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Integrating Forest Succession Modeling and a Physics-Based Fire Behavior Model to Support Long-Term Prescribed Fire Management

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Abstract: *Background*: Fire modeling is a key prescribed fire planning tool, but there are limited operational tools for integrating current models of forest change and fire behavior. *Aims*: We sought to integrate a widely used forest succession model, LANDIS-II, with a powerful fire behavior model, QUIC-Fire, into a flexible workflow for assessing fire behavior in projected future fuel conditions. *Methods*: Using aboveground biomass, we matched LANDIS-II data to cohorts of trees in Forest Inventory and Analysis (FIA) data by predicting tree age across all FIA data using Random Forest modeling. We then voxelized those tree crowns along with surface fuels to create 3D fire model inputs. *Key Results*: We presented L2-QF, a novel crosswalk methodology between cohort-based LANDIS-II successional outputs and individual tree characteristics to create three-dimensional fuel arrays for QUIC-Fire. We demonstrated L2-QF by modeling forest change through time in multiple climate and management scenarios, then used the projected future fuel conditions to model fire behavior and effects. *Conclusions*: L2-QF can be used by fire practitioners to inform adaptive management, as highlighted by our workflow demonstration. *Implications*: By integrating long-term ecosystem changes into everyday fire planning, L2-QF allows fire managers to stay proactive in variable future conditions.

Keywords: prescribed fire; LANDIS-II; QUIC-Fire; adaptive management; ecological modeling; fire behavior; longleaf pine; 3D fuels

Introduction

Wildland fire is necessary in many ecosystems globally to maintain critical levels of animal and plant diversity (He *et al.* 2019; McLauchlan *et al.* 2020). Land managers of fire-adapted ecosystems use prescribed fire to mimic low-intensity fires, which maintain forest structures and ecological processes while decreasing the chances of high-intensity stand-replacing fires (Ryan *et al.* 2013). The frequency and intensity of prescribed fires affect how a forest stand develops, later impacting the fire behavior experienced by the stand in subsequent burns (Fernandes and Botelho 2003; McLauchlan *et al.* 2020). To help ensure that fire goals are achieved, land managers rely on a suite of planning tools: short-term fire models to estimate fire behavior for day-of-burn conditions, and long-term ecosystem process models to simulate future stand development (Ryan *et al.* 2013). However, there are currently limited pathways for integrating these models to understand how a landscape's future fire conditions may be impacted by different fire regimes and weather forecasts. As land managers are increasingly considering these dynamics in their planning, the integration of short- and long-term prescribed fire planning tools has become crucial for restoring and maintaining fire-adapted ecosystems (Loudermilk *et al.* 2017; Jonko *et al.* 2024).

Ecosystem process modeling is a common tool used to capture elements of forest succession in response to various disturbance regimes (e.g., projections of climate variability, wildland fire, insects and diseases, land use change, and harvesting). LANDIS-II (Scheller *et al.* 2007) is a landscape-class ecosystem process model that has been widely used in long-term forest planning (Gustafson *et al.* 2007; Lin *et al.* 2023; Suárez-Muñoz *et al.* 2023). In addition to simulating nutrient fluxes and biomass changes in response to tree growth, death, and regeneration, LANDIS-II can also simulate the impact of fire on succession (Robbins *et al.* 2024). In the model, wildland fire is calibrated with empirical data and operates through strategic implementation (prescription management) and through semi-stochastic processes (wildfire ignition potential and fire weather) in two dimensions (Scheller *et al.* 2019). While useful for modeling landscape-scale fire effects, LANDIS-II does not simulate process-based fire behavior and cannot represent the fine-scale fire dynamics that arise from complex fuel structures, varied ignition patterns, and fire-atmospheric interactions. Consequently, LANDIS-II's ability to inform nuanced fire management is constrained. Integrating LANDIS-II with a three-dimensional, physics-based fire model would enable the simulation of fire behavior and fire danger in response to changing environmental conditions, making the modeling more relevant for land management practices.

High-fidelity physics-based fire models incorporate three-dimensional (3D) fire-atmosphere interactions to simulate detailed fire behavior and effects, improving prescribed fire training and implementation (Parsons *et al.* 2023). QUIC-Fire (Linn *et al.* 2020) is a fast-running fire behavior model that takes in detailed 3D inputs of vegetation, weather conditions, and ignition patterns. QUIC-Fire outputs can be used to produce spatially explicit fire behavior simulations, aiding fire managers in developing burn plans that align with management objectives. Physics-based fire models like QUIC-Fire represent a promising future for operational prescribed fire planning but require detailed vegetation data to build the fine-scale 3D fuel inputs. This creates a major obstacle when converting the coarse-scale, two-dimensional (2D) outputs from LANDIS-II into a fine-scale, 3D input for QUIC-Fire. While the integration of QUIC-Fire and LANDIS-II has obvious utility, a thoughtful workflow is needed to address the scaling incompatibility issues between the two models. Linking LANDIS-II to a 3D, physics-based fire model like QUIC-Fire could give land managers a tool to understand how fire behavior and fire danger would change on their landscape as ecosystems experience succession and various land management scenarios.

Prescribed fire practitioners make the profound decision to manage our lands with fire and deserve the utmost support from research and development to continue to build useful tools for both short and long-term management (Hiers *et al.* 2020). Here, we contribute to that goal by presenting a novel method of linking LANDIS-II to QUIC-Fire, which we call L2-QF. By converting coarse-scale, 2D information on tree species-age classes from LANDIS-II into a dataset of individual tree characteristics, we were able to create fine-scale, 3D fuels inputs for QUIC-Fire and other next-generation fire models. We describe L2-QF, then provide a demonstration in an actively managed landscape, presenting an example of the method's application and management-centered results that could be derived. We discuss how these coupled simulations are useful for long-term prescribed fire management and planning, as well as how this approach can be used to integrate other models with similar scales and processes.

Workflow Description

Overview

LANDIS-II (v7.0) (Scheller *et al.* 2007) integrates various ecosystem processes and disturbances at the landscape scale and over decadal or century periods. LANDIS-II uses a gridded landscape where each cell contains multiple species-age cohorts of plants whose growth and succession are governed by resource availability, dispersal, and disturbance resistance. At each time step, species

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composition, age, and biomass are calculated, which allows for the subsequent calculation of demographic and structural forest change. LANDIS-II has been successfully implemented for understanding ecosystem dynamics, succession, insects, fire, wind, dispersal, harvesting, fuel treatment effectiveness, and climate research (Syphard *et al.* 2011; Loudermilk *et al.* 2013, 2014, 2017; Robbins *et al.* 2023). L2-QF simulates forest succession through species-specific competition for light, water, and nutrients. It also simulates vegetation growth and response to disturbance, which is determined by unique species attributes (e.g., shade tolerance and growth rate). Dead biomass (woody and leaf litter) and soil organic carbon are also tracked, which crucially allow rough estimations of both above- and below-ground fuel components as the forest undergoes succession.

QUIC-Fire is a high-fidelity, physics-based fire behavior model designed to conduct detailed spatial fire behavior simulations. By representing 3D fuels, topography, and ignition patterns, then simulating how winds interact with fire-generated plumes and vegetation, QUIC-Fire captures complex, fine-scale fire behavior that empirical or quasi-empirical models cannot. This makes it ideal for quantifying how changes to atmospheric and fuel conditions impact fire behavior. QUIC-Fire combines the QUIC-URB wind solver (Singh *et al.* 2008) with a cellular automata fire spread model to simulate fire-atmospheric feedbacks without the need for solving computational fluid dynamics equations. This innovation allows QUIC-Fire to produce similar results to more complex models, like FIRETEC (Linn and Cunningham 2005) and FDS (Mell *et al.* 2007), with ~1/2000 the computational cost (Linn *et al.* 2020).

Connecting LANDIS-II and QUIC-fire requires a multi-step process to transform tree cohorts and carbon pools from LANDIS-II to the three-dimensional arrays of fuel parameters (i.e. bulk density and moisture content) required to run QUIC-Fire (Fig. 1). As it is not spatially explicit within a given cell, LANDIS-II presents tree cohorts in terms of aboveground biomass (g m^{-2}) grouped by species and age. In order to build an array of fuels to represent these cohorts, we developed a novel method for representing these cohorts as groups of individual trees with associated characteristics describing their shape, size, and location. We then used a tree canopy voxelization program (Los Alamos National Laboratory 2024) to create the necessary three-dimensional fuel inputs for QUIC-Fire. Alongside this process, the necessary surface fuels are interpolated from LANDIS-II litter outputs (g m^{-2}). The L2-QF workflow is described in detail below.

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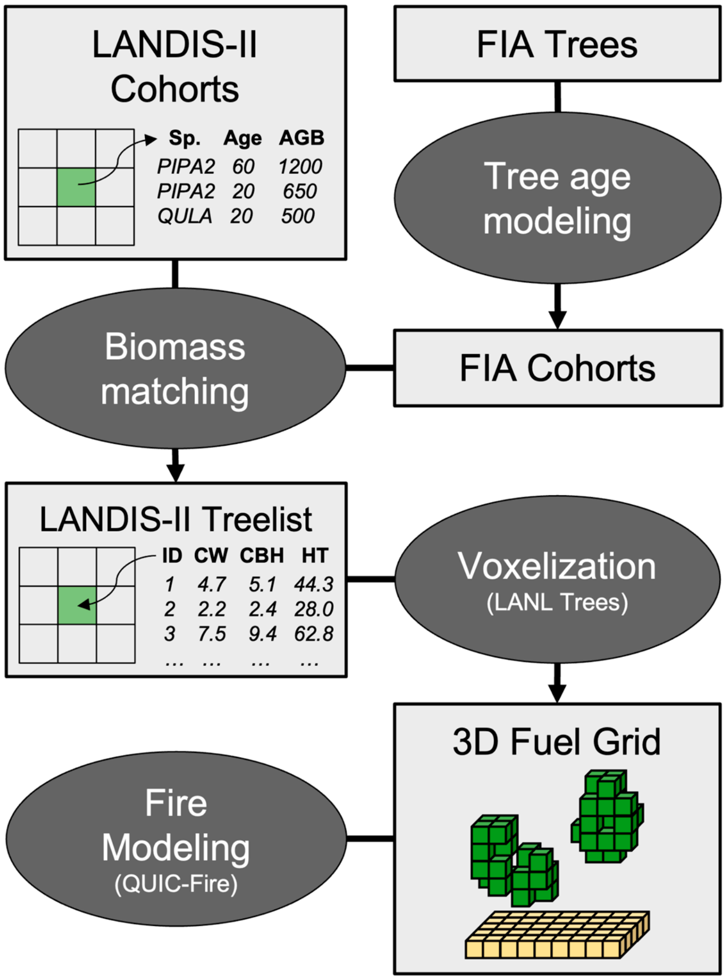

Figure 1. Workflow for the one-way coupling of vegetation dynamics model LANDIS-II (Scheller *et al.* 2007) and fire behavior model QUIC-Fire (Linn *et al.* 2020). Visualizations in gray boxes show example datasets. FIA = USFS Forest Inventory and Analysis program (Smith 2002); AGB = Aboveground Biomass; CW = Crown Width; CBH = Crown Base Height; HT = Height; LANL = Los Alamos National Lab; 3D = Three-dimensional.

Parameterizing LANDIS-II

The L2-QF workflow assumes the user has already parameterized the LANDIS-II model to the necessary ecological phenomena of their study extent. The model requires inputs specifying the initial tree communities, climate data, and other input files for the succession plugin. Our workflow, currently in its first iteration, requires the LANDIS-II simulation to use the Net Ecosystem Carbon and Nitrogen (NECN) Succession extension (v4.2) (Scheller *et al.* 2011) the Net Ecosystem Carbon and Nitrogen (NECN) succession extension, which is widely used in LANDIS-II studies (Martin *et al.* 2015; Creutzburg *et al.* 2017; Flanagan *et al.* 2019; McDowell *et al.* 2021; Robbins *et al.* 2024; Jones *et al.* 2024). L2-QF also requires the Community Biomass Output extension (see Supplemental Material).

LANDIS-II to Treelist

A key challenge in linking LANDIS-II to QUIC-Fire is the difference in spatial scales. LANDIS-II was designed to simulate forest change at broad, landscape scales (10,000-100,000s of hectares), and the typical cell size is around or above 1 ha. QUIC-Fire, on the other hand, simulates coupled fire and atmospheric processes at a horizontal resolution of 1-2 m. Fuels data are read by QUIC-Fire in the form of volumetric pixels (voxels), arranged in 3D space to represent individual tree canopies and surface fuels. However, LANDIS-II tracks forest change not in terms of individual trees, but as cohorts of species-age-biomss classes. At these two disparate scales, fuels, especially trees, are characterized differently, which poses a challenge when downscaling from a LANDIS-II output to a

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QUIC-Fire input. To couple the two models, we developed a method to transform LANDIS-II cohort data into an arrangement of 3D voxels representing individual trees (Fig. 1). The first step in this process is to create a data frame of individual trees with associated attributes (hereafter, “treelist”) from the LANDIS-II cohorts.

Tree Age Modeling

LANDIS-II cohort data are presented in species-age-biomass classes and thus lack the individual tree component data required for QUIC-Fire. Therefore, these and other attributes must be estimated to create a 3D fuel structure. We used data from the US Forest Service Forest Inventory and Analysis program (FIA) (Smith 2002) to model the likely tree communities represented by LANDIS-II cohorts. We grouped trees of the same species-age class for each FIA plot, creating cohorts of trees that are analogous to LANDIS-II cohorts. Cohorts are grouped by tree age; however, tree age is not recorded uniformly across the FIA sampling (USDA 2023). Notably, tree age is only recorded in two FIA regions: the Pacific Northwest and Rocky Mountain regions. Moreover, age is not sampled for all trees. In the Pacific Northwest region, one tree of each species in each crown class for each site condition is sampled, and no timber hardwoods other than red alder (*Alnus rubra*) are sampled. In the Rocky Mountain region, one tree of each species and broad diameter class is sampled per plot. To address this data gap, we developed a method for predicting the age of every tree in the FIA dataset from the existing age data and other regularly included FIA data about the individual, the stand, and the plot location.

We built a statistical model characterizing the relationship between tree age and a suite of predictors for each of the four major species groups denoted by FIA (MAJOR_SPGRPCD column). We chose a Random Forest model framework because they are robust to correlated predictors and to nonlinear relationships between predictors and the response (Breiman 2001). The four models predicted tree age for major species groups: 1) Pines (*Pinus spp.*), 2) other conifers (e.g. *Abies spp., Tsuga spp., Pseduotsuga spp.*, etc.), 3) soft hardwoods (e.g. *Fraxinus spp., Acer spp., Liriodendron spp.*), and 4) hard hardwoods (e.g. *Fagus spp., Quercus spp.*). For the response, we used total tree age (TOTAGE column in FIA) when available, else we used age measured at breast height (BHAGE column in FIA) plus ten. We chose seven predictor variables that affect tree growth (Table S1) and constructed predictive age models in Python using *sklearn* (Pedregosa *et al.* 2011) and *skranger* (Wright and Ziegler 2017; Flynn 2020). The hyperparameters for each model were tuned using 10-fold cross-validation for each major species group. The final model was trained on all the data, and validated using 10-fold cross-validation. This evaluation revealed that tree age was relatively well-predicted by our models for each of the four species groups, with R-squared values ranging from 0.70 to 0.74 (Fig. S4, S5). Root mean square error (RMSE) values were lowest for young trees, with all four models showing an RMSE of less than 20 (two 10-year age classes) for trees less than 50 years old (Fig. S6). Trees 100-150 years old never had an RMSE higher than 40 years, though trees over 200 years old were not well-predicted by our models (RMSE > 70 years). After evaluation was complete, we saved the resulting model fit Python object to be used in the workflow for predicting age for all trees in any FIA plot.

Forest Inventory and Analysis Matching

After grouping FIA trees into species-age cohorts, we compared the per-area biomass of each LANDIS-II cohort to the biomass of all FIA cohorts of the same species and age. We then used the cohort of FIA trees that was closest in biomass to represent that LANDIS-II cohort. Next, we replicated each individual tree based on the expansion factor between the FIA plot size (TPA_UNADJ column in FIA) and the LANDIS-II grid cell size, and placed the resulting trees at random x, y locations within the LANDIS-II cell (See Fig. 2 for example cells).

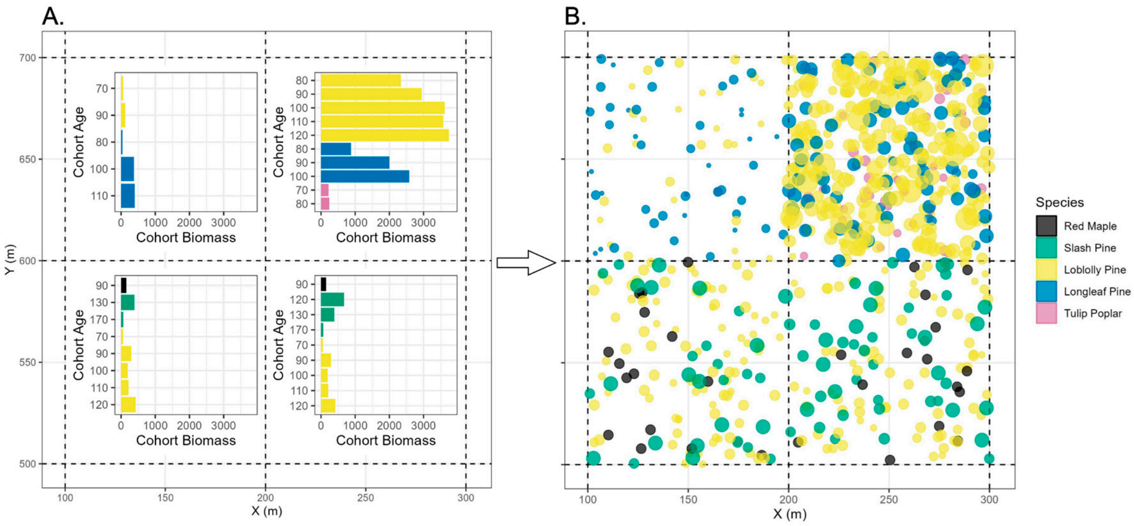

Figure 2. Treelist generation from LANDIS-II cohorts in four example LANDIS-II grid cells, delineated by dashed lines. (A) shows the biomass of each species-age cohort output by LANDIS-II; (B) shows the resulting treelist, where canopy diameter is represented by point size. Individual trees are placed randomly within a LANDIS-II grid cell.

A majority of the tree biometric variables that are necessary for building a 3D fuels array are available from FIA. Tree height, diameter, and ocularly estimated height to crown base are all recorded for all trees in the FIA dataset. However, since crown width (diameter) is a required component for describing the shape of the canopies, we calculated it for each tree species of a given diameter. We used empirically established relationships of diameter at breast height (DBH) (Dixon 2002) to calculate crown diameter for all species.

Surface Fuels

In addition to tracking tree cohorts, LANDIS-II simulates nutrient fluxes, including carbon in discrete pools. The NECN succession plugin processes these carbon fluxes to produce grids of surface litter, which we use as surface fuel inputs for QUIC-Fire. We use bivariate spline interpolation to convert surface fuels to the QUIC-Fire resolution. At this time the workflow does not represent herbaceous fuel, since it is not tracked by LANDIS.

Voxelization of the Treelist

The result of the LANDIS-II output processing is a list of trees and associated attributes for the entire domain, along with a discreet location for each tree. The attributes and locations are then processed by an open-source software called *Trees*, developed by the Los Alamos National Laboratory (2024) (hereafter, LANL Trees), which creates a voxelized three-dimensional array of canopy fine fuels. To define the shape of the canopy, it uses total tree height, height to crown base, crown width, and a species-specific factor defining at which height the canopy is widest (CL factor). These attributes are processed to produce a rotational solid for each tree crown. Once the shape is defined, user-defined attributes are applied to the crown fuels defining crown fuel bulk density, moisture, and optionally foliage size scale. These attributes, along with the CL factor, are defined by the user for each species prior to running the workflow. Last, the canopy geometries are voxelized to the QUIC-Fire grid by determining the fraction of each tree's fine fuel that occupies each 3D cell (Fig. 3). The resulting files are ready to be used as inputs by QUIC-Fire or another physics-based fire model.

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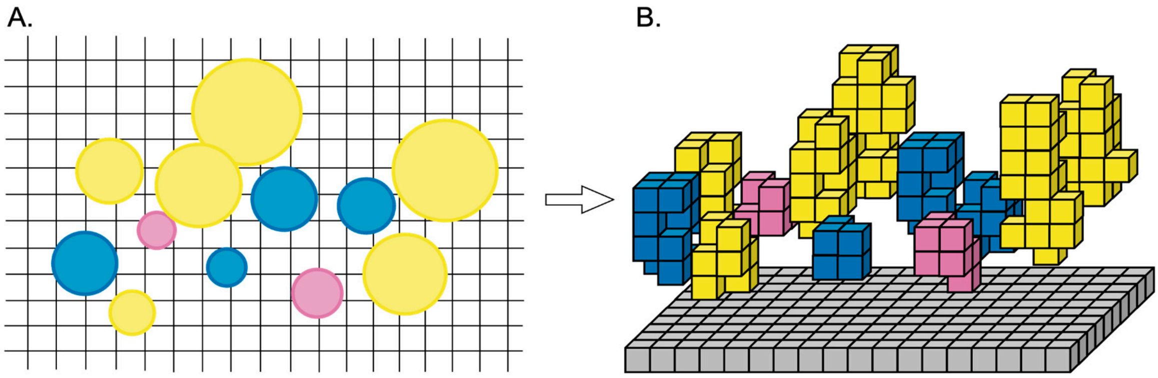

Figure 3. Example of voxelization from (A) spatially explicit treelist to (B) 3D fuel grid. Disc sizes in (A) represent unique canopy measurements such as crown width, crown length, and crown base height; these characteristics are processed by a fuel voxelation program to produce 3D representations of fine fuel loading (B). Colors represent tree species, which may have different fuel density or moisture parameters; gray cubes indicate surface fuels.

Fire Simulation

The flexibility in LANDIS-II parameterization is mirrored for the fire modeling step. Parameters governing the fire model such as wind speed, wind direction, and surface fuel moisture can be set by the user within the workflow code prior to starting the workflow. However, these and other fire modeling parameters such as topography and ignitions may be added to or modified in the fire simulation after the LANDIS-II outputs are converted to voxelized fuels.

Workflow Demonstration

Forest managers may want to evaluate the potential outcomes of different management plans under different projected climate scenarios. By coupling LANDIS-II with QUIC-Fire, these evaluations can include self-determining fire behavior. To demonstrate how this coupling might be used in a management planning scenario, we applied our framework to a real-life management unit that utilizes prescribed fire. Here, we simulated multiple forest succession scenarios and then used the outputs to parameterize fire behavior simulations, showing how fire behavior and outcomes may inform management decisions.

Study Area

Our demonstration landscape is Ft. Bragg (formerly Ft. Liberty) Army Base, Fayetteville, North Carolina, U.S.A. As an active military base, the land is managed with extensive prescribed fire and timber harvesting, which supports military training activities and environmental requirements. The resulting ecosystem is predominantly longleaf pine (*Pinus palustris)*-wiregrass (*Aristida stricta*) which was formerly common in the southeastern United States (Ware *et al.* 1993). Other important tree species include loblolly pine (*P. taeda*), shortleaf pine (*P. echinata*), and hardwoods (*Quercus spp.*, *Liquidambar styraciflua*, *Lirodendron tulipifera*) (Fig S1). Additional benefits of the extensive forest management are a high floristic diversity (Sorrie *et al.* 2006) and the preservation of an ecosystem preferred by the red-cockaded woodpecker (*Dryobates borealis*), a federally listed endangered species. Ft. Bragg manages over 50 km² of forests annually, making it an ideal location to demonstrate long-term fire management tools.

LANDIS-II Parameterization

The Fort Bragg landscape has been previously parameterized for LANDIS-II by Lucash et al. (2019) and used in Schrum et al. (2020) and Lucash et al. (2022). These parameterizations include initial tree communities, soil properties, climate projections, management units, and disturbance

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dynamics. We brought this parameterization in line with NECN v7 as it represents a more robust removal of prescribed fire fuels in concert with LANDIS-II fire models (see Supplemental Material). To demonstrate how a LANDIS-II to QUIC-Fire workflow can be used in a forest planning scenario, we compared prescribed fire behavior following four LANDIS-II simulations with varying climate and disturbance inputs. The Fort Bragg simulations included two climate projections: a high temperature, low precipitation scenario (hereafter, Hot-Dry) and a high temperature, high precipitation scenario (hereafter, Hot-Wet). Prescribed fire treatments were applied in the LANDIS-II simulation using the Social Climate Related Fire (SCRPPLE) extension (Scheller *et al.* 2019) under a two year and five-year fire return interval. These climate and prescribed fire scenarios were applied as a 2x2 factorial design for a total of four LANDIS-II scenarios (Table 1). Each LANDIS-II run was simulated for 50 years.

Table 1. Design of LANDIS-II to QUIC-Fire demonstration modeling ensemble. Fire rotation refers to the frequency of prescribed fires using Social Climate Related Pyrogenic Processes and their Landscape Effects (SCRPPLE) extension.

LANDIS-II				**QUIC-Fire**	
Fire Rotation		**Climate Projection**		**Fuel Conditions**	**Wind Conditions**
2-year	**5-year**	**Hot-Dry**	**Hot-Wet**	**Surface: 10% FMC Canopy: 100% FMC**	**Speed: 2.23 ms^{-1} Direction: 270°**
X		X		X	X
X			X	X	X
	X	X		X	X
	X		X	X	X

Note: FMC, fuel moisture content.

QUIC-Fire Simulations

We evaluated fire behavior after each of the four LANDIS-II runs under uniform burn conditions. We chose a 500 x5 00 m square burn plot in a forest type representative of prescribed burning areas in Fort Bragg (Sorrie *et al.* 2006) (Fig. S1, S2). We added a 50 m buffer on all sides of the burn plot to minimize simulation edge effects. We set an 8 m control line around the plot where surface fuels were removed (Fig. S3). Winds were set to a constant speed of 2.23 ms^{-1} at 6.1 m, and wind direction was set to 270 degrees for the entire simulation. Fuel moisture and wind conditions were held constant in all simulations, using values judged to be reasonable by local experts (Table 2). Topography was acquired from the USGS 3D Elevation Program (U.S. Geological Survey 2023). Fuels were ignited along the upwind border of the burn plot (Fig. S3). All fuel arrangement, loading, and height were output from the workflow, and was the only input that varied between QUIC-Fire simulations. Simulations were set to run for 10,800 s (3 hr) and were halted when all fire and plume activity ceased. Fire and wind dynamics were calculated by the model every in-simulation second, and metrics were output every 30 simulation seconds.

Fire Behavior Analyses

QUIC-Fire includes outputs describing fuel conditions (density, moisture), wind conditions during the fire (u-, w-, and v-directions), emissions (CO, PM2.5, water), and energy dynamics (fire reaction rate, energy to atmosphere, energy release at the surface). To demonstrate how the results of a LANDIS-II to QUIC-Fire coupling could be used to inform prescribed fire management, we chose to primarily focus on fuel consumption, as consumption outcomes represent an important planning target and evaluation metric. We summarized fuel consumption by finding the percent reduction of initial fuel loading at each 30 s output timestep. To investigate which canopy fuels burned, we also

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calculated the final percent consumption for each 1 m vertical layer. We divided our analyses of the fuels into surface (< 1 m) and canopy (≥ 1 m) since they represent different vegetation types, fire behavior dynamics, management targets, and methods of model parameterization. Managers may also be interested in the height at which canopy fuels are consumed, since most burning prescriptions aim to leave large trees undamaged.

QUIC-Fire Results

Varying prescribed burn rotations and climate scenarios in LANDIS-II led to differences in simulated prescribed burn effects in QUIC-Fire, though overall fire behavior was similar (Fig. 4A). All four scenarios showed near-total consumption of surface fuels (Fig. 4B), which is expected since surface fuel moisture was relatively low (10%) for all simulations (Table 1). Canopy fuel consumption was most affected by burn rotation, with a 5-year rotation leading to higher rates of canopy consumption (53-54%) than a 2-year rotation (45-46%) (Fig. 4B). The combination of a 5-year fire rotation in the Hot-Wet climate scenario led to increased consumption of canopy fuels above 5 m: 33% greater than the next highest (2-year fire rotation in Hot-Dry climate scenario) and about 45% greater than the other two scenarios (Fig. 4C).

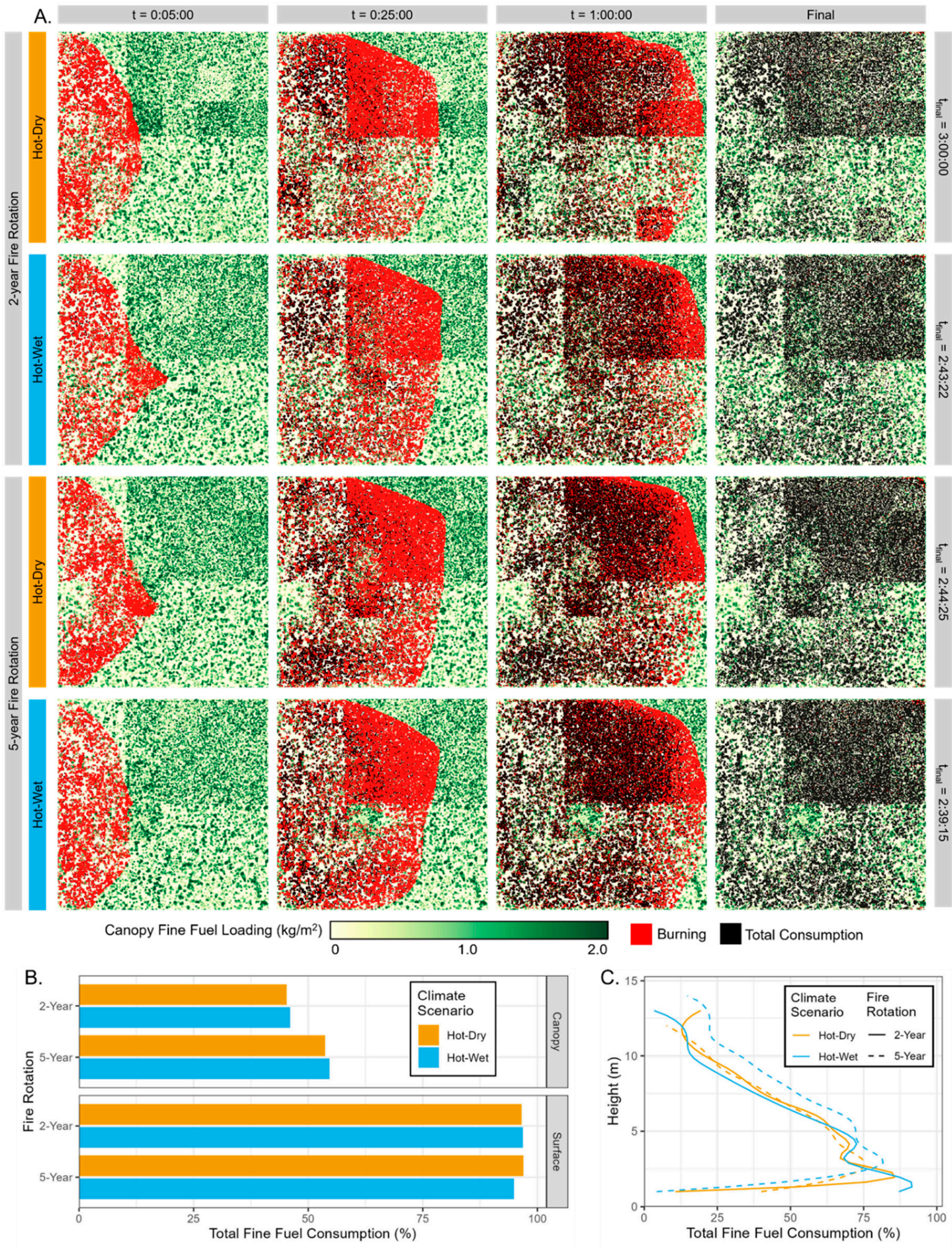

Figure 4. Demonstration results for QUIC-Fire simulations of four LANDIS-II scenarios. (A) Fire progression through canopy fuels at selected times. Simulations were halted at 3 hours or once all fire activity ceased; final simulation times are listed on righthand side. (B) Total percent consumption for canopy and surface fuels. (C) Total percent consumption of canopy fuels across the vertical profile of the canopy.

Discussion

The L2-QF workflow was intended specifically for prescribed fire practitioners in fire-adapted ecosystems. By bringing projections about future forest succession into current fire management planning, fire practitioners can identify potential future threats to this critical habitat. This is vital

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because many burn programs, especially in the southeast US, maintain habitat that is threatened by uncertain drought patterns and interacting disturbances, such as hurricanes, wildfires, invasive species, or insect outbreaks (Mitchell *et al.* 2014). Prescribed fire practitioners are increasingly interested in how QUIC-Fire could help to inform their long-term prescribed fire planning through initiatives such as the Innovation Landscape Network –a collaborative effort between fire practitioners and researchers to innovate and support prescribed fire management. This research expands the potential application space for QUIC-Fire to support these initiatives with a successional component now included. Prescribed fire practitioners currently have no analog to indicate how their forests may respond to variable weather or drought patterns, or how that could create unique fuel conditions. Our framework provides a path to understanding these changes, where LANDIS-II simulates future forest changes and QUIC-Fire illustrates how these changes can influence fire intensity and fire spread. Because our workflow places few restrictions on LANDIS-II or QUIC-Fire parameterization, the user has the flexibility to incorporate any level of landscape complexity necessary.

Our demonstration of L2-QF is purposefully straightforward to illustrate that even basic changes in future conditions (in this case fuel loading) can have distinct differences in fire intensity, spread, and crown fire transition. Our results show simulated changes in precipitation and temperature can influence fire behavior and fire effects, especially related to tree canopy biomass consumption. For example, a 5-year burn rotation led to surface fuel buildup and increased tree regeneration that contributed to ladder fuel conditions and ultimately more canopy consumption (Wagner 1977; Hakkenberg *et al.* 2024). Increased tree regeneration was seen even more strongly in the Hot-Wet climate scenario (Fig. S2), leading to more crown fire in large, mature trees. In total, these results could indicate that a 2-year fire rotation would be better for maintaining desired prescribed fire behavior and resulting fire effects, and could be especially important to consider in hotter and wetter conditions.

Because of the broad applicability of both LANDIS-II and physics-based fire models, we anticipate a variety of use cases for our workflow. Thus, our workflow can be used to produce inputs for multiple physics-based fire behavior models. While QUIC-Fire is explicitly included as the endpoint of our framework and demonstration, the process of creating and voxelizing a treelist can be used to create inputs for a number of other 3D fire simulation models, such as FIRETEC or FDS. Additionally, because the treelist is output as a separate file, it can be used in any voxelization platform that takes a treelist as an input, including FastFuels (Marcozzi *et al.* 2025).

The coupling of LANDIS-II and QUIC-Fire is promising for long-term prescribed fire planning, but there are considerations to examine. Among the main innovations in our workflow was the age modeling of all trees in the FIA dataset. Though trees of the same size can vary greatly in age (Coomes and Allen 2007), the models performed reasonably well for grouping trees into 10- to 20-year age cohorts, especially in younger trees where errors in age prediction are more consequential. The models also performed better for hardwoods than for conifers (Fig. S5), even though training data for hardwoods was more limited. Though the models were trained on data in the western US, the models performed relatively well even when predicting across a wide range of species that were not present in the training data. This gives us confidence that predictions for species of the same taxa should be similarly well-predicted in different regions, yet a focused effort for examining variations among regional tree species could be explored.

Our current workflow distributes trees randomly within a LANDIS-II grid cell. We did not integrate a method to clump or disperse the trees because those dynamics can vary within and between study sites. However, because the tree list that results from the FIA cohort matching is simply a data frame of trees with associated coordinates, a user can alter those coordinates however they see fit before using the list to construct a fuel array. Furthermore, L2-QF creates surface fuel inputs from tree leaf litter simulated in LANDIS-II, which may not encompass all fire-carrying surface fuel, such as grasses or shrubs that are often abundant in frequently burned systems. Thus, tree distributions and surface fuels should be examined before QUIC-Fire simulations are conducted.

Conclusion

Here we present a new linkage between a widely used forest succession model LANDIS-II, and a physics-based fire behavior model, QUIC-Fire. By developing crosswalks with the FIA database and a recently developed tree canopy voxelization software, we present the first formalized method of converting LANDIS-II species-age cohorts to discretized trees with unique size and shape characteristics. Though we chose to demonstrate a linkage to QUIC-Fire, the workflow is generalizable and can link to any fire or fuel modeling method that receives a list of tree characteristics or voxelized representation of fine fuel. Our demonstration highlights the ability of our workflow to assess fire behavior and effects in response to different management scenarios and climate scenarios, which could provide managers and researchers with a novel tool for understanding the complexities of fire and changing fuel conditions.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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