Using remote sensing information for landscape-level, spatially explicit maps of surface fuels across forest ecosystems

White paper to address the question, "Implications for this approach to work without other types of sites/ecosystems, particularly with more diverse overstories"

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Problem statement

High-resolution (≤ 5m), spatially explicit maps of surface fuels are required to predict fire behavior, fuel consumption, emissions, and fire effects. These are key elements used to make informed decisions on wildfire suppression actions and the management of prescribed fires across large landscapes. Statistical models using predictor variables derived from remotely sensed data, particularly from airborne laser scanning (ALS) data, are commonly used to synoptically estimate forest structure attributes and canopy fuels. Nevertheless, this methodology cannot overcome several challenges to characterizing with confidence the distribution of the surface fuel loads at high spatial resolution. The infeasibility of gathering sufficient reference data to represent the full range of heterogenous conditions observed on the forest floor limits the scope and the transferability of data-driven modelling approaches (Keane, 2015; Keane et al., 2001). Both passive optical and active remotely sensed data have low sensitivity to variation in the sub-canopy layers of the forest where surface fuels accumulate, which results in less precise and accurate estimates (Table 5 of Bright et al., 2022).

In forest ecosystems, the distribution of the surface fuels comprising the fuel bed (including grasses, forbs, shrubs, downed wood, litter, and duff) is driven by the overstory. For instance, more litter and down woody debris (DWD) accumulate under tree crowns and near tree boles than in canopy gaps (Ferrari and Sugita, 1996). Relatively deeper duff (partially to fully decomposed litter) accumulations are observed near the base of large trees, especially if fire is excluded (Varner et al., 2005). Characterizing the spatial variability of trees and gaps and the canopy fuels associated with tree crowns provides a pathway to indirectly estimate loads for surface fuel components that originate from the trees (as opposed to shrubs and herbaceous fuels) and to model, in a spatially explicit manner, the inherent discontinuity of the surface fuel layer across diverse forest ecosystems (Ferrari and Sugita, 1996; Yarie, 2000).

Objective

The Objects project (RC20-1346) seeks to exploit the assumed relationship between overstory and surface fuels to develop high-resolution (5m), spatially explicit maps of tree-derived surface fuel components at the scale that tree crowns vary.

Technical approach

We follow an object-oriented approach that leverages airborne laser scanning (ALS) data and the cutting-edge forest structure information it provides (Figure 1). Trees (or tree clumps) are geographic features (i.e., objects) that can be mapped and characterized at landscape scales by integrating remote sensing, image segmentation techniques, and machine learning modeling techniques. ALS is the best remotely sensed technology available to characterize forest canopy structure from tree to stand to landscape levels (Beland et al., 2019; van Leeuwen and Nieuwenhuis, 2010). At the tree level, ALS can be used for stem mapping, individual tree crown segmentation, and retrieval of relevant crown attributes such as foliage biomass or crown bulk density (Jakubowski et al., 2013; Li et al., 2012; Rocha et al., 2023; Roussel et al., 2020; Silva et al., 2016).

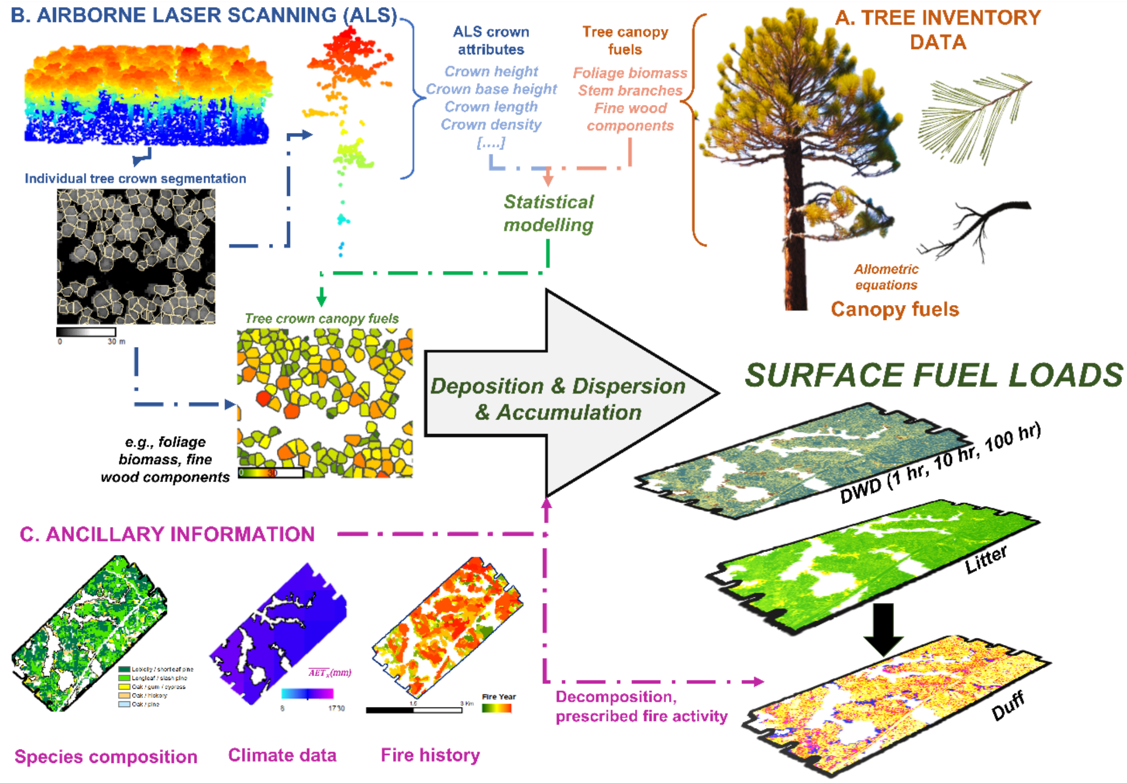

Figure 1. Objects project (RC20-1346) workflow to map tree related surface fuels, i.e., litter, down woody debris (DWD), and duff at the tree scale.

Our study sites to date are in predominantly longleaf pine forests in the southeastern US where prescribed fire is used in a frequent fire management regime to maintain the health, productivity, and diversity of southern pine forest ecosystems. We first focused on the litter component since it is often the majority contributor to surface fuel loading, followed by duff, in frequent fire-mediated longleaf pine ecosystems (Hudak et al., 2020). In these conditions, litter accumulation and its distribution over the forest floor are mainly driven by both overstory foliar biomass and by the time since the last fire. Following this, we have developed a conceptually simple yet physically based, spatially explicit model to quantify litter loads that involves two main steps: (1) modelling of annual litter production and (2) modelling of litter deposition and accumulation with time since fire (Sánchez-López et al., 2023). Current work since then is expanding this approach to estimate production, deposition, and accumulation of the woody fuel inputs to the fuel bed that constitute the 1hr, 10hr, 100hr and 1000hr components of surface fuels, and from there the duff component.

In the first step, we estimate annual tree leaf litter production using ALS data to delineate individual tree crowns and to estimate crown foliage biomass. Tree inventory data provides the foliage biomass dataset used as the response variable and crown attributes extracted from the ALS point cloud are used as predictors in a random forest model. Tree crown leaf litterfall or annual litter production, i.e., the amount of foliage biomass annually shed by the tree, is calculated as a fraction of the estimated crown foliage biomass, determined by the expected leaf longevity of the dominant species. We rasterize the outputs at high spatial resolution (5m) to simulate litter dispersion over neighboring areas using a convolution filter. In the second step, we quantify tree leaf litter accumulation through a spatially explicit implementation of the established Olson (1963) accumulation and negative decay model (Olson, 1963; Zazali et al., 2020). In this case, we use as the Olson model parameters the annual tree leaf litter production map obtained in the previous step, decomposition estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS) actual evapotranspiration product (Gholz et al., 2000; Senay and Kagone, 2019), and time since fire from history records.

Starting with its simplicity, the Sánchez-López et al. (2023) model has advantages that outperform previous methods. For instance, the model does not rely on litter biomass measurements collected in the field to derive estimates. Instead, it models foliage biomass from tree inventory data, which is more consistent, widely available, and easier to collect and in the field than litter biomass. Inventory data also has the advantage that it can be used as inputs to forest growth engines (e.g., Forest Vegetation Simulator, FVS) with growth projection capabilities. The model was tested and validated in several management and research units located in Florida, Georgia, and South Carolina, covering a large range of conditions within longleaf pine forests under frequent prescribed fire management (most often between 1-4 years return interval). Results and accuracy assessments suggest that this is a robust and transferable model (Sánchez-López et al., 2023). Therefore, within these systems and where ALS and information on prescribed management plans are available, we can provide forest managers with annual maps at 5 m spatial resolution of tree leaf litter loads.

We are expanding this framework to estimate loads of other fuel components that can be related to litter inputs (i.e., duff) or to the tree overstory canopy (i.e., DWD) (Figure 1). Estimates for these fuel components would also be estimated indirectly from remotely sensed data inputs, as was done for the litter component, albeit they will be conditioned on the litter estimates, adding one more degree of separation and hence greater relative uncertainty. We aim to calibrate these models based on logical assumptions (e.g., tree litter and DWD inputs fall beneath the tree crowns) and available literature, while using locally available field data to validate the modeled estimates.

The details described previously to model the litter component can be replicated to model the DWD components that also originate from the trees. We will estimate the amount of 1 hr, 10 hr, and 100 hr fuels in the tree crowns and model DWD fall and accumulation rates (Reinhardt, 2003); therefore, specific branch biomass models need to be trained (similarly to training the foliage biomass model). The 1000 hr fuels will accumulate as a function of tree fall rates. While these fuels might be more discontinuously distributed on the forest floor compared to the litter component, we expect to realistically estimate the loads at the unit and stand- levels.

Duff accumulates from the breakdown of litter and DWD. Longleaf pine forests develop deeper duff layers when fire is excluded, especially at the base of trees (Varner et al. 2005). Therefore, the litter and DWD maps developed at the tree scale will be used as input to model duff accumulation with different fire return intervals. We are testing some preliminary hypotheses at Osceola National Forest (Florida). The area consists of winter experimental burn units within flatwood pine communities that are part of the long-term fire experiment that was first established in 1958 in a randomized block design to evaluate different fire return interval effects on fuel accumulation. This is an exceptional opportunity to test our modelling approach because of the experimental design and because both ALS data and field data consisting of duff measurements are available. In a first analysis, we used the litter production maps obtained from the Sánchez-López et al. (2023) model as the input, assumed that a percentage of the litter is annually decomposed and incorporated into the duff layer, and that another percentage is removed from the pool when prescribed fire is performed (Figure 2).

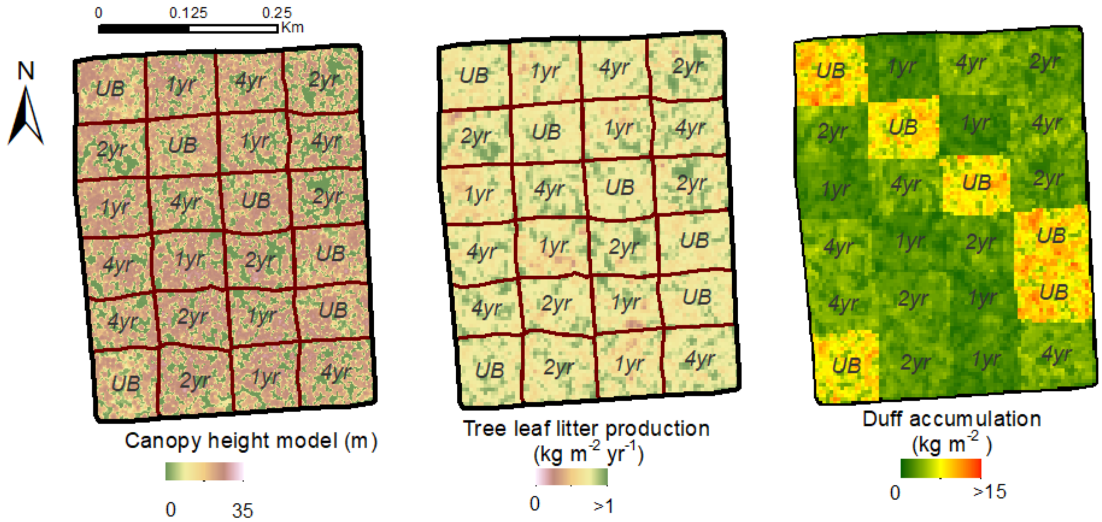

Figure 2. Research units maintained at 1yr, 2yr, or 4yr fire return intervals, and unburnt units (UB) at Osceola National Forest (ONF). The canopy height model derived from airborne laser scanning (ALS) is displayed in the background (left), the annual tree leaf litter production (center) as per Sánchez-López et al. (2023), and simulated duff accumulation (right) based on preliminary analysis.

Surface fuel modelling in other forest types

The Sánchez-López et al. (2023) approach just described aligns with our strategic goal to apply this model in other forest ecosystems dominated by different tree species in different environmental conditions. With that goal in mind, some of the model inputs consisted of available remote sensing-based products for the conterminous US. For instance, a forest type group map at 30 m resolution (Wilson and Emily, 2021) was used to assess the expected leaf longevity of the dominant species and estimate litterfall; and an actual evapotranspiration product derived from MODIS (Senay and Kagone, 2019) was used to estimate decomposition of leaf litter (Gholz et al., 2000). This provides strategic advantages to apply the model in other forest ecosystems at large scale since the same datasets are available nationally. Nevertheless, some adjustments are undoubtedly required to implement the model in sites with more diverse overstories and species compositions, and additional factors related to the forest type that influences both deposition patterns and decomposition need to be carefully addressed.

Classifying individual tree crowns into functional types (e.g., conifers, evergreen, or deciduous broadleaf) from available remotely sensed datasets is feasible and would facilitate the spatially explicit representation of different canopy-derived fuel components (e.g., litter and DWD) and the refinement of the foliage and branch biomass random forest models by vegetation functional types and by climatic regions, thus enabling its use more confidently in other ecosystems dominated by deciduous or mixed species.

Spatially explicit maps of litter and DWD typology will enhance the assessment of the ecological processes driving fuel deposition and accumulation. Litterfall rates could be updated for each crown based on the expected leaf longevity associated with each functional type rather than on the predominant species of the site defined by a 30 m map. A better assessment of decomposition also will be possible, as this process is highly influenced by litter type (Bezkorovaynaya, 2005; Keane, 2008; Krishna and Mohan, 2017; Prescott, 2002). Needle cast has different chemical composition (e.g., lignin content), physical properties (e.g., specific area), and nutrient content compared to leaves from deciduous species, which influences decomposition. In Sánchez-López et al. (2023), we estimated decomposition through a linear model developed for pine needles as part of the Long Intersite Decomposition Experiment (LIDET) (Gholz et al., 2000). In this regard, we could similarly implement the decomposition models developed for deciduous leaves in sites dominated by deciduous species.

Figure 3. Unburnt patch under a large live oak after prescribed fire at Eglin AFB (March 2022).

Besides that, spatially explicit fuel bed type maps are key to capture fine scale fire effects. For instance, mesic oaks in open pine woodlands provide a negative feedback on fire behavior which may result in unburned patches (Whelan et al., 2021) (Figure 3). These spatially explicit maps will facilitate the assessment of the relative importance of local variation in fine fuel loads relative to fire direction and how that influences heat release. While there are available sources of information on fuel bed types, such as the Fuel Characteristic Classification System (FCCS) fuel bed type maps published by LANDFIRE, the higher resolution provided by lidar-based modelling approaches will facilitate the assessment of the relative importance of local variation in fine fuel loads relative to fire direction and how that influences heat release, for instance. From the methodological standpoint, multispectral imagery at high spatial resolution (e.g., Worldview imagery, which were acquired at our Objects project burn sites) can provide the information required to perform tree functional type classification at the crown level (Immitzer et al., 2012). Note that our approach relies on ALS data for the delineation of the individual tree crowns and for retrieving the crown attributes used as covariates on the random forest model. Vegetation and spectral indices can be retrieved at the individual tree crown level and be used as additional predictors for both classifying the crowns of specific vegetation functional types and for re-training the random forest models of foliage biomass. Imagery is already available at some of the study sites such as Ft Stewart, which we will designate as a preliminary testing site.

On another note, leaf-dispersal models developed from field observations can improve the representation of the spatial array of leaves and needles over the forest floor. Our simplified dispersion framework is based on a convolution filter with a 3x3 kernel size that evenly distributes litter in neighboring areas and assumes that most of the litter remains under the tree crown. However, there might be an anisotropic distribution of litter driven by wind direction during leaf abscission. Leaf dispersal parameters derived either mechanistically (McDanold et al., 2023) or empirically from data and neighborhood models (Blaydes et al., 2022) could be converted to convolution filter parameters to simulate dispersion by our approach.

Outside of the study sites, Forest Inventory and Analysis (FIA) tree data can provide the unbiased measurements needed to define the relationships between these surface fuel components and overstory crown biomass. FIA provides a systematic, design-based sampling framework that permits unbiased estimation of forest and fuel attributes predicted from models trained using FIA plot data; for instance, to train models that inform the relationship between foliage canopy loads and litter surface loads, or canopy bulk density and DWD loads. Using FIA data will also contribute to the implementation of the proposed approach in forest sites with more diverse overstory communities.

Conclusion and Next Steps

The framework presented herein combines remotely sensed and field datasets within a conceptual framework. This innovative approach allows us to blend our knowledge of ecological concepts associated with the fuel accumulation process with state-of-the-art modeling techniques, including machine learning. Through the utilization of ALS data, we are already able to provide forest managers with annual updates on litter loads in longleaf pine forests throughout the southeastern region of the United States. Furthermore, this framework presents exciting possibilities for additional applications, such as the precise simulation of surface fuels in synthetic forests using tools like FastFuels. Ultimately, our objective is to generate landscape-level, high-resolution, spatially explicit maps of surface fuels that deliver realistic surface fuel load estimates, furnishing foresters with valuable insights to support their management objectives effectively.

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13. SUPPLEMENTARY NOTES

14. ABSTRACT
The first objective of this project was to develop an online data archive of high-resolution climate model projections for North America from the CORDEX program as a resource for research and decision-making communities concerned with climate impacts and adaptation, including those operating and managing military installations at different organizational levels. This archive provides easy access to high-quality, well-vetted future climate information for variables of interest to end-users at spatial and temporal resolutions needed for different decision-making contexts.
An additional objective of the project was to perform regional process-oriented evaluations of the model outputs in selected regions, in order to provide appropriate guidance for proper usage of the data, demonstrate appropriate methodologies for performing such evaluations, and advance the state of the art of those methodologies and scientific understanding of the issues evaluated. These analyses are based on an approach established in previous scientific work (Bukovsky, et al., 2013, 2015) of determining the drivers of phenomena that govern climate impacts of interest and evaluating those to understand whether projected changes are credible.
Finally, the last objective of the project was to apply the "Perfect Model" (PM) evaluation framework to popular statistical downscaling (SD) and bias correction technique using data from the archive in order to evaluate whether the assumptions underlying those technique hold under conditions of climate change. In this framework, high resolution climate model outputs are used as a proxy for observations from the future in order to evaluate whether the statistical relationships between model outputs and observations used in these techniques remain applicable as climate changes.

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