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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 models of forest change and fire behavior. **Aims.** We sought to integrate a forest succession model, LANDIS-II, with a fire behavior model, QUIC-Fire, into a 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 using Random Forest modeling. We then used tree attributes from FIA to create three-dimensional QUIC-Fire inputs representing fine fuel density. **Key results.** We presented L2-QF, a novel crosswalk between cohort-based LANDIS-II outputs and individual tree characteristics to create three-dimensional fuel arrays for QUIC-Fire. We demonstrated the utility of 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.** Our demonstration shows fire behavior in QUIC-Fire is responsive to forest succession effects of the LANDIS-II scenarios, allowing 3D simulations of fire under future conditions. **Implications.** L2-QF can be used to explore how fire behavior may be influenced by broader-scale biophysical and ecological processes. Future advancements are planned to expand this coupling to a deployable tool.

Keywords: 3D fuels, adaptive management, ecological modeling, fire behavior, fire behavior model, forest succession modeling, LANDIS-II, longleaf pine, prescribed fire, QUIC-Fire.

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 stable and resilient forest structure and ecological processes while decreasing fuels hazards and fire risk and maintaining public and community safety (Ryan *et al.* 2013). The frequency, intensity and spread pattern of prescribed fires affect a forest stand's short-term response (e.g. consumption, death) and longer-term recovery (e.g. sprouting, regeneration, growth), impacting fire behavior in subsequent burns (Fernandes and Botelho 2003; McLauchlan *et al.* 2020; Loudermilk *et al.* 2022). As such, managers and practitioners of prescribed fire have much to consider in short- and long-term planning, including daily to yearly weather patterns, site characteristics (e.g. topography, ecosystem type and state, management boundaries), and planned and unplanned disturbances (e.g. harvesting, tornadoes, disease, insect outbreaks), notwithstanding policy and logistical challenges. To aid in conducting effective prescribed fires in the face of such complexity, several modeling tools exist. Highly resolved fire–atmosphere models can be used as a tool to examine site-level fire behavior dynamics, including effects of variable

Collection: Multi-Scale Measurements in Support of Improved Fire, Fuel, and Smoke Models of Landscape-Level Wildland Fires fuel moisture conditions or spatial ignition patterns within a given managed area (Linn and Reisner, 2002; Koo *et al.* 2012; Marshall *et al.* 2020). Further, ecosystem process models can be used to examine changes in stand development (forest succession) patterns and broader-scale effects of fire regimes through time (yearly to multi-century) and over entire landscapes (up to and exceeding 10,000 km^2; Scheller *et al.* 2007; Ryan *et al.* 2013). Although both are designed for distinct purposes, their coupling could broaden their application by providing, for example, a unique opportunity to assess future site-level fire behavior given changes to long-term successional trajectories, all in a scenario-planning environment. There is currently, however, no known approach for integrating these two types of models.

Ecosystem process modeling is commonly used to simulate multi-decadal to multi-century forest succession in response to various model 'scenarios' of, for example, climate, wildland fire, insects and diseases, land use change and harvesting (Foster *et al.* 2018; Fisher and Koven 2020; Rammer *et al.* 2024). LANDIS-II (Scheller *et al.* 2007) is one such model, which has been utilized to improve our understanding of ecosystem dynamics, succession, insects, fire, wind, dispersal, harvesting, fuel treatment effectiveness and climate research (Gustafson *et al.* 2007; Syphard *et al.* 2011; Loudermilk *et al.* 2013, 2014; Loudermilk *et al.* 2017*a*; Lin *et al.* 2023; Robbins *et al.* 2023; Suárez-Muñoz *et al.* 2023), and has links to long-term forest planning (Martin *et al.* 2015; Hurteau 2017; Flanagan *et al.* 2019; Schrum *et al.* 2020; McDowell *et al.* 2021). It simulates forest succession, nutrient fluxes, soil and root dynamics, and biomass changes in response to tree growth, death and regeneration, including impacts of fire regimes on forest succession (Scheller *et al.* 2019; Robbins *et al.* 2024). Live aboveground biomass, dead biomass (woody and leaf litter) and soil organic carbon are all tracked, which crucially allows rough estimations of both above- and below-ground fuel components as the forest undergoes succession. Wildland fire within LANDIS-II incorporates fire ignition locations, spread and vegetation response, all represented by probabilities and calibrated with empirical data on regional fire regimes and known species response to fire (Scheller *et al.* 2019). Although this creates a modeling environment for broad landscape-scale response to fire regimes, it is constrained by its lack of site-level dynamics that are management-relevant (e.g. different ignition types and patterns, within-management unit consumption variability, fireline intensity; Robbins *et al.* 2024).

Physics-based three-dimensional (3D) fire behavior models are better suited to simulate these finer-scale dynamics (Hiers *et al.* 2009; Parsons *et al.* 2011). In particular, QUIC-Fire (Linn *et al.* 2020) is a fast-running model that combines the QUIC-URB wind solver (Singh *et al.* 2008) with cellular automata fire spread to simulate fire–atmospheric feedbacks with ~1/2000 the computational cost of more complex models like FIRETEC (Linn and Cunningham 2005) and the Fire Dynamics Simulator (FDS; Mell *et al.* 2007). By representing 3D fuels, topography and ignition patterns, then simulating how winds interact with fire-generated plumes and vegetation, QUIC-Fire explicitly models complex, fine-scale fire behavior. This makes it ideal for quantifying how changes to atmospheric and fuel conditions impact fire behavior and associated changes to vegetation. As fine-scale (1–2 m) 3D fuel inputs (e.g. fuel structure, density, moisture content) become more available through emerging tools like FastFuels (Marcozzi *et al.* 2025) and the Trees program (Los Alamos National Laboratory 2024), physics-based fire models like QUIC-Fire could aid in future operational prescribed fire planning because all aspects of a site-level fire can be represented within the model (Parsons *et al.* 2023). Developing methods of using these tools to transform data from ecosystem process models like LANDIS-II would thus increase the application space for both model classes, particularly the ability to simulate prescribed fire under future successional and non-fire disturbance stand structures.

Although LANDIS-II describes the canopy and surface live and dead fuels required for QUIC-Fire, the discrepancies in dimension (2D vs 3D) and scale (generally hectares vs meters) between the models are major obstacles to their integration. QUIC-Fire requires the 3D structure of all individual tree canopies, whereas LANDIS-II tracks only the biomass of tree species cohorts by age, providing no explicit information on their size, stem density, or position within a hectare-scale grid cell. Here, we present an approach to linking these two models, which we call L2-QF, by using new and existing technologies to transform coarse-scale, 2D information on tree species–age classes from LANDIS-II into fine-scale, 3D fuels inputs for QUIC-Fire. We describe L2-QF, then provide a demonstration in an actively managed landscape, illustrating the influence from two different fire regimes (2 and 5 year fire rotation) and two climate scenarios (Hot–Dry and Hot–Wet) on four unique fuel conditions and resulting effects on site-level fire behavior, intensity and fuel consumption. We then discuss how these coupled simulations are useful for long-term prescribed fire management and planning.

Workflow description

Overview

Creating a crosswalk between LANDIS-II and QUIC-Fire requires a method of resolving the differences in spatial scale and detail considered by each model. LANDIS-II (Scheller *et al.* 2007) conducts simulations at the landscape scale where each grid cell, typically 1–10 ha, contains tree information (such as biomass) that is summarized by species and age cohort. QUIC-fire, however, simulates fire at a more local scale and requires a 3D grid where each 1–4 m^3 volumetric pixel ('voxel') contains information on fine fuel density and moisture content. L2-QF is a modular, multi-step process to transform the coarse-scale 2D tree cohorts and carbon pools from LANDIS-II to the fine-scale 3D arrays of fuel parameters that can be passed to QUIC-Fire (Fig. 1).

First, we developed a novel method of representing LANDIS-II cohorts as an inventory of individual trees with associated characteristics describing their shape, size and location. This involved (1) modeling the approximate age of all tree species in the US Forest Service Forest Inventory and Analysis (FIA) dataset (Smith 2002; Burrill *et al.* 2023) to group FIA tree observations into species–age cohorts, and (2) matching the species–age cohorts in each LANDIS-II grid cell to a cohort of FIA trees with the most similar aboveground biomass. Next, we used an open-source tree canopy voxelization program called Trees, developed by the Los Alamos National Laboratory (2024; hereafter, LANL Trees) to represent the dimensions and characteristics of the matched cohorts in gridded 3D space, creating the necessary 3D tree canopy fuel inputs for QUIC-Fire. Last, surface fuels required for QUIC-Fire were created by interpolating the tree litter outputs (g m^{-2}) from LANDIS-II. A detailed description of the L2-QF workflow follows.

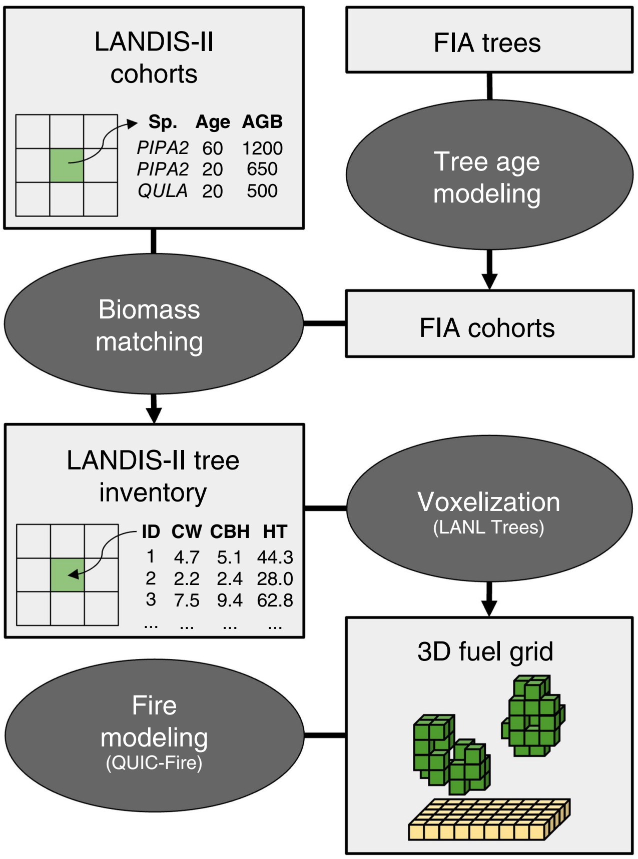

Fig. 1. Visualization of the workflow for coupling the vegetation dynamics model LANDIS-II (Scheller *et al.* 2007) and the fire behavior model QUIC-Fire (Linn *et al.* 2020). Ovals show workflow steps outlined in the Workflow description and boxes show initial and intermediate datasets with example values. Abbreviations: FIA, US Forest Service Forest Inventory and Analysis program (Smith 2002); Sp., species; AGB, aboveground biomass (g m^{-2}); CW, crown width (m); CBH, crown base height (m); HT, height (ft); LANL, Los Alamos National Laboratory; 3D, three-dimensional.

Parameterizing LANDIS-II

The L2-QF workflow assumes the user has already parameterized the LANDIS-II model (v7.0) to the necessary ecological parameters of their study extent. LANDIS-II requires inputs specifying the initial tree communities, climate data and other input files depending on the chosen succession extension. Our current workflow requires the Net Ecosystem Carbon and Nitrogen (NECN) succession extension (v4.2; Scheller *et al.* 2011), which is widely used (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 (https://landis-ii-foundation.github.io/Extension-Output-Biomass-Community/), which provides community-level data in a spatial grid at the level of the LANDIS-II cell. For more details on LANDIS-II requirements, see the Supplementary Material.

Converting 2D LANDIS-II cohort data to a 3D tree inventory

The first step in the L2-QF workflow is to represent the species–age tree cohorts in LANDIS-II output data as an inventory of individual trees with attributes that describe the crown shapes and locations. Tree density and crown structural attributes were obtained from FIA using the modeling steps described below.

Tree age modeling in Forest Inventory and Analysis data

To determine a representative tree inventory for each LANDIS-II tree cohort, we selected analogous cohorts from FIA plots. Cohorts in LANDIS-II are grouped by tree age; however, tree age is only recorded in two FIA regions: the Pacific Northwest and Rocky Mountain regions (Burrill *et al.* 2023). 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 data regularly available from the FIA 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 designated by FIA (MAJOR_SPGRPCD column). We chose the predictor set – diameter at breast height, height, canopy class, physiognomic class, site index, stand age and live tree basal area – based on ecological relevance (Supplementary Table S1). We used a Random Forest model framework because they are robust to correlated predictors and to non-linear relationships between predictors and the response (Breiman 2001). The four models predicted tree age for major species groups: (1) Pines (*Pinus* spp.), (2) non-pine conifers (e.g. *Abies* spp., *Tsuga* spp., *Pseudotsuga* spp.), (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 10. Together with the seven predictor variables (Supplementary Table S1), we 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 models were trained on all the data and validated using 10-fold cross-validation. Evaluation showed that tree age was well predicted by our models for each of the four species groups, with R-squared values ranging from 0.70 to 0.74 (Supplementary Figs 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 (Supplementary 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 models to be utilized by the workflow for predicting age for all trees in any FIA plot.

Species–age cohort matching

After predicting the age of all trees in the FIA dataset, the trees in each FIA plot were grouped by species and age ranges according to the LANDIS-II specifications (most commonly 10-year cohorts). Using these 'FIA cohorts', we compared the per-area aboveground biomass of each LANDIS-II cohort with the aboveground biomass of all FIA cohorts of the same species and age. We then selected the FIA cohort with the smallest absolute difference in aboveground biomass and used those trees to represent the LANDIS-II cohort for that grid cell. As LANDIS-II grid cells are larger than FIA plots, 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. Last, the resulting trees were placed at random spatial locations within the LANDIS-II cell (see Fig. 2 for example cells).

Surface fuel parameterization

The NECN succession extension to LANDIS-II processes carbon fluxes to produce grids of surface tree litter loading, which we used to create surface fuel inputs for QUIC-Fire. To convert surface fuels to the QUIC-Fire resolution and smooth the abrupt changes in loading between LANDIS-II grid cell boundaries, we used bivariate spline interpolation. At this time, L2-QF does not process or represent herbaceous fuel.

Voxelization of the tree inventory

The result of the LANDIS-II output processing is an inventory of trees and associated attributes for the entire domain,

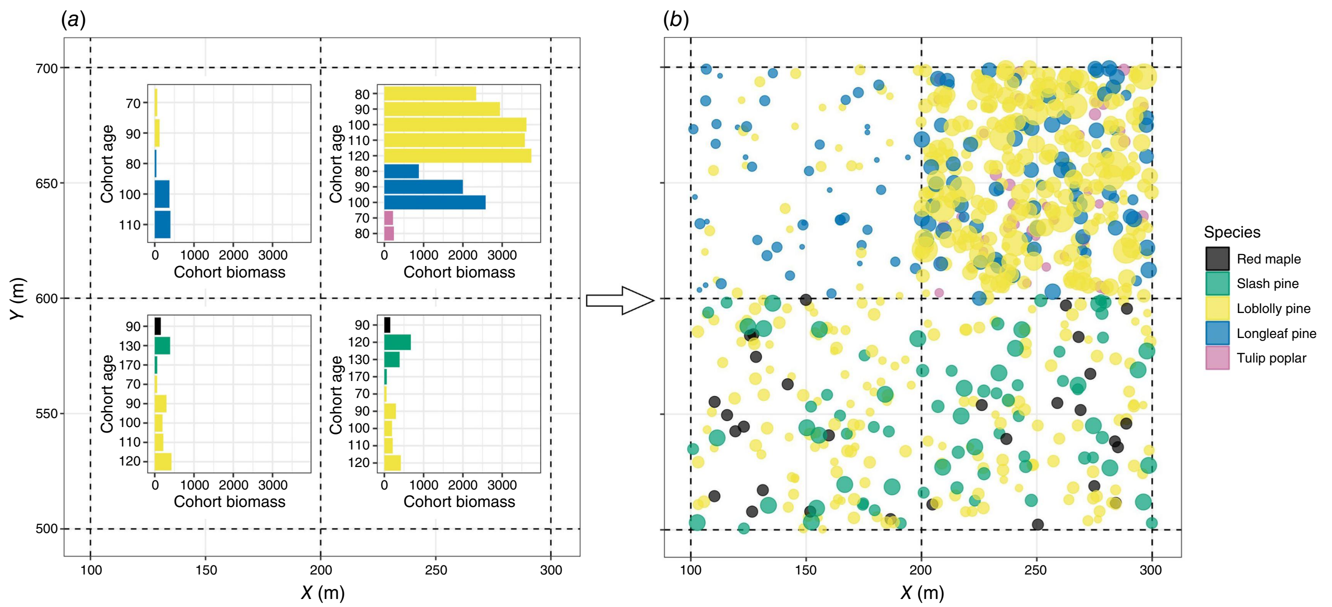

Fig. 2. Tree inventory generation from LANDIS-II cohorts in four example LANDIS-II grid cells, delineated by dashed lines. (*a*) Biomass of each species–age cohort output by LANDIS-II; (*b*) the resulting tree inventory, where canopy diameter is represented by point size. Colors indicate tree species and point size in (*b*) corresponds to relative crown diameter.

along with a discrete location for each tree. To create a voxelized 3D array of canopy fuel arrangement, we used LANL Trees. Though the current version of L2-QF uses LANL Trees, other canopy voxelization software that uses a tree inventory as an input (such as FastFuels; Marcozzi *et al.* 2025) may be used in its place. To define the shape of the canopy, LANL Trees uses total tree height, height to crown base, crown width and a species-specific factor defining the height at which the crown is widest (crown length (CL) factor). A majority of these tree biometric variables – tree height, diameter and ocularly compacted height to crown base – are recorded for all trees in the FIA dataset. To estimate uncompacted crown base height from ocularly compacted crown base height, we used a correction factor of 0.17, which we approximated from the relevant literature (Monleon *et al.* 2004; Toney and Reeves 2009; Randolph 2010; Westfall *et al.* 2019). As crown width (diameter) is not recorded by FIA, we calculated it using empirical relationships compiled in the Forest Vegetation Simulator (Dixon 2002). CL factor must be specified by the user. These attributes are then processed to produce a rotational solid for each tree crown (Fig. 3*a*, *b*). Once the shape is defined, user-defined attributes – canopy fuel bulk density, moisture and nominal fuel size (proportional to surface area-to-volume ratio; Table 1) – are applied to the crown fuels. The aboveground biomass used in the FIA matching process is not utilized by LANL Trees. 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*c*). The resulting files are ready to be used as inputs by QUIC-Fire.

Simulating fire behavior in QUIC-Fire

The voxelization of LANDIS-II tree cohorts and surface fuels provides the QUIC-Fire simulation with 3D bulk density arrays, but other parameters required by the fire model such as wind speed, wind direction and fuel moisture content (canopy and surface) must be set by the user. A suite of the most important QUIC-Fire parameters can be set in an L2-QF input file prior to starting the workflow (Table 1). The current iteration of L2-QF supports in-built rectangle ignitions in QUIC-Fire, commonly used to parameterize a single-line ignition pattern. The workflow currently defaults to flat topography, and does not have an automated option for custom topography. However, if more advanced users wish to add custom topography or make modifications to the fire simulation parameters, L2-QF can be run in discrete steps to allow those modifications, rather than as a single automated process.

Workflow demonstration

To present an example of the workflow's implementation, we demonstrate L2-QF by testing 'scenarios' of climate and

Table 1. QUIC-Fire input parameters for automated L2-QF workflow.

QUIC-Fire parameter	Unit	Default value
Canopy fuel bulk density	kg m^{-3}	0.7
Canopy fuel moisture content	% of dry mass	100
Canopy nominal fuel size	m	0.0005
Crown length (CL) factor	Dimensionless	0.8
Surface fuel moisture content	% of dry mass	10
Surface fuel height	m	0.2
Surface nominal fuel size	m	0.0005
Wind speed	m s^{-1}	2.23
Wind direction	°	270
Ignition *y*-direction minimum	m	Domain *y*-length × 0.25
Ignition *y*-direction length	m	100
Ignition *x*-direction minimum	m	Domain *x*-length × 0.25
Ignition *x*-direction length	m	10

All parameters may be modified by the user.

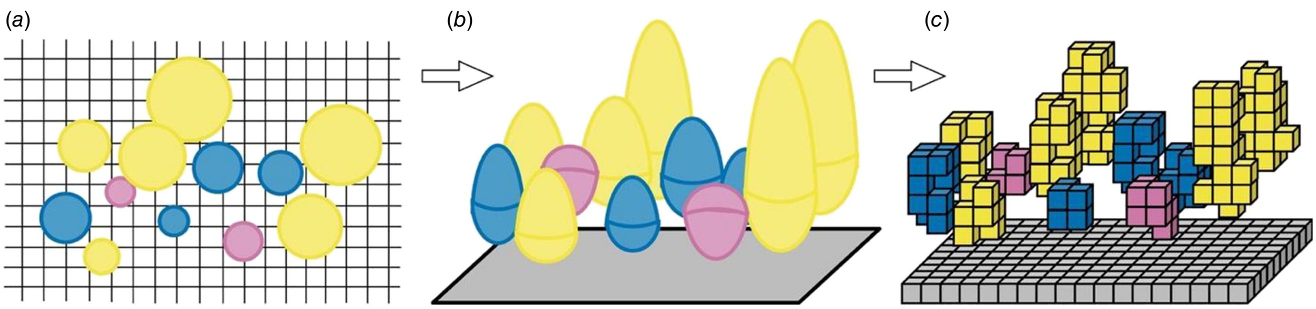

Fig. 3. Example of voxelization from (*a*) spatially explicit tree inventory to (*b*) 3D rotational solids to (*c*) a 3D fuel grid. Disc sizes in (*a*) represent unique canopy measurements such as crown width, crown length, crown base height and crown length (CL) factor; these characteristics are processed by the LANL Trees program (Los Alamos National Laboratory 2024) to produce 3D volumes of fine fuel loading (*b*), and finally discretized volumetric pixels ('voxels'; *c*). Colors represent tree species, which may have different fuel density or moisture parameters; gray faces and cubes show the surface.

management actions in a real-life management unit that is actively managed with prescribed fire. The results of this demonstration are not intended to present wholly accurate scientific findings, but rather to show how the workflow may be used. We simulated multiple forest succession scenarios in LANDIS-II and then used the outputs to parameterize fire behavior simulations in QUIC-Fire, showing how the fire behavior outcomes may inform a management decision, namely prescribed fire frequency based on canopy fuel consumption.

Study area

Our demonstration landscape is Fort Bragg (formerly Fort Liberty) Army Base, Fayetteville, North Carolina, USA. 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*, *Liriodendron tulipifera*) (Supplementary 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. Fort Bragg manages over 50 km^2 of forests annually, making it an ideal location to demonstrate long-term fire management tools.

LANDIS-II parameterization

The Fort Bragg landscape was 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 dynamics. We brought this parameterization in line with NECN v7 as it represents a more robust representation of prescribed fire fuel dynamics in concert with LANDIS-II fire models (see Supplementary Material). The Fort Bragg parameterization comprises four total forest succession scenarios with two climate projections and two prescribed fire treatment plans. The climate scenarios were two predictions for 2010–2060 from the Coupled Model Intercomparison Project Phase 5 with Representative Concentration Pathway 8.5: 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 Pyrogenic Processes and their Landscape Effects extension (Scheller *et al.* 2019) with fire rotations of 2 and 5 years. Prescribed burn frequencies were chosen by Lucash *et al.* (2019) based on collaboration with land managers at Fort Bragg to represent two plausible prescribed burn plans. These climate and prescribed fire scenarios were applied as a 2 × 2 factorial design for a total of four LANDIS-II scenarios (Table 2). Each LANDIS-II run was simulated for 50 years.

QUIC-Fire simulations

We evaluated fire behavior after each of the four LANDIS-II runs under uniform burn conditions. We chose a 500 × 500 m^2 burn plot within Fort Bragg dominated by mature longleaf and loblolly pine with small contribution from turkey oak (*Quercus laevis*), which is representative of forests that are managed with prescribed fire (Sorrie *et al.* 2006; Supplementary Figs 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 (Supplementary Fig. S3). Fuel moisture and wind conditions were held constant in all simulations, using values judged to be reasonable by local experts (Table 2). Winds were set to a constant speed of 2.23 m s^{-1} at 6.1 m,

Table 2. Design of LANDIS-II to QUIC-Fire demonstration modeling ensemble.

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 m s^{-1} Direction: 270°
X		X		X	X
X			X	X	X
	X	X		X	X
	X		X	X	X

Fire rotation refers to the frequency of prescribed fires using Social Climate Related Pyrogenic Processes and their Landscape Effects extension.
FMC, fuel moisture content

and wind direction was set to 270° for the entire simulation. Surface fuel moisture was set to 10%, canopy fuel moisture to 100%, surface fuel height to 0.2 m and nominal size of all fuels to 0.5 mm. Topography was acquired from the US Geological Survey (USGS) 3D Elevation Program (US Geological Survey 2023), and added to the QUIC-Fire simulation outside of the automated L2-QF workflow. Fuels were ignited in a 10-m wide line along the length of the upwind border of the analysis area (ignitions did not extend into the buffer area; Supplementary Fig. S3). All fuel arrangement, loading and height values were output from the workflow, and were the only inputs that varied between QUIC-Fire simulations. Simulations were set to run for 10,800 s (3 h) 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 (either instantaneous or averaged, depending on the metric) were output after every 30 in-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, particulate matter ≤ 2.5 μm ($PM_{2.5}$), water) and energy dynamics (fire reaction rate, energy to atmosphere, energy release at the surface). For this L2-QF demonstration, we chose to focus on fuel consumption, an important planning metric that can be used to assess which fuels burned (e.g. canopy vs surface fuels), where fuels burned (consumption pattern) and how quickly fuels burned (fire timing and spread rate), all of which have a direct relationship with fire intensity and resulting plant and ecosystem response after the fire. We summarized fuel consumption by using the instantaneous fuel density output to find the percentage reduction of initial fuel loading at each 30 s output timestep. To investigate which canopy fuels burned, we also calculated the final percentage consumption for each 1 m vertical layer. We divided our analyses of the fuels into surface (<1 m) and canopy (≥ 1 m) because they represent different vegetation types, fuel height layers, fire behavior dynamics, management targets and methods of model parameterization.

Demonstration results and discussion

Varying prescribed burn rotations and climate scenarios in LANDIS-II led to broadly similar fire spread patterns and timing in QUIC-Fire (Fig. 4*a*), but the scenarios led to large differences in fire effects, especially in the canopy (Fig. 4*b*, *c*). All four scenarios showed near-total consumption of surface fuels (Fig. 4*b*), which was expected because low surface fuel moisture contents (10%; Table 2) are associated with high fuel consumption (Vaughan *et al.* 2021). Canopy fuel consumption varied between the two prescribed fire frequencies, with a 5-year rotation leading to higher rates of canopy consumption (53–54%) than a 2-year rotation (45–46%) (Fig. 4*b*). 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 ~45% greater than the other two scenarios (Fig. 4*c*). This is associated with higher surface fuel build-up and increased tree regeneration in the 5-year burn rotation (Supplementary Fig. S2), which may have contributed to more ladder fuel conditions and ultimately more crown fire (Wagner 1977; Hakkenberg *et al.* 2024). Of the two scenarios with 5-year burn rotations, the Hot–Wet climate scenario had greater biomass of younger trees and more surface fuel accumulation (Supplementary Fig. S2), likely leading to more crown fire initiation and subsequent canopy consumption in large, mature trees. This could cause overstory mortality of large trees, which does not align with longleaf management goals, especially those aimed at conserving habitat for the red-cockaded woodpecker (Hooper 1988). These results might lead a manager to prefer a more frequent prescribed burn rotation (i.e. 2-year vs 5-year) to decrease the potential for canopy consumption in the future.

Our demonstration of L2-QF was purposefully straightforward, illustrating how differences in forest succession can lead to fundamental changes to fuel conditions that drive site-level fire intensity and resulting fire effects. First, changes to the fire regime had an impact on long-term fuel loading conditions. Second, simulated changes in precipitation and temperature can influence forest growth and resulting fire behavior and fire effects, especially related to tree canopy biomass consumption. Validation of the simulated fire behavior was outside the scope of our simple workflow demonstration, especially as the simulations were conducted in a predicted future fuelbed, but future work should build on studies evaluating QUIC-Fire against real-world burns (Gallagher *et al.* 2021; Robinson *et al.* 2023).

Discussion

This project introduces a workflow aimed at integrating fine-scale, 3D fire modeling aimed at prescribed fire management into broad-scale ecosystem process modeling. Using L2-QF, we applied simulated changes in vegetative fuel conditions from LANDIS-II and used those as inputs to simulate fire behavior in QUIC-Fire, illustrating the influence of future climate and vegetation change on resulting surface and canopy fuel consumption patterns. This advancement allows assessment of broader-scale ecological processes and non-fire disturbances in the context of fire behavior and effects commonly observed by fire practitioners during and after a fire, potentially enhancing proactive management capabilities. This could be particularly vital because many prescribed burn programs, especially in the southeastern US, maintain critical endangered and endemic species habitats that are defined, in part, by 3D structure (Conner and Locke

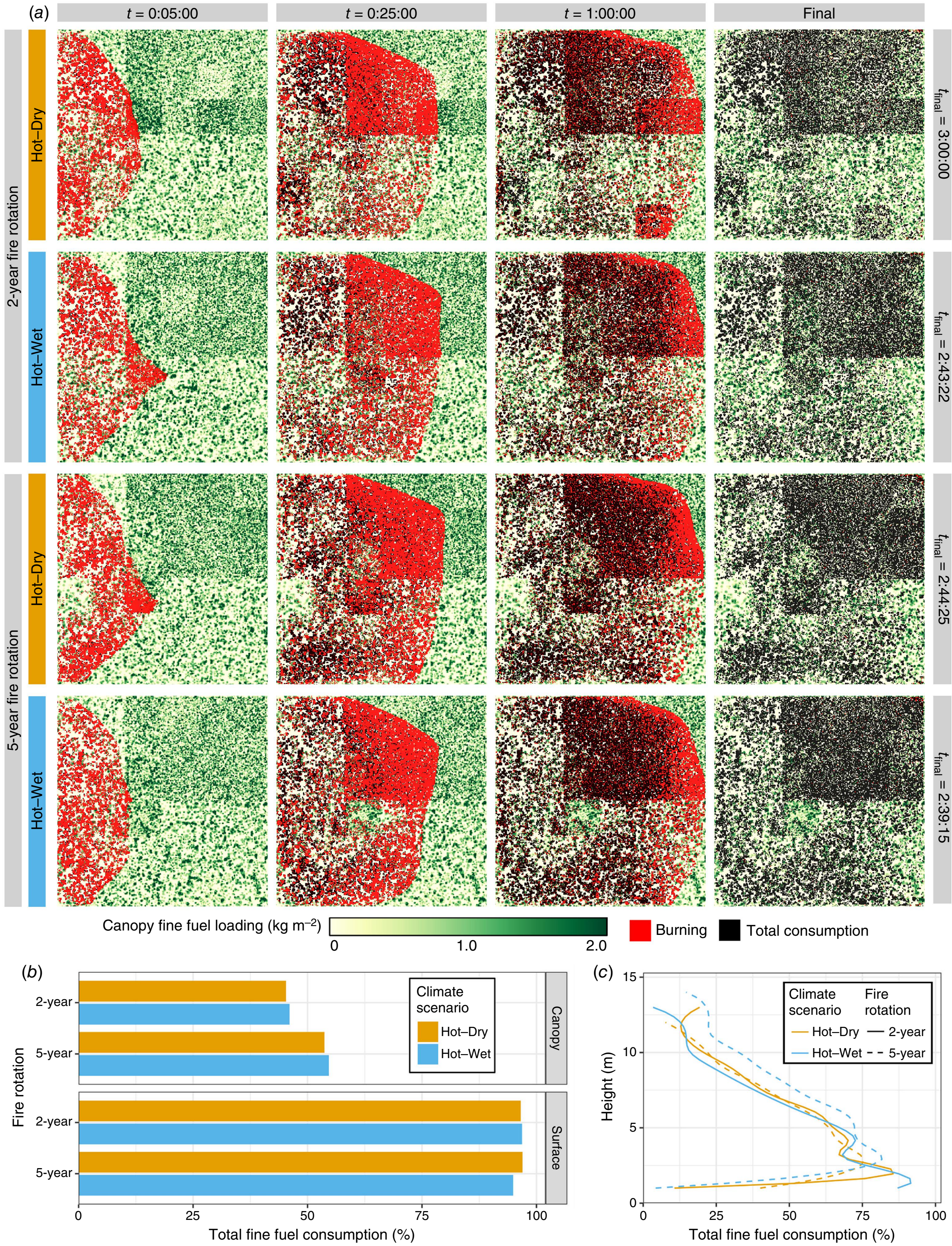

Fig. 4. Demonstration results for QUIC-Fire simulations of four LANDIS-II scenarios. (*a*) Fire progression through canopy fine fuels (height >1 m) at selected times. Each square shows vertically integrated fuel loading (green shades) on an *x*–*y* grid (500 × 500 m) for a given scenario and simulation time. Red indicates combustion occurring at an *x*–*y* location, and black shows cells with consumed fuels. Simulations were halted at 3 h or once all fire activity ceased; final simulation times (t_{final}) are listed on right-hand side. (*b*) Total percentage consumption for canopy and surface fuels in each simulation. (*c*) Total percentage consumption of canopy fine fuels across the vertical profile of the canopy.

1979; Brudvig et al. 2014; Connell et al. 2019). These habitats are locally managed, yet are impacted by broader-scale ecological forces such as drought patterns, and interacting disturbances, such as hurricanes, wildfires, invasive species or insect outbreaks (Mitchell et al. 2014).

A key goal of L2-QF was to create an automated workflow that connects a series of modular components, which allows the components to be updated or replaced as projects or technologies evolve. One component that may be considered for future improvement is 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), making individual tree ages difficult to predict (Stevens et al. 2016), our models offer an approach to scaling up the ability to represent species–age cohorts from field inventory data. Our models performed reasonably well (RMSE 12–19 years) for predicting the age of trees less than 50 years old (Supplementary Fig. S6), where errors in age prediction are more consequential for fire behavior because these canopies may lead to crown fire transition (Atchley et al. 2021). Although we acknowledge that the higher error for trees older than 100 years (RMSE > 40) likely leads to some misestimation of crown dimensions and tree density, we anticipate that most L2-QF use cases will focus on prescribed fire, where differences in fuel structure high above the surface will likely be less consequential and mainly associated with buoyant plume entrainment (Bonner et al. 2024).

Given the paucity of FIA age data in our study region, we were required to train this model using measured tree age from the Rocky Mountain region. Transferring predictions trained on these data to a region within the southeastern US could potentially lead to higher uncertainties for eastern tree species, especially hardwoods, and introduce error into our findings on the relationship of climate and management under future scenarios (Hu et al. 2009; Lu et al. 2025). However, our method provides the necessary structure to demonstrate the interoperability of these two modeling approaches, performing well across a wide range of species (Supplementary Fig. S5). The inclusion of regional predictor variables (climate, topography and geography) has been shown to provide greater predictive capability (Lu et al. 2025) but require a greater effort in data assimilation: our effort only includes data found within the FIA, and does not require re-integrating changes in future climate in the prediction of age. Still, incorporating such methods can provide additional fidelity in age prediction, particularly for near-term predictions. The modular nature of L2-Qf allows for incorporating allometry relationships from other national-scale age models (e.g. Lu et al. 2025), regional modeling (e.g. Odom and Ford 2021), or from the recently introduced Rapid Initial Communities Builder (Flanagan et al. 2026), which models age from FIA for eastern tree species with LANDIS-II as its target.

The canopy fuel voxelization process may also benefit from continued development. LANL Trees requires direct user input of species-specific traits, most notably crown base height and CL factor. As CL factor is a parameter specific to LANL Trees, there have been no research validation or modeling efforts. For crown base height, the current L2-QF workflow uses an estimated universal conversion factor to translate ocularly compacted crown base height to uncompacted, but future work could incorporate species- and age-specific equations where they are available (e.g. Monleon et al. 2004; Toney and Reeves 2009; Randolph 2010; Westfall et al. 2019). Alternatively, the modular nature of L2-QF could allow LANL Trees to be replaced by another voxelization software, such as FastFuels (Marcozzi et al. 2025), which has built-in allometry modeling.

Future consideration should also be placed on the spatial location and clustering of tree stands, surface fuel loads and ignition patterns. When assigning spatial locations to trees within a LANDIS-II grid cell, L2-QF places them randomly, leading to a more uniform canopy fuel structure that has been shown to influence crown fire initiation (Parsons et al. 2011). Because spatial heterogeneity of trees varies widely by site and species (Larson and Churchill 2012), an investigation of spatial modeling methods, such as point processes (e.g. Stamatellos and Panourgias 2005; Lister and Leites 2018), is necessary. Furthermore, the current version of L2-QF creates surface fuel inputs from only the 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 (Loudermilk et al. 2017b; Shearman et al. 2019). Though shrub communities may be represented in LANDIS-II, representing shrubby vegetation in 3D fire models is an area of active research (e.g. Tutland et al. 2025). Last, the automated L2-QF workflow currently supports single-line ignitions as a user input. However, L2-QF makes accommodations for advanced modification of QUIC-Fire inputs by giving the option to export intermediate files such as the tree inventory and the fuel arrays, which can be altered before ultimately being passed to QUIC-Fire.

Additionally, the fuel arrays that L2-QF creates for QUIC-Fire can be modified to pass into other physics-based fire behavior models, such as FIRETEC (Linn et al. 2002), where little to no alteration would be required, or FDS (Mell et al. 2007), which would involve incorporating data on parameters like conductivity and emissivity. The ability to incorporate improved or alternative technologies and modeling into the next generations of L2-QF is a key feature of its design, helping it more quickly approach being a deployable tool. Prescribed fire practitioners currently have no analog to indicate how fire behavior in their forests may respond to processes that take place over broader spatial and temporal scales, and our framework provides a path to understanding these dynamics.

Conclusion

Here, we present a new tool, L2-QF, which integrates 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 use of the QUIC-Fire model requires a license agreement, L2-QF is modular and can link to other fire or fuel models that receive an inventory of tree characteristics or a voxel-based representation of fine fuels. Our demonstration highlights the ability of L2-QF to assess fire behavior and effects in response to different management and climate scenarios, providing a path for understanding the complexities of fire regimes, broader-scale ecological processes and changing fuel conditions. Through co-production efforts, particularly those associated with the Innovation Landscape Network (https://serdp-estcp.mil/page/38f0be40-b397-446f-bf1f-a401fe12423f/innovation-landscapes-network), L2-QF could be demonstrated in a collaborative environment between fire practitioners and research to further innovate this coupling. Future connections to surface fuel modeling and improved tree age estimation can move L2-QF closer to a deployable management planning tool. Ultimately, this study illustrates a promising new approach to assessing site-level fire behavior as it is more broadly impacted by landscape-level processes and disturbances, and how it can be used in fire management decision space.

Supplementary material

Supplementary material can be accessed from the article page online.

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Data availability. The L2-QF code base is now available as part of the Disturbance Response Model (DRM) code base at: https://github.com/lanl/drm-fates/tree/main/1.LANDIS-MODEL. LANDIS-II code is available at https://github.com/LANDIS-II-Foundation. LANDIS-II model parameterizations are available through https://github.com/LANDIS-II-Foundation/Project-Fort-Bragg-NC and Supplementary Material. Additional code and data used for the L2-QF demonstration are available through https://github.com/ntutland/L2-QF. Other data used in the L2-QF are available through the USFS Forest Inventory and Analysis database and are publicly available. A preprint version of this article is available at https://www.preprints.org/manuscript/202502.1796/v1.

Conflicts of interest. The authors declare they have no conflicts of interest.

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