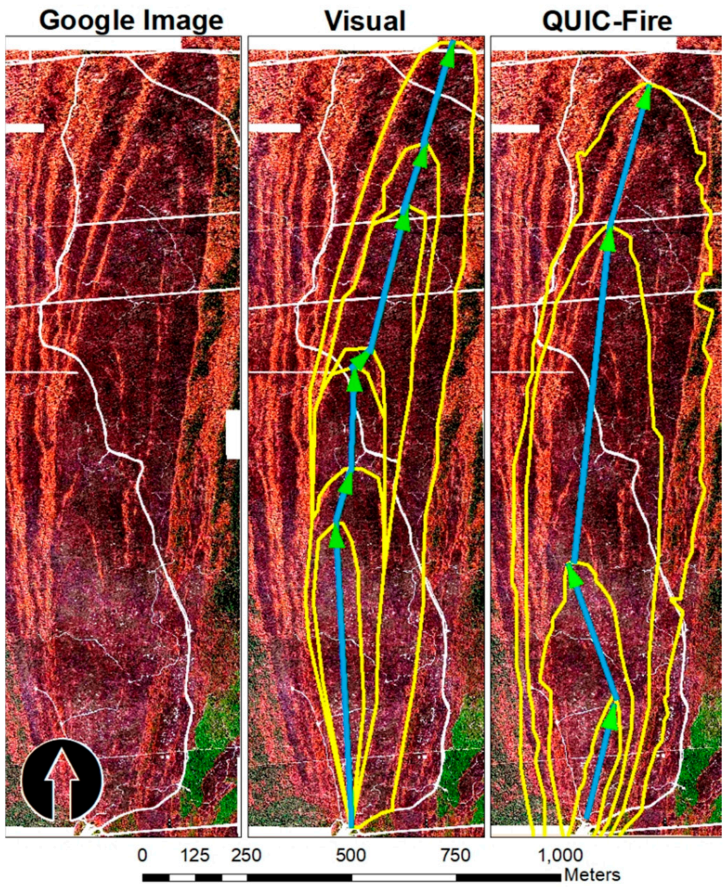

Figure 5. Comparison of visually estimated fire path of progression based on fire suppression staff observations and patterns in tree crown streets visible in post-fire Google imagery, and QUIC-Fire estimated progression (e.g., simulation scenario S0).

2.4. Modeling Alternate Scenarios

Beyond the Spring Hill Fire reconstruction simulation, which we will denote henceforth as "S0", nine additional simulations were performed to explore how scenarios of hypothetical prior management and wildfire scenarios would have impacted fuels, and thus the outcome of the fire (Figure 6, Table 2). For simulations S1–S7, canopies and surface fuels were adjusted to parameterize fuel distributions and fuel loadings of forests as though they had experienced prior fire regimes of either repeated prescribed fire or wildfire (Figure 6, [24,38,39]). Apart from scenarios S0 and S1, all of the scenarios were parameterized with a 25% reduction in stand density relative to the original reconstruction, to reflect the expected thinning effect experienced by a stand with a recent history of prescribed fire or wildfire. The canopy structure for scenarios S2–S5 was modified to represent structures characteristic of prescribed fire management. Scenarios S2 and S3 had the midstory removed to reflect long-term prescribed fire management that creates an open stand with a tall, uniform canopy over a shrubby understory on this landscape. In scenarios S4 and S5, the midstory was included, but the trees' shapes were adjusted so that canopies were elevated, maintaining a gap between surface fuels and fuels above them. Scenarios S6 and S7 were parameterized to represent a stand that had experienced repeated wildfire, which skews canopy fuel distribution toward the lower levels in the PNR due to prolific epicormic sprouting creating strong connectivity between surface, midstory, and canopy fuels [24]. Each of these conditions was run with original surface fuel load values (e.g., S0) or 50% surface fuel loading to evaluate the impact of surface fuel reductions on fire behavior (e.g., S1, S3, S5, and S7 had 50% of fuel removed from the surface cells, see Table 2). Finally, scenarios S8 and S9 explore the influence of a dense scrub oak layer, which can dominate understories in pine–oak forests, on fire behavior. Canopy conditions for S8 and S9 were identical to S2, however shrub characteristics were modified to reflect dense scrub oak domination in S8 or no shrubs in S9 (Figure 6). Modifications to fuel structure and loading are listed below in Table 2, while visualizations of fuel structure are provided in Figure 6.

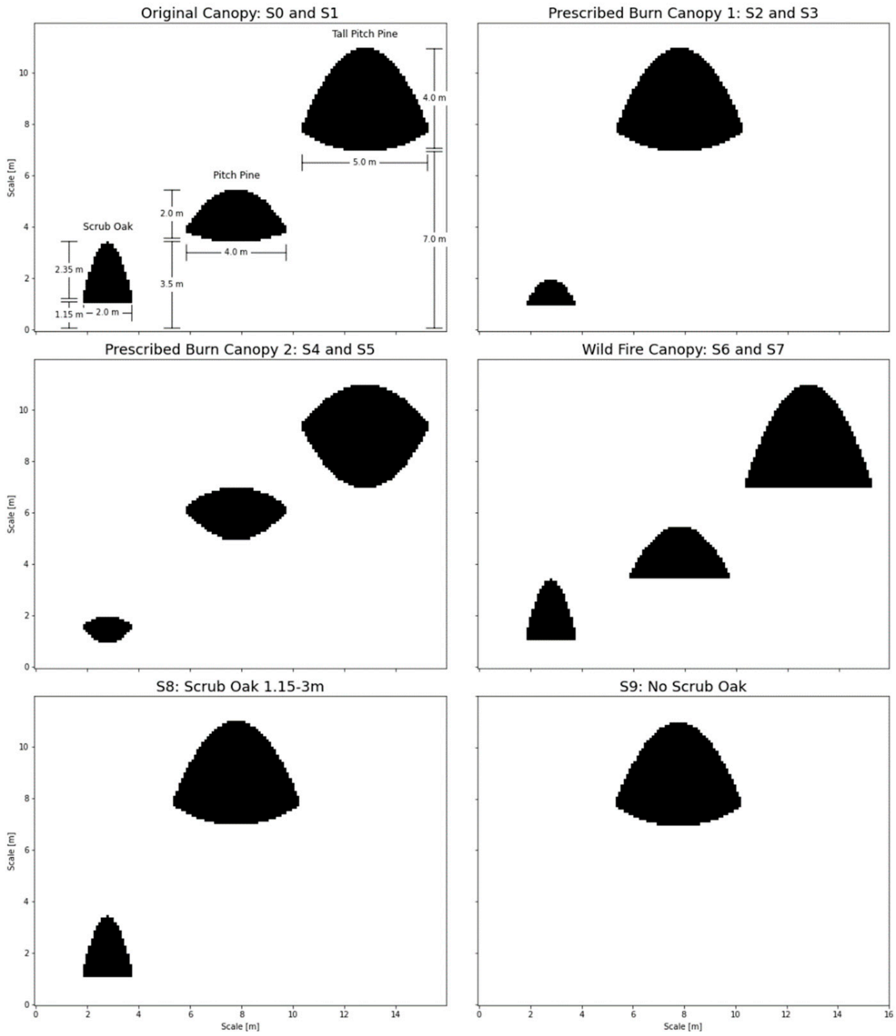

Figure 6. Visualization of woody vegetation parameterization for scenarios S0–S9.

Table 2. Surface and canopy fuel parameter specifications for each model scenario.

Scenario	Surface Fuels		Vegetation Presence		General Structure		
	Original Loading	50% Loading	Understory	Midstory	Spring Hill Fire Original Fuel Structure	Simulated Structure of Repeated Prescribed Fire	Simulated Structure of Repeated Wildfire
S0	X		X	X	X		
S1		X	X	X	X		
S2	X		X			X	
S3		X	X	X		X	
S4	X		X	X		X	
S5		X	X	X		X	
S6	X		X	X			X
S7		X	X	X			X
S8	X		X *			X	
S9	X					X	

* denotes that the understory fuel structure was designed to reflect dense scrub oak understory fuels.

We simulated each scenario (e.g., S0–S9) three times and observed the average rate of spread (ROS_{avg}), maximum rate of spread (ROS_{max}), average rate of growth (ROG_{avg}), maximum rate of growth (ROG_{max}), and final fire size. We used t-tests to determine if differences in outputs were related to differences in model parameterization or to stochasticity in QUIC-Fire's spread functions. We also used t-tests to explore how fire exclusion influenced the Spring Hill fire and how alternative wildfire history or fuel management (repeated prescribed fire, repeated wildfire, fire exclusion) could have significantly altered outcomes during the fire.

3. Results and Discussion

3.1. Simulation Validation

The simulation results for the first hour of the Spring Hill Fire were closely matched to field observations of the fire spread at that time with some minor differences. We found that out of 151,899 pixels impacted by either the predicted or actual fire footprint, 69% were true positives, 25% were false positives, and 6% were false negatives (Figure 7). As is evidenced in Figure 5, QUIC-Fire slightly underpredicted the distance the head had traveled within the first hour of the fire, with the actual fire traveling a path of 1929 m to just past Baptist Road versus the QUIC-Fire progression traveling 1805 m to the road just south of Baptist Road (a 6% difference). Similarly, the distance from the origin to the farthest point of the fire was estimated to be 1889 m and 1774 m, for the visual and QUIC-Fire estimates of progression, respectively—also amounting to a 6% difference in distance traveled.

In addition to the reconstructed fire traveling slightly less distance from the origin, it was slightly wider than the actual fire (Figure 7). This may have been due to a model error or input error through an oversimplification in our fuel parameterization or dynamics of the ambient wind field. Additionally, this variation was potentially due to an assumptions made in the fuel breaks, such as the failure to incorporate a large gravel pit immediately upwind of the fire with which the heel of the fire would have interacted. This feature represented a prominent fuel break that limited the backing spread of the actual Spring Hill Fire to the south; however, the absence of which allowed the simulated fires to progress slightly farther south than was realistic (Figure 5). Fire lines in close proximity often influence each other and localize wind conditions [4,40]; we surmise that the additional duration of the active backing fire in the simulations would have interacted with the headfire to slow its initial forward spread and potentially augment its lateral spread at the beginning of the fire. Nonetheless, these differences were relatively minor in the overall pattern or burned area. We note that the QUIC-Fire outputs illustrated tree crown streets, or long linear patterns of unburnt trees (See Appendix A)

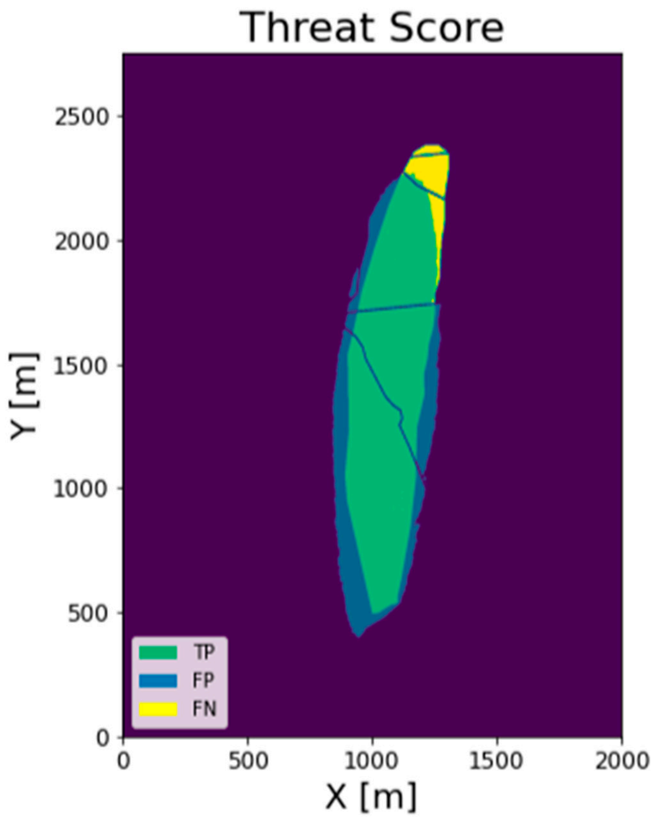

Figure 7. Visualization of threat score analysis comparing the simulated fire footprint to the field estimated burn plot 1 h after initial ignition. The green area represents the true positives, while the blue and yellow regions denote false positive and false negatives.

3.2. Modeling Alternate Scenarios

Results of each alternative fuel scenario simulation were significantly different in terms of final fire size, with the exception of S1 and S7 not being significantly different from each other—indicating that differences in simulation outcomes were due to differences in model parameterization rather than stochasticity in QUIC-Fire's wind and fire-spread functions, that inevitably drive heterogeneity between simulations and are necessary to represent realistic fire behavior. Reducing fuel loading by 50% had the most important influence on reducing fire size, ROG_{avg}, and ROG_{max}. The greatest fire size of any scenario was 56.5 ha and was produced by the full fuel loading–fire exclusion case (i.e., original Spring Hill Fire scenario, S0), while the scenario of 50% fuel loading–frequent prescribed burning (scenario S3) produced a fire size of only 25.4 ha, amounting to a 55% reduction in area (Figure 8). ROG_{avg} ranged from approximately 21–23% under 50% fuel conditions, and about 25–26% under full fuel conditions. However, ROG_{max} in 50% fuel conditions averaged around 100%, while under full fuel conditions it ranged between approximately 140–190% (Figure 8).

Fuel loading was of primary importance and fuel structure of secondary importance in controlling fire size. Halving surface fuel loading approximately halved fire size, while the fuel structure resulting from frequent prescribed burning reduced fire size by about 20%, and the fuel structure resulting from frequent wildfires had minimal effects (Figure 9). ROS_{avg} was reduced primarily by the fuel structure associated with frequent prescribed fire, and secondarily by fuel loading; however, ROS_{mas} was actually about 10% greater when frequent prescribed burning occurred and fuels were reduced by 50%, compared to other scenarios (Figure 9). Conversely, decreased ROG_{avg} and ROG_{max} were primarily related to decreased surface fuel loading, with frequent prescribed fire fuel structure only having a minor reducing influence. Overall, the fuel structure associated with prescribed burning significantly reduced average rate of spread, whereas halving the surface fuel load significantly reduced final fire size and rate of growth characteristics (Table 3). This highlights the importance of both fuel loading and structure management to reduce fire spread and improve fire suppression opportunities or safety during prescribed burning. Likewise, the sensitivity of the simulations to fuel loading and structure additionally highlights the importance of precise and accurate fuel inputs. Overly general fuel structure, and loading and moisture values that do not adequately reflect the heterogeneity of an actual burn unit of interest are unlikely to provide realistic results, or worse, may provide misguided results.

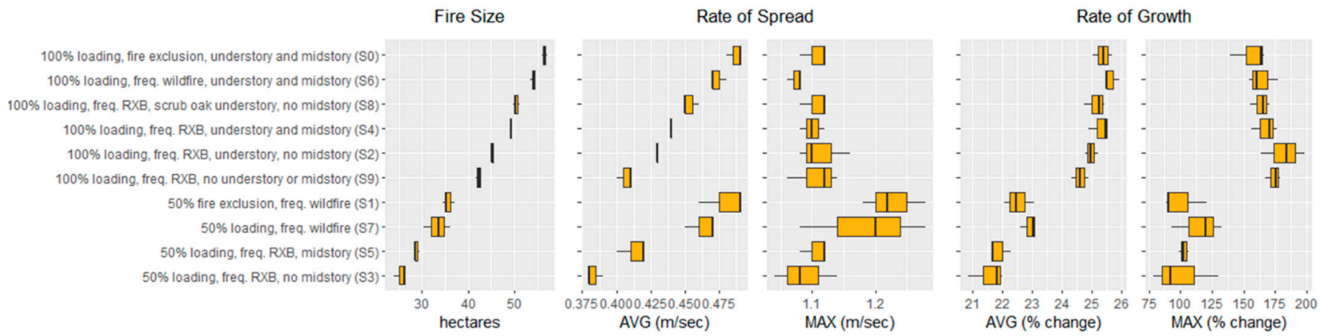

Figure 8. Fire size, rate of spread, and rate of growth results for 10 simulation scenarios differing in prior wildfire and prescribed fire management histories and fuel loading. Boxes refer to 1st–3rd quartile, thick vertical lines within boxes refer to median, and whiskers indicate minimum and maximum values of data distributions.

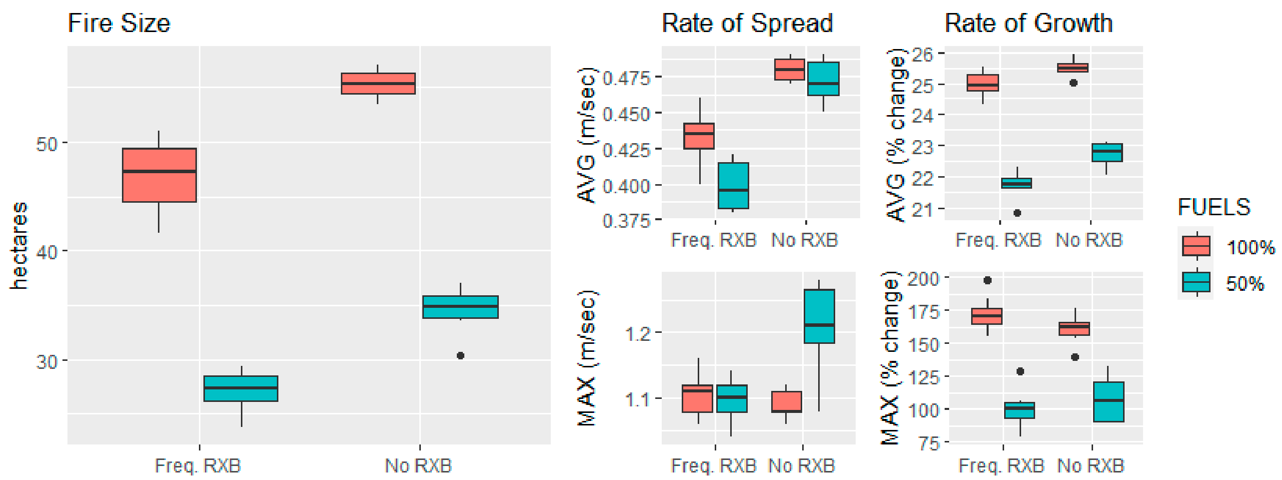

Figure 9. Influence of frequent prescribed burning structure and fuel loading on outcomes of Spring Hill Fire simulation scenarios. Boxes refer to 1st–3rd quartile, thick vertical lines within boxes refer to median, and whiskers indicate minimum and maximum values of data distributions.

Table 3. T-test results of fuel management scenarios.

Test	Metric	T-Stat	*p*-Value
Repeated Prescribed Fire vs. Other Scenarios (e.g., Repeated Wildfire and Fire Exclusion)	Area Burned	−1.190	0.247
	ROGavg	−0.271	0.789
	ROGmax	1.143	0.263
	ROSavg	−7.809	<0.001
	ROSmax	−1.845	0.088
100% Fuel Loading vs. 50% Fuel Loading	Area Burned	10.839	<0.001
	ROGavg	13.767	<0.001
	ROGmax	10.750	<0.001
	ROSavg	1.063	0.302
	ROSmax	−2.101	0.056

In practice, the modification of fire-excluded fuels often requires more than a one-time treatment; however, this work is illustrative in understanding how restoration of fire-excluded pitch pine forests, or those that are similar, with prescribed burning can gradually reduce fire danger. Over time, frequent prescribed burning gradually reduces fuel loading [38,41,42] and shifts canopy structure, most notably in that it elevates the live crown and promotes a gap space between surface fuels and canopy fuels [24]. Previous work focusing on fuels and forest structure suggest that between 2–5 prescribed fires may be required to achieve the maximum levels of fuel and structure modification, which we suggest are reflected by the scenarios S3 and S5 (Figure 8). Resultant fuel structures must then be maintained through time as fuel loads gradually reaccumulate and forest structure densifies [24,43]. We highlight that the simulations presented here only reflect the specific weather, ignition, fuel moisture, and fuel composition conditions of the Spring Hill Fire, and caution that other combinations of these conditions (such as additional extreme fire weather) could challenge fuel reduction strategies in ways not represented by the conditions seen during the Spring Hill Fire. We also note that shifting fuel structure in a vertically compact environment like the Pine Plains, where genetically controlled stature limits maximum tree height to ~3–4 m, may be unrealistic to the degree needed to influence fire behavior under high wind and low relative humidity conditions that typify large wildfire events.

3.3. Additional Considerations

In addition to guiding forest management, QUIC-Fire simulations such as this study can be an important learning tool for training firefighters. As [44] points out, wildland firefighters need more experience, but gaining the most informative kinds of experience can be dangerous or infrequently available. For instance, increasingly extreme burning conditions in recent decades have necessitated that firefighters assume worst-case conditions, which to all but a well-seasoned firefighter includes many unfamiliar fuels and local conditions that are difficult to train for. However, QUIC-Fire or similar tools can enable firefighters to explore different fuel compositions and configurations under a variety of weather and topography scenarios to hone their knowledge of fire behavior under different scenarios. Similarly, QUIC-Fire can also account for complex, irregular, and interacting ignition patterns which are critical to success during extreme fire behavior scenarios, burnout operations, and prescribed burning, but are difficult to train for use in traditional classroom or field methods.

QUIC-Fire uses a simplified representation of energy transport designed to account for the wind-dominated fire spread of the head fire and the creeping fire spread that occurs in the flanking and backing fire [4]. The tool does capture the two-way fire atmospheric feedbacks which are critical to estimating non-linear fire phenomenon listed by this reviewer. It should be noted that the equations for wind-dominated fire spread do incorporate randomness when calculating the travel distance for each energy packet, which capture the effects of short-range spotting. As a result of the model's ability to account for short-range spotting, the simulation shows fire-to-jumping road features. Our model simulations included short range spotting and we point to Figure 7, which illustrates the fire crossing a fuel break (i.e., a road), which was possible due to the firebrand component. However, long-range spotting was not an issue in the actual fire and thus we did not consider it in the modeling effort; however, QUIC-Fire has functions that are capable of estimating long-range spotting. We also highlight that our simulation produced similar tree "crown street" features as were observed at the original fire, highlighting the model's ability to predict emerging fire behavior characteristics and fire effects that result from coupled fire–atmospheric interactions (See Appendix A).

Even though the model is non-deterministic, we have found that the final burn plot is relatively consistent in longer simulated runs and that localized fire behavior became less relevant in simulations over an hour long. The ability to predict specific instances of extreme fire–atmospheric interactions such as fire whirls, eruptive fire, and downburst requires coupled fire–atmospheric feedbacks; local to "whole-fire" feedbacks are within the capabilities QUIC-Fire but will be dependent on the scale and complexity of the initializing windfield, whereas larger events such as outflows or seabreeze interactions would require coupling to larger mesoscale atmospheric models. As an analogy, predicting the specific location and movement of eddies in a turbulent flow is computationally intensive, but representing the overall effect on the speed of the flow is a tractable and achievable goal.

There were multiple challenges associated with data use that we encountered in this study that must inform future users. First, despite the numerous weather stations in the vicinity of the fire, the correlation between these data and observations during the fire were weak due to a variety of factors that could not all be corrected. We found that wind data was often stored in formats that were too imprecise with regards to fire behavior (e.g., half hourly or in terms of cardinal directions) and may be worth considering in long-term fire weather monitoring efforts. In addition, creating fuels in the model required integrating fuel data from multiple sources, which was time consuming and required substantial formatting from raw data to model parameters. Experience with fuel parameterization would reduce the burden of this task almost to the point of negligibility; however, a sophisticated understanding of actual fuel distributions and actual fire behavior are critical skills for the successful user. We point out that no single person involved in this study possessed all skills necessary to parameterize, simulate, validate, and analyze the fire scenarios, and thus a diverse team of local fire managers, fire scientists, and fire behavior modelers will be helpful in the success of simulation efforts.

While this study represents a successful evaluation of QUIC-Fire performance, there remains a substantial need for additional test simulations against fine-scale fire behavior data collected in the field under a broader range of fuel, weather, and ignition conditions to fully understand the strengths and weakness of QUIC-Fire or other physics-based fire-behavior models [45]. Identifying and utilizing "model landscapes" where fuel and fire behavior have been well documented in high-resolution existing datasets would enable rapid model parameterization and efficient model testing and refinement. At the same time, new fuels and fire effect monitoring efforts that account for three-dimensional heterogeneity in fuels can also fill in critical gaps in our ability to represent fuels at fine scales in other landscapes and expand the testing of QUIC-Fire. To that extent, not all existing fuels and fire effect strategies incorporate the appropriate data to parameterize QUIC-Fire or other physics-based models, and there is a need for new monitoring strategies that include highly resolved representations of vertical fuel load distributions, fuel species distributions, and live and dead fuel moisture [46,47]. Likewise, there is a need for datasets that account for the spatial heterogeneity in fine-scale fire behavior and interacting firelines to accelerate the testing and refinement of QUIC-Fire and other physics-based fire behavior models (such as the Wildland Fire Dynamics Simulator, WFDS [15]).

All models are simplifications of reality, and different fire behavior models have different strengths and weaknesses. The utilization of ensemble approaches can be immensely helpful in identifying model prediction uncertainty, but the ability to leverage this approach hinges on the pace at which physics-based fire behavior models develop together. This also reflects the need in future research for the testing and refinement of computational fluid dynamics models of smoke emissions and dispersion and linkages that will enable them to be run in concert with physics-based fire behavior models [48,49]. This simulation of the Spring Hill Fire, however, highlights the opportunity to test new models under high-resolution data conditions, as well as the need for compiling and archiving high resolution datasets like this one for future model testing and user training purposes.

4. Conclusions

Through rapid solving coupled-fire–atmospheric modeling tools, there is the potential for fire behavior modeling to follow a similar path as other types of disaster forecasting via ensemble modeling that integrates multiple different models to identify ranges of outcomes. We successfully evaluated QUIC-Fire simulation of a wind-driven wildfire and demonstrated how alternate fuel conditions that contrasted the actual fire exclusion condition leading up to the fire may have reduced the complexity of suppressing the 2019 New Jersey Pinelands Spring Hill Fire. The results of our exploration into alternate scenarios highlight the importance of fuel management in reducing fire spread and growth, but also how fuel reduction and structural modification from frequent prescribed fires limit different aspects of fire behavior. This study provides a demonstration of how fire managers can use physics-based fire behavior models like QUIC-Fire to explore management scenarios for planning fuel management strategies and for training purposes, and highlights important considerations for data needs to maximize the success of simulation efforts.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

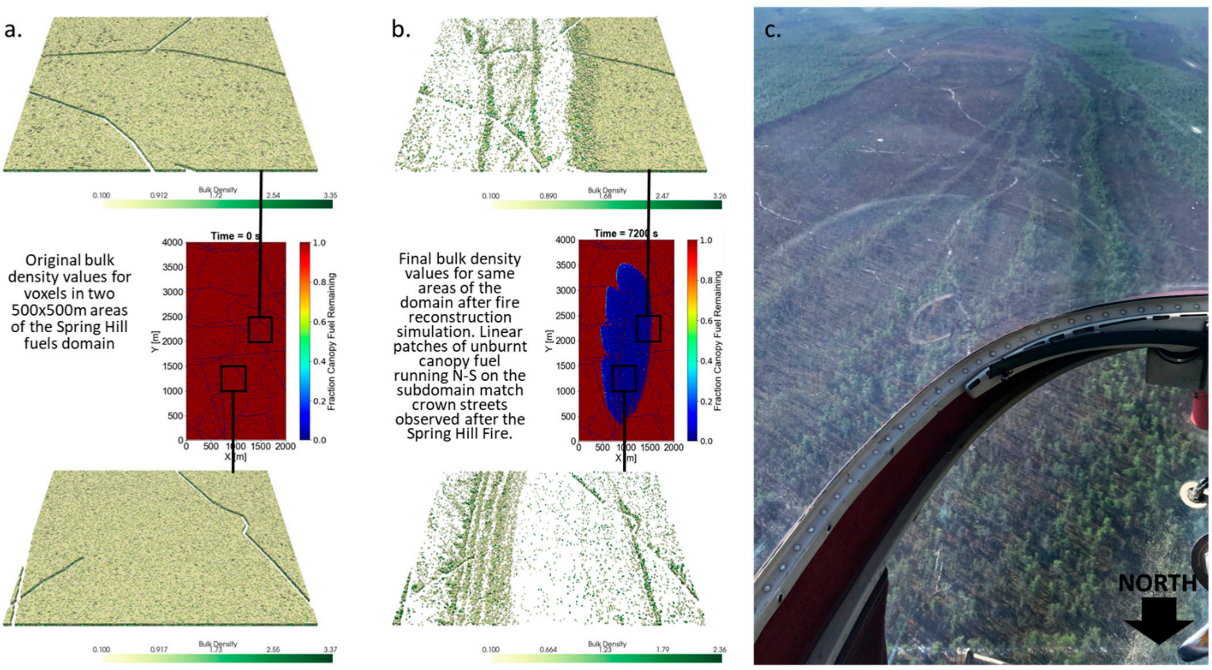

Figure A1. Tree crown streets, or long linear patterns of unburnt trees, were produced by the Spring Hill Fire reconstruction: (**a**,**b**) closely matched those observed following the actual fire (**c**). 3D renderings of QUIC-Fire outputs were created using the Python Pyvista library [50].

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