ADVANCES IN FOREST FIRE RESEARCH

2022

Edited by
DOMINGOS XAVIER VIEGAS
LUÍS MÁRIO RIBEIRO

Sensitivity of LIDAR Derived Fuel Cells to Fire Modeling at Laboratory Scale

Anthony Marcozzi*[1]; Jesse Johnson[1]; Russell Parsons[2]; Jacob Downs[1]

[1]*University of Montana. 32 Campus Dr, Missoula, MT 59812, USA, {anthony.marcozzi@umconnect.umt.edu, jesse.johnson@mso.umt.edu, jacob.downs@umconnect.umt.edu}*
[2] *USDA Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory. 5775 Hwy 10 West, Missoula, MT 59808, USA, {russell.a.parsons@usda.gov}*

**Corresponding author*

Keywords

CFD, Fire behavior, LIDAR, DAKOTA, Fuel modeling

Abstract

Computational models of wildfires are an important tool for fire managers and scientists. However, fuel inputs to wildfire models can be difficult to represent with sufficient detail to be both computationally efficient and representative of observations. Recent advances in fuel mapping with airborne and terrestrial laser scanning (LIDAR) techniques present new opportunities to capture variation in fuels within a tree canopy and on a landscape. In this paper, we develop a technique for building 3D representations of vegetation from point clouds created by Terrestrial Laser Scans (TLS). Our voxel based approach can be extended to represent heterogeneous crown fuels as collections of fuel cells in modern 3D Computational Fluid Dynamics wild fire models such as FDS, QUIC-Fire, or FIRETEC. We evaluated the effectiveness of our technique at different fuel cell resolutions by using the DAKOTA optimization toolkit to compare simulated fire behavior in FDS with observed burn data collected during a series of experiments at the Missoula Fire Sciences Laboratory. The primary finding was that within the search space of point cloud derived fuel cells, we find accurate descriptions of observed fire behavior with the FDS model. We also find that within our search space, regions of global minima are consistent across fuel cells at different resolutions. This finding suggests that while new techniques are capable of characterizing fuel models with a high degree of fidelity, high resolution 3D fuel models do not improve parity with observed fire behavior in the FDS fire model. The results of this paper offer fire modelers guidelines for translating LIDAR data to 3D fire models, and what fuel cell resolution can best capture accurate fire behavior.

1. Introduction

Wildfires are an increasingly visible natural phenomenon across the globe. In the United States, 43,371 structures were lost due to wildfires from 2016-2019 (National Interagency Fire Center 2019), and the Wildland Urban Interface (WUI), the area where houses and vegetation intersect, was the fastest growing land use type in the United States from 1990-2015 (Radeloff et al. 2018). Despite the threat to homes in the WUI, wildfires have historically been an integral part of North American forest, brush, and grassland ecosystems, and by pursuing a policy of wildfire suppression since the early 20th century, land managers have altered fire regimes in much of North America (Arno and Brown 1991). In addition to a more complicated landscape from an expanded WUI and altered fire regimes from fuel loading, fire managers also have to account for the effects of a warming climate on fire conditions. The number of areas with the potential to be adversely affected by wildfires has increased in the 21st century. Tools for mitigating the threat of wildfire to fire sensitive areas, such as the WUI, have traditionally included a combination of thinning projects and prescribed burns (Arno and Brown 1991). Unfortunately, the tools developed to evaluate the efficacy of such projects on a local scale rely on limiting assumptions, cannot be generalized across landscapes, and do not account for rapidly changing fire regimes due to climate change (Parsons et al. 2018).

Physics based Computational Fluid Dynamic (CFD) models present a possible solution to these problems by providing a mechanism to study fire behavior in heterogeneous vegetation and dynamic fire environment conditions (Linn et al. 2020). However, CFD models must be coupled with accurate models of fuel to realistically represent fire behavior (Parsons et al. 2011, Atchley et al. 2021).

Fortunately, rapid advancements in remote sensing techniques have introduced new methods capable of meeting the data requirements of physics based fire models. LIDAR is a promising remote sensing technology for the 3D characterization of vegetation and fuels (Hudak et al. 2017). Point clouds are capable of measuring vegetation height, cover, and relative density – all of which play important roles in determining fire behavior. Critically, these fuel measurements play an important role in determining the transition relationship between quasi steady-state surface fires and more extreme fire behavior such as torching and crowning, which can be crucial to understanding the fire risk of a given landscape (Parsons et al. 2017).

Despite these promising advancements in fire and fuels modeling, there are still significant gaps in the research linking fuel models to the fire modeling environment. Fire modelers must balance careful tradeoffs between computational expense, data collection, and grid resolution when deciding how to represent vegetation as 3D gridded input data. To date, no comparisons have been published between observed fire behavior and simulated fire behavior of LIDAR-derived fuel cells. This paper explores the concept of altering three-dimensional fuel cells in terms of moisture content, bulk density, and resolution to provide an algorithmic approach to translating LIDAR point clouds into a CFD based simulation environment.

Leveraging TLS and mass over time data collected in 2021 on burning saplings at the Missoula Fire Sciences Laboratory, we developed a methodology for representing complex vegetation in three-dimensional fuel cells. Then, we tested the effect of fuel cell descriptors such as fuel moisture content, bulk density, and resolution on modeled fire behavior in the FDS model. We present our methodology, which can be used to translate point cloud data to any CFD fire model with gridded fuel inputs such as FDS, FIRETEC, or QUIC-Fire. Lastly, we provide fire modelers with heuristics for making decisions on fuel cell fidelity in order to balance simulation accuracy with computational requirements using the FDS model.

2. Methods

The sapling burn experiments reported here were conducted in the Missoula Fire Sciences Laboratory burn chamber. The experiment was designed to examine the effect of drought stress on tree mortality when exposed to two controlled levels of fire intensity. We acquired 123 saplings of two species, Engelmann spruce (*Picea engelmannii*) and Ponderosa pine (*Pinus ponderosa*), from a local nursery. Saplings were acquired in May and stored in planter containers filled with soil and with the roots intact. During this storage period, half of the saplings from each species were given a low water treatment of water every one to two weeks so as to mimic conditions of a drought environment. The other half were adequately watered every three days so as to encourage normal development.

Each day of the experiment, saplings were transported to the burn chamber and ignited over a pair of concentric ring gas burners. During the ignition period, each sapling was exposed to one of three fire intensity categories: no fire treatment, low burner treatment, or high burner treatment. At the time of the fire treatment, a tree was placed through the hole such that the tree stand rested on a scale. Additionally, the weight of the sapling was recorded during the burning period with a load balance transmitting at 0.5 Hz.

For each sapling, three-dimensional scans were collected from a Leica Geosystems BLK360 Terrestrial Laser Scanner. Two scans were taken from the same location before and after the burn treatment. The TLS was run at a high density setting with a reported resolution of 5mm at 10 meters. Because the scans were taken in the same location, static references in the burn chamber were present to facilitate spatial referencing. The two scans were co-registered using Cyclone Register 360 software from Leica Geosystems in order to create a single 3D point cloud. Figure 1 shows the experimental setup with LIDAR scanner.

Figure 1- Experimental setup with LIDAR scanner at the Missoula Fire Sciences Laboratory

There are several challenges associated with correlating 3D point clouds to fine fuel mass and location without the use of destructive sampling. A higher point cloud density does not necessarily correlate to a higher density of foliage or stem biomass. A voxel based representation of the experimental saplings offers numerous advantages. Duplicated points from stitching multiple scans are represented as a single voxel, voxels represent points returned to the scanner in addition to points occluded by overlapping woody material, and voxels are one step closer to the concept of a 3D fuel cell necessary for input to a CFD fire model (Hosoi and Omasa 2006).

Our voxelization technique begins by identifying reference voxels. A reference voxel is the smallest possible voxel representation of a point cloud given the physical constraints of the TLS device and the scanning environment. Reference voxels have a Boolean value indicating the presence or absence of points within the voxel. We chose 1cm x 1cm x 1cm voxels for our reference voxel size due to the reported 5mm point density at 10 meters of the TLS device. We construct voxels at coarser resolutions by creating a voxel grid in the point cloud domain and counting the number of reference voxels that occur within the voxel at the desired resolution. When the voxel is converted to a fuel cell, biomass is distributed in proportion to the number of contained reference voxels.

We conducted a multidimensional parameter study using the DAKOTA optimization toolkit. Each n-dimensional sample generated by DAKOTA contains parameters for fuel cell resolution, fuel moisture content, and total dry foliage mass. We used the FDS lagrangian particle model to simulate the experimental burn for each sapling at five different fuel cell resolutions. FDS outputs foliage mass at 100 Hz which we used to compute a loss function between simulated and modeled fire behavior. Figure 2 shows a complement of five FDS simulations of the same sapling across five different fuel cell resolutions.

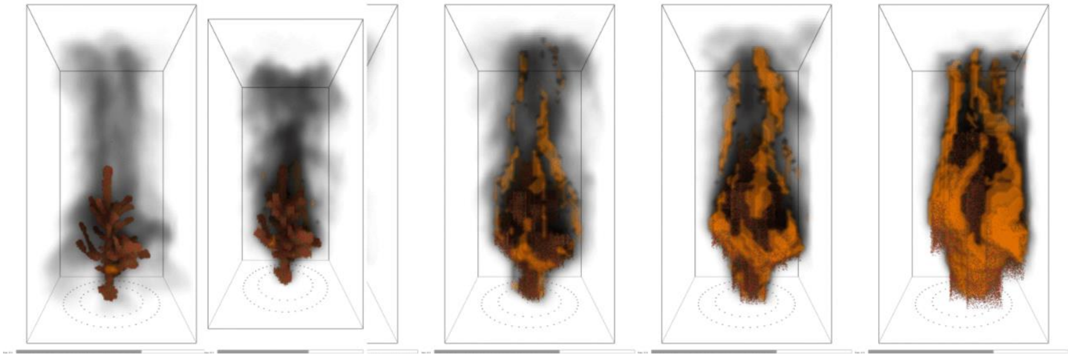

Figure 2 - FDS simulations of a burning sapling at different fuel cell resolutions

3. Results

We computed the RMSE of each simulation in the parameter sweep across sixteen saplings. For each sapling, we found the minimum RMSE determined from comparing the mass loss curves for observed and simulated burns. Figure 3 shows the minimum RMSE found in the set of simulations for Engelmann spruce sapling S63. We observe close parity between the simulated and observed mass loss in both the shape of the curves and the resulting change in mass.

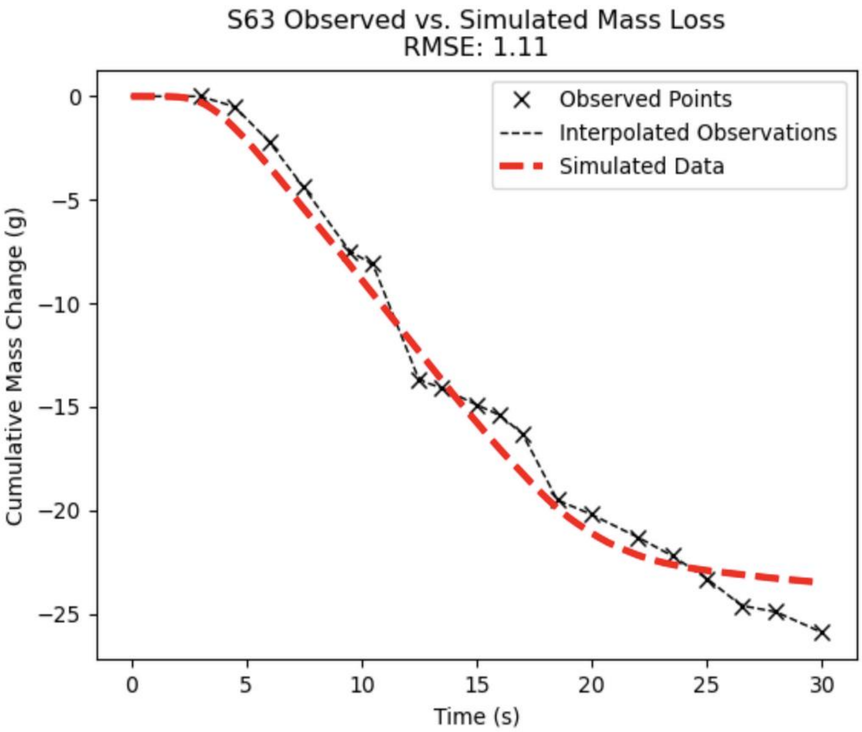

Figure 3 - Comparison between simulated and observed curves of cumulative mass change. This is the lowest RMSE value found out of the 16,384 model runs.

The correspondence between RMSE and the independent variables allows us to examine the space sampled by DAKOTA in our multidimensional parameter study. Figure 4 shows the results of the numerical experiment as described above for one Engelmann spruce sapling. Each pane in the image represents a parameter sweep across 2D points for a given fuel cell resolution. Each pixel has a value for fuel moisture content and dry foliage mass. Fuel moisture content was sampled uniformly in the range [20, 350]%, and dry foliage mass was sampled in the range [10, 80]g for a total of 256 points for each sampled fuel cell resolution.

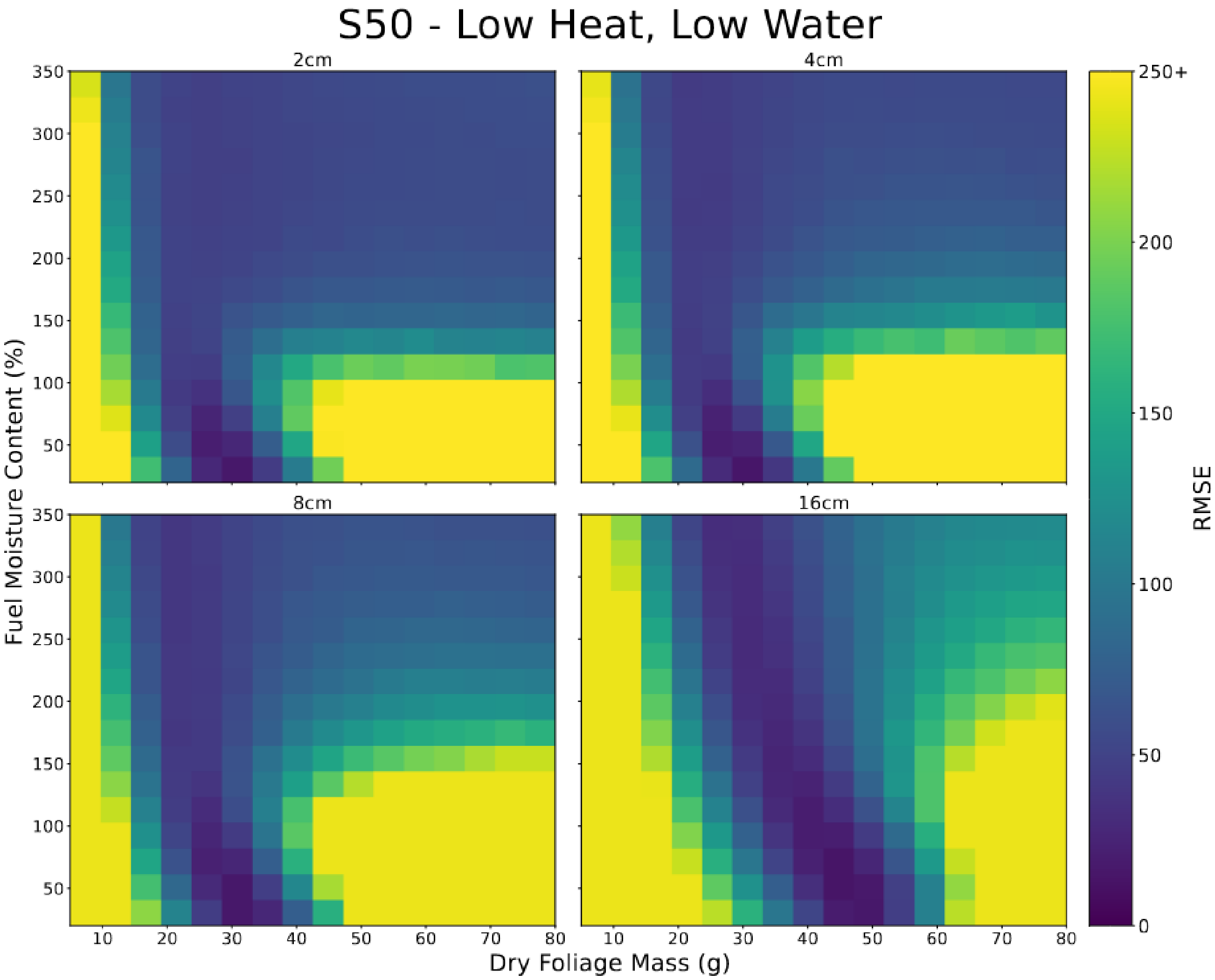

Figure 4 - Distribution of RMSE values for the full 1,024 samples in the parameter sweep for sapling S50. The upper left pane is for simulations with a fuel cell resolution of 2cm, upper right for 4cm, bottom left for 8cm, and bottom right for 16cm. The x and y axis of each pane correspond to the sampled range of dry foliage mass and fuel moisture content. Each pixel is colored according to the RMSE resulting from the comparison between the simulated model output and the observed data for sapling S50.

The multidimensional parameter study identifies a region of consistent minima across all fuel cell resolutions. The model is sensitive to dry foliage mass values as evidenced by the areas of high RMSE below 25g and above 50g along the x-axis in figure 4. Minimum RMSE values occur at higher dry foliage mass values for the coarsest fuel cell resolution of 16cm x 16cm x 16cm. Additionally, the model shows sensitivity to fuel moisture content. This effect is more pronounced when dry foliage mass is high, and the model appears less sensitive to fuel moisture content when the dry foliage mass is low. The parameter sweep identifies a consistent region of minima across all fuel cell resolutions. We find that the coarsest fuel cell resolution expands the area of RMSE minima across a larger range of dry foliage mass values.

In addition to the parameter space plots for individual saplings, we also analyze the effects of independent variables on RMSE. We compute the Pearson correlation coefficients between dry foliage mass, fuel moisture content, and fuel cell resolution on the logarithm of RMSE for each of the sixteen multidimensional parameter studies. The distribution of correlation coefficients are displayed in Figure 6. This result suggests that fuel cell resolution has a significantly lower ability to predict RMSE than dry foliage mass or fuel moisture content.

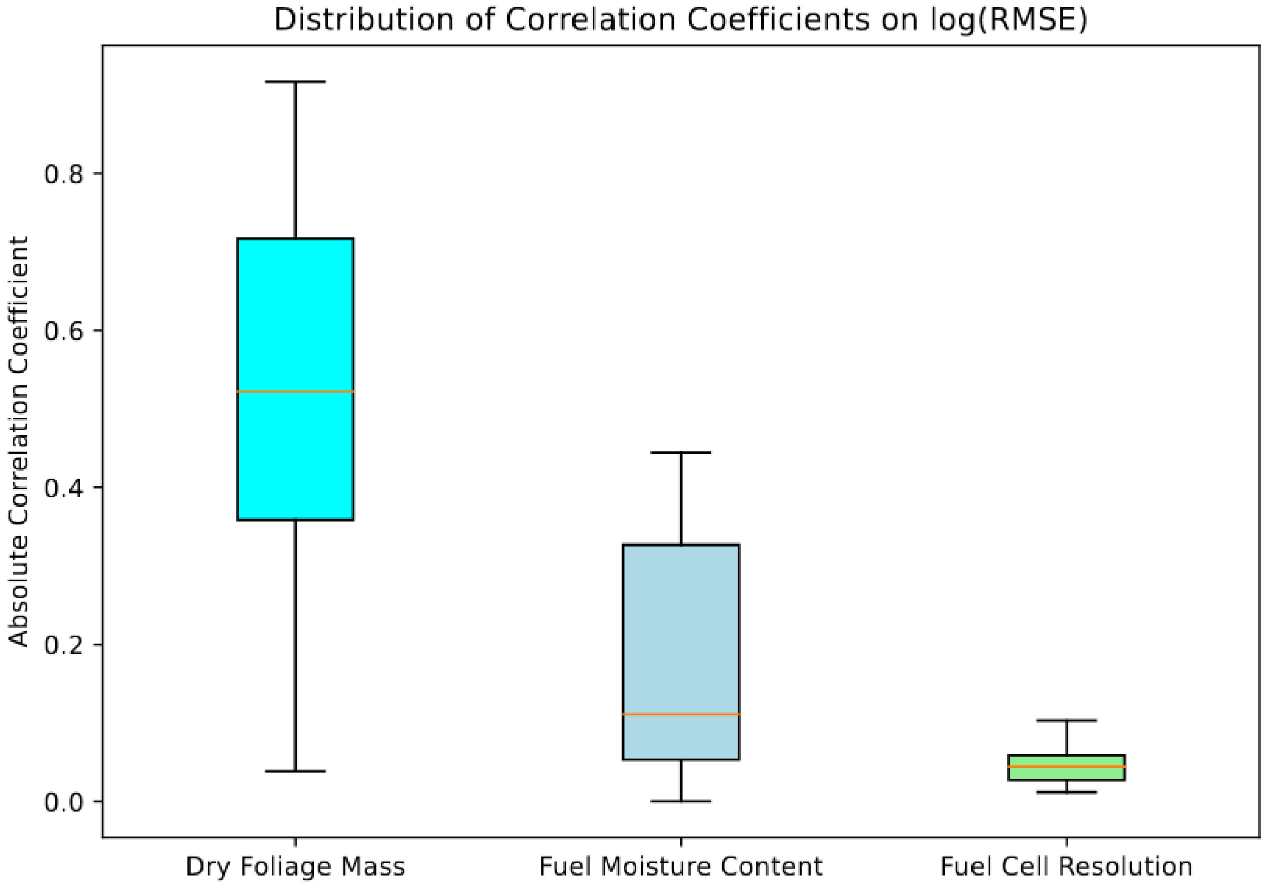

Figure 6 - Box and whisker plot of the distribution of correlation coefficients between log(RMSE) and three independent variables: Dry Foliage Mass, Fuel Moisture Content, and Fuel Cell Resolution for n=16 saplings. The box extends from the first quartile (Q1) to the third quartile (Q3) of the data, with a line at the median. Whiskers extend from the lowest correlation coefficient to the highest correlation coefficient in the data. We take the absolute value of the correlation coefficient in order to capture the magnitude, but not the direction, of the correlation.

4. Discussion

In this study we developed a methodology for describing heterogeneous canopy fuel loads using LIDAR point clouds. Next, we conducted a series of numerical experiments examining the effectiveness of this technique by comparing FDS model output with observed load balance data taken from a series of experimental tree burns. We used DAKOTA to conduct a parameter sweep on fuel moisture content and dry foliage mass and identified physically plausible local minima. Additionally, we found that our sampling technique identified an area of RMSE minima for all fuel cell resolutions, and that the area was consistent for 2-8cm resolution fuel cells.

Our fuel cell methodology represents a first step at achieving this goal of linking data from LIDAR points clouds and coupled fire-atmospheric models. While we found close parity between our fire simulations in FDS and observational data using our 3D fuel models, many opportunities for further research and refinement exist. For example, our technique tends to over-sample reference voxels associated with the stem of the saplings. The result of this phenomenon is the over-weighting of combustible thermally thin foliage concentrated in the middle of the 3D fuel model. This phenomenon likely results in an overestimation of mass loss when the vegetation is exposed to a heat source in a fire effects model. Future research can expand on previous work segmenting foliage from woody material in LIDAR point clouds (Seielstad *et al.* 2011) in order to improve our methodology by characterizing reference voxels by vegetative return type.

Both fine and coarse fuel cell grids were capable of accurately characterizing observed mass loss in a simulation environment. Based on these results, we conclude that if the primary goal of a simulation is to reproduce the burning behavior of a 3D fuel model, then a coarse fuel cell grid can successfully balance tradeoffs between computational complexity and representative heterogeneity. While high resolution LIDAR data can improve the representative heterogeneity of 3D fuel models, we find that high resolution fuel descriptions do not improve model results.

Additionally, the importance of dry foliage mass and fuel moisture content suggest that fire modelers should have a high level of confidence in their fuel attributes in order to have confidence in model results. Non-destructive biomass estimates of vegetation are an active area of research. Our study suggests that obtaining accurate biomass estimates is crucial for achieving model accuracy. More work is needed to examine the relationship between biomass measurements from traditional field techniques or derived from LIDAR data, and fuel inputs to couple fire-atmospheric models.

One major shortcoming of our study is that we were unable to evaluate the relationship between numerically identified fuel attributes from RMSE minima and actual fuel attributes measured from vegetation samples. While the majority of parameter spaces resulted in physically plausible fuel attributes, regions of RMSE minima also contained physically implausible minima. For example, our numerical experiments consistently identified regions of high dry foliage mass and low fuel moisture content as minima. This often contradicted known high water treatments applied to the sapling.

Future research can examine the role of branchwood in thermal degradation, velocity fields, and moisture content. The role of DAKOTA can expand to include additional parameters, simulation designs, and more advanced analysis techniques. Additional investigations into the effects of more detailed 3D fuel models on fire behavior models will help us better understand how to apply coupled fire-atmospheric fire models to real world problems like prescribed burn planning.

5. References

Atchley, A. L., Linn, R., Jonko, A., Hoffman, C., Hyman, J. D., Pimont, F., Sieg, C., & Middleton, R. S. (2021). Effects of fuel spatial distribution on wildland fire behavior. International Journal of Wildland Fire, 30(3), 179–189. https://doi.org/10.1071/WF20096

Arno, S. F., and J. K. Brown. (1991). Overcoming the paradox in managing wildland fire. Western Wildlands 17:40-46.

Hiers, J. Kevin, Joseph J. O’Brien, J. Morgan Varner, Bret W. Butler, Matthew Dickinson, James Furman, Michael Gallagher, et al. 2020. “Prescribed Fire Science: The Case for a Refined Research Agenda.” Fire Ecology 16 (1). https://doi.org/10.1186/s42408-020-0070-8.

Hosoi, F., & Omasa, K. (2006). Voxel-based 3-D modeling of individual trees for estimating leaf area density using high-resolution portable scanning lidar. *IEEE Transactions on Geoscience and Remote Sensing*, *44*(12), 3610–3618. https://doi.org/10.1109/TGRS.2006.881743

Hudak, A., Prichard, S., Keane, R., Loudermilk, L., Parsons, R., Seielstad, C., Rowell, E., & Skowronski, N. (2017). *Hierarchical 3D fuel and consumption maps to support physics-based fire modeling* (Issue June). www.firescience.gov

Linn, R. R., Goodrick, S. L., Brambilla, S., Brown, M. J., Middleton, R. S., O’Brien, J. J., & Hiers, J. K. (2020). QUIC-fire: A fast-running simulation tool for prescribed fire planning. *Environmental Modelling and Software*, *125*, 104616. https://doi.org/10.1016/j.envsoft.2019.104616

Loudermilk, E. Louise, J. Kevin Hiers, Joseph J. O’Brien, Robert J. Mitchell, Abhinav Singhania, Juan C. Fernandez, Wendell P. Cropper, and K. Clint Slatton. 2009. “Ground-Based LIDAR: A Novel Approach to Quantify Fine-Scale Fuelbed Characteristics.” International Journal of Wildland Fire 18 (6): 676–85. https://doi.org/10.1071/WF07138.

Mell, W., Jenkins, M. A., Gould, J., & Cheney, P. (2007). A physics-based approach to modelling grassland fires. *International Journal of Wildland Fire*, *16*(1), 1–22. https://doi.org/10.1071/WF06002

Mell, W., Maranghides, A., McDermott, R., & Manzello, S. L. (2009). Numerical simulation and experiments of burning douglas fir trees. *Combustion and Flame*, *156*(10), 2023–2041. https://doi.org/10.1016/j.combustflame.2009.06.015

National Interagency Fire Center (U.S.). (2019). *Wildland fire statistics*. Boise, Idaho : National Interagency Fire Center

Parsons, R. A., Mell, W. E., & McCauley, P. (2011). Linking 3D spatial models of fuels and fire: Effects of spatial heterogeneity on fire behavior. *Ecological Modelling*, *222*(3), 679–691. https://doi.org/10.1016/j.ecolmodel.2010.10.023

Parsons, R., Linn, R., Pimont, F., Hoffman, C., Sauer, J., Winterkamp, J., Sieg, C., & Jolly, W. (2017). Numerical Investigation of Aggregated Fuel Spatial Pattern Impacts on Fire Behavior. *Land*, *6*(2), 43. https://doi.org/10.3390/land6020043

Parsons, R.A. *et al.* (2018) 'Modeling thinning effects on fire behavior with STANDFIRE', *Annals of Forest Science*, 75(1). doi:10.1007/s13595-017-0686-2.

Pimont, Fraņois, Jean Luc Dupuy, Rodman R. Linn, and Sylvain Dupont. 2009. "Validation of FIRETEC Wind-Flows over a Canopy and a Fuel-Break." International Journal of Wildland Fire 18 (7): 775–90. https://doi.org/10.1071/WF07130.

Radeloff, V.C. *et al.* (2018) 'Rapid growth of the US wildland-urban interface raises wildfire risk', *Proceedings of the National Academy of Sciences of the United States of America*, 115(13), pp. 3314–3319. doi:10.1073/pnas.1718850115.

Rowell, Eric, E. Louise Loudermilk, Carl Seielstad, and Joseph J. O'Brien. 2016. "Using Simulated 3D Surface Fuelbeds and Terrestrial Laser Scan Data to Develop Inputs to Fire Behavior Models." Canadian Journal of Remote Sensing 42 (5): 443–59. https://doi.org/10.1080/07038992.2016.1220827.

Seielstad, Carl, Crystal Stonesifer, Eric Rowell, and Lloyd Queen. 2011. "Deriving Fuel Mass by Size Class in Douglas-Fir (Pseudotsuga Menziesii) Using Terrestrial Laser Scanning." Remote Sensing 3 (8): 1691–1709. https://doi.org/10.3390/rs3081691.