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A spatially explicit model of litter accumulation in fire maintained longleaf pine forest ecosystems of the Southeastern USA

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Keywords

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Abstract

The continuity and depth of the surface litter and duff layers are major drivers of fire spread and fuel consumption. Nevertheless, its spatially explicit quantification over relatively large areas remains unresolved: local fuel heterogeneity introduces large uncertainties in estimates derived from field-based models and sparse data samples. Besides that, the sensitivity of remote sensors to surface litter loads is limited, particularly under canopy cover. In fire-maintained pine forests of the Southeastern US, surface fuel accumulation and its distribution over the forest floor are mainly driven by vegetation productivity, decomposition, and years since fire (YSF). Traditional ecological and stand-level models provide a means to equilibrate between opposing rates of deposition and decomposition as a function of YSF at the landscape level but don't account for spatial heterogeneity.

We developed a top-down, object-based approach for wall-to-wall estimation of surface litter loads using TSF records, the ecologically based Olson model, and tree crown objects derived from airborne laser scanning (ALS) data. The approach involves, first, the spatially explicit estimation of litter production through a tree crown production model. This model is driven by tree crown attributes extracted from the ALS point clouds, and it is informed by tree inventory data and allometric equations, including vegetation leaf turnover rates. Second, litter accumulation is estimated using the fire-driven Olson equation, which models accumulation progressively with time until decomposition balances deposition and a steady state of accumulation is reached. The methodology is demonstrated at several fire-maintained longleaf pine forest management units in southeastern USA, where tree inventory data, surface litter loads, prescribed fire records, and ALS data are available for testing and validation of the methodology. Comparison between modeled estimates and observed litter loads shows a relatively good agreement (RMSD=0.24 [kg m-2]; BIAS 0.004 [kg m-2]). This suggests that the proposed approach to indirectly map patterns of litter production and litter accumulation can provide a realistic means to map the continuity of the litter layer, thus overcoming the limitation of traditional ecological landscape models to account for spatial heterogeneity. This high-resolution map of litter loads will be further valuable as input to physics-based fire behavior and spread models and to improve the spatially explicit characterization of the duff layer.

1. Background and goals

High spatial resolution maps of surface fuels are critically needed by the carbon and fire communities, being especially relevant for forest managers that operationally use prescribed fires to maintain forest health and wildlife habitat in the longleaf pine forests of the southeastern US. Unfortunately, such maps are missing for most forested sites: the sensitivity of remote sensors to surface litter loads is limited, particularly under canopy cover, and the high heterogeneity of surface fine fuels and the lack of enough reference data (i.e., field measurements) limits the scope of data-driven modelling techniques (Keane, 2015; Keane et al., 2001).

In these longleaf pine forests, surface fuel accumulation and its distribution over the forest floor are mainly driven by vegetation productivity, decomposition, and years since fire (YSF) (López-Senespleda et al., 2021; Prescott, 2002; Zazali et al., 2020). Traditional ecological models such as the Olson model (Olson, 1963) provide a means to equilibrate between opposing rates of deposition and decomposition as a function of TSF at the landscape level but generally don't account for spatial heterogeneity.

In the absence of disturbances at a specific location (e.g., under a specific tree crown), litter accumulates proportionally to the foliage biomass (FB) produced aboveground and deposited on the ground as litterfall until it decomposes into duff (Zazali et al., 2020). Therefore, characterizing the spatial variability of FB driven by the forest canopy would provide a means to describe surface fuel dynamics at the tree-level scale. Nowadays, remote sensing, and particularly airborne laser scanning (ALS) data, provides the most practical means to characterize tree aboveground biomass across entire forest landscapes at high spatial resolution, as shown in the many studies on tree detection and crown delineation, and on modelling tree attributes including height, volume, and/or biomass (e.g, Chen et al., 2007; Hudak et al., 2008; Jakubowski et al., 2013; Li et al., 2012; Roussel et al., 2020; Silva et al., 2016; Wan Mohd Jaafar et al., 2018).

In this study, we propose an object-based approach to map litter loads at high spatial resolution by mapping patterns of tree leaf litter production (i.e., litterfall) and quantifying litter accumulation through time with a spatially explicit implementation of the Olson model. This approach assumes that, locally, the amount and distribution of litter over the forest floor are mainly driven by litter production, i.e., by aboveground biomass and canopy characteristics (López-Senespleda et al., 2021; Prescott, 2002), and that due to the overstory inputs, litter loads are higher under trees than in gaps and edges.

2. Materials

The methodology was tested in three forest management units (i.e., 608A, 703C, L2F) at Eglin Air Force Base (AFB) in the panhandle of Florida (Figure 1). These sites undergo frequent prescribed burning that serves to maintain the native wildlife of the predominant longleaf pine ecosystem and facilitate military training.

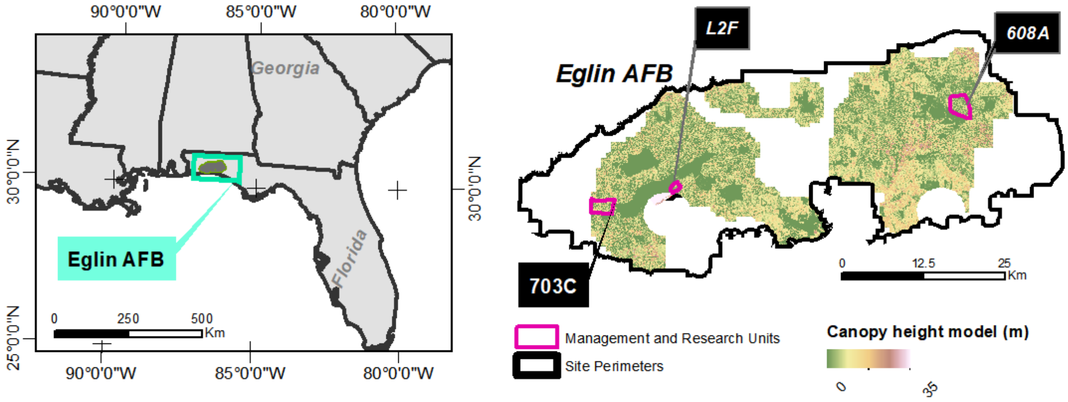

Figure 1. Location of the L2F, 608A, and 703C management units at Eglin Air Force Base (AFB). The canopy height model derived from airborne laser scanning (ALS) is displayed as background where ALS data is available.

ALS data were acquired in 2018 and points clouds were delivered by the provider in binary format (.las) with ground points labeled. The point cloud was normalized, converting points to height above ground, and a canopy height model (1-meter spatial resolution) was created.

A total of 166 litter biomass samples within the three management units were collected over square litter clip plots (0.25-1 m^2) in the framework of the RXCADRE project (2008-2012) (Ottmar et al., 2015) (Table 1, Figure 2). These data were used for accuracy assessment of the proposed methodology.

Table 1. Number of field clip plots, and minimum, mean, maximum, and standard deviation of the litter biomass (LB) [kg m^{-2}]. YSF: years since fire in the management unit at the time of the data collection.

Units	**Sampling Year**	**YSF**	**# samples**	**Min LB** [kg m^{-2}]	**Mean LB** [kg m^{-2}]	**Max LB** [kg m^{-2}]	**Std Dev.** [kg m^{-2}]
L2F	2012	3	66	0.04	0.48	1.27	0.31
608A	2011	2	60	0.05	0.34	0.75	0.15
703C	2011	2	40	0.07	0.33	0.72	0.16

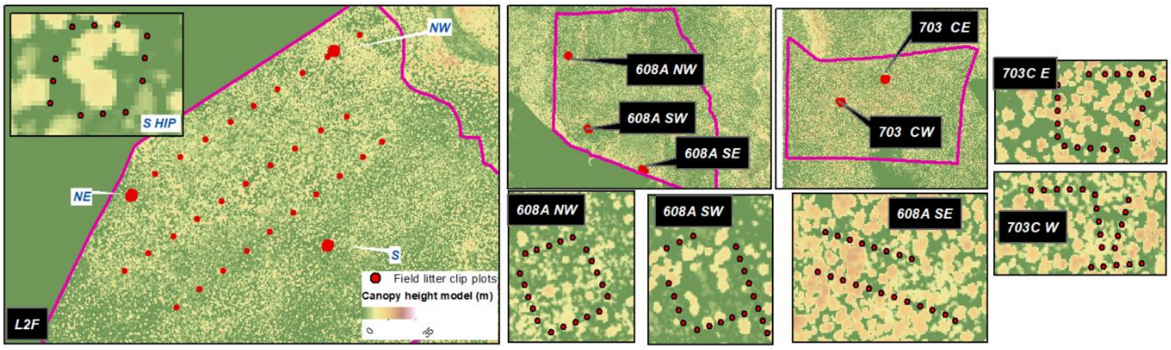

Figure 2. Location of the 166 litter clip plots established in 2011 and 2012 within the L2F, 608A, and 703C units at Eglin AFB.

3. Methods

Our proposed methodology involves the spatially explicit estimation of annual litter production following a biomass abundace approach in which littefall is proportionally estimated from tree FB. FB is modelled at the crown level from ALS data and random forest (RF) modelling, and informed by tree inventory data. Litter production maps are rasterized (5 m) and used, together with decomposition rates, to quantify litter accumulation after fire with a spatially explicit implementation of the Olson model (Figure 3).

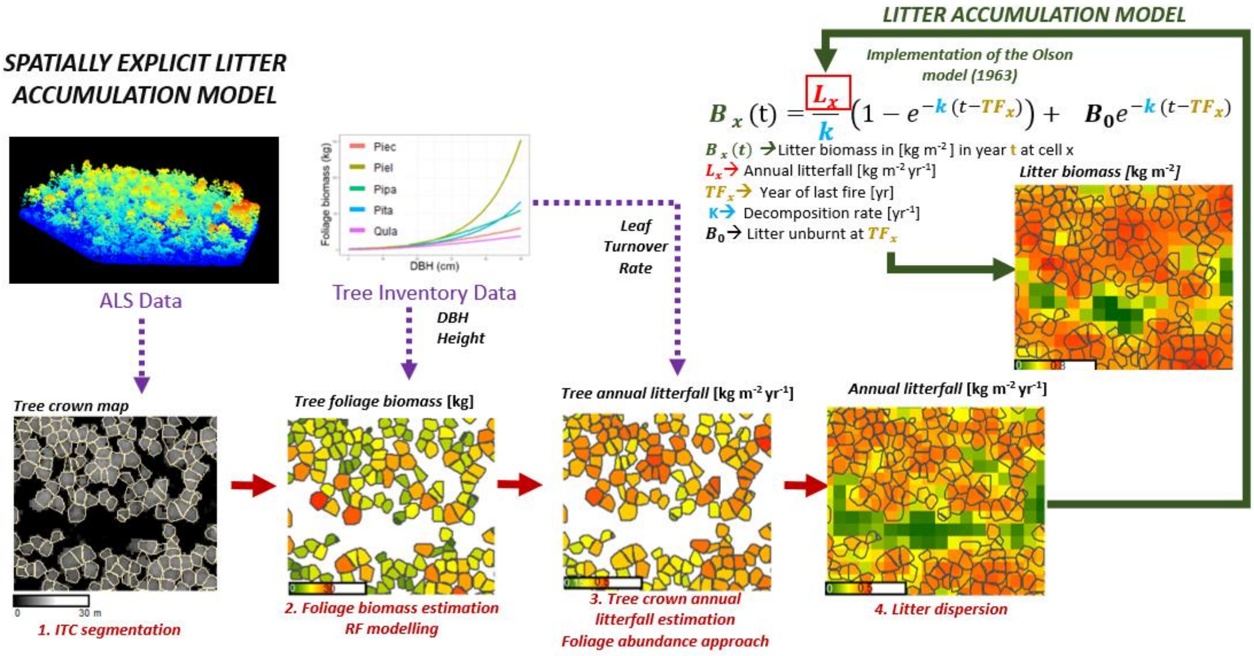

Figure 3. Workflow of the spatially explicit model of litter accumulation based on a tree crown-level litter production model.

3.1. Litter Production model

The spatially explicit estimation of litter production involves four processing steps: (1) generation of a tree crown map through segmentation of the ALS data, and computation of tree crown attributes also from the ALS data; (2) estimation of the total foliar biomass of each tree crown, by applying a RF model; (3) estimation of annual litterfall at the crown level following a FB abundance approach; and (4) annual litterfall distribution over the forest floor using a convolution filter (Figure 3).

Individual tree crown delineation was performed on the ALS canopy height model applying Silva's tree segmentation algorithm (Silva et al., 2016). A set of attributes was obtained for each crown from the 3D point cloud, and a RF model (Breiman, 2001) was calibrated to estimate crown FB. We used tree field inventory data to determine FB from dbh-height allometric equations. These FB estimates were used as the response variable in the RF model, and the corresponding crown attributes were used as the predictor variables.

Once FB was estimated at the crown level, litterfall was proportionally estimated from tree FB applying leaf turnover rates that were based on leaf longevity of the dominant species observed in the study area (Neumann et al., 2018; White et al., 2000). Estimates of litterfall from tree crowns were rasterized and mapped at 5 m spatial resolution which approximates the size of the dominant tree crown in this ecosystem. Finally, to consider a dispersion rate of litterfall from the tree driven by external factors such as topography or weather, a convolution filter was applied.

3.2. Litter Accumulation

Total litter accumulation after fire was calculated through a spatially explicit implementation of the Olson model (Eq. 1):

$$B_x(t) = \frac{L_x}{k}\left(1 - e^{-k_x(t-TF_x)}\right) + B_0 e^{-k_x(t-TF_x)} \qquad (Eq. 1)$$

where $B_x(t)$ [kg m^{-2}] is litter biomass accumulated in a cell x in year t; L_x is the steady annual accumulation rate, i.e., annual litter production or litterfall [kg m^{-2} yr^{-1}]; TF_x is the year of the last fire in a cell x; k is the decomposition rate in a cell x [yr^{-1}]; and B_0 is litter remaining after the previous burn [kg m^{-2}]. Based on the post fire litter samples collected at Eglin AFB, B_0 was established at 0.04 [kg m^{-2}] (Ottmar et al., 2015).

Climate and litter quality (e.g., percentage of lignin) and litter traits (e.g., leaf area) are main drivers of decomposition (Berg, 2014; Gholz et al., 2000; Meentemeyer, 1978). The dominant species on the study sites was longleaf pine. Accordingly, decomposition was calculated applying the single regression model calibrated for pine needles as part of the Long-term Intersite Decomposition Experiment (LIDET) that uses actual evapotranspiration (AET) as the only predictor variable. AET was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) derived product available at https://earlywarning.usgs.gov (accessed on 9th of September 2021) (Senay et al., 2013).

The model was run for 2 YSF at the 703C and 608 A units, and for 3 YSF at the L2F unit, with YSF calculated at the time of the field data collection (Table 1).

3.3. Model assessment

Accuracy assessment was performed by comparing the litter loads observed at each of the 166 litter clip plots (Figure 2) with the predicted litter loads on the litter accumulation map. Model accuracy was evaluated using Root Mean Square Difference (RMSD) and BIAS statistics:

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2}{n}} \qquad (Eq. 2)$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right) \qquad (Eq. 3)$$

where n is the number of field litter clip plots, Y_i is the observed litter biomass for a given clip plot *i*, and $\hat{Y}_i$ is the predicted litter biomass corresponding with the cell value spatially intersecting the center of the field litter clip plot.

4. Results

The average litter production at the 608A, 703C, and L2F units was 0.13, 0.18, and 0.17 [kg m^{-2} yr^{-1}] respectively (Figure 4).

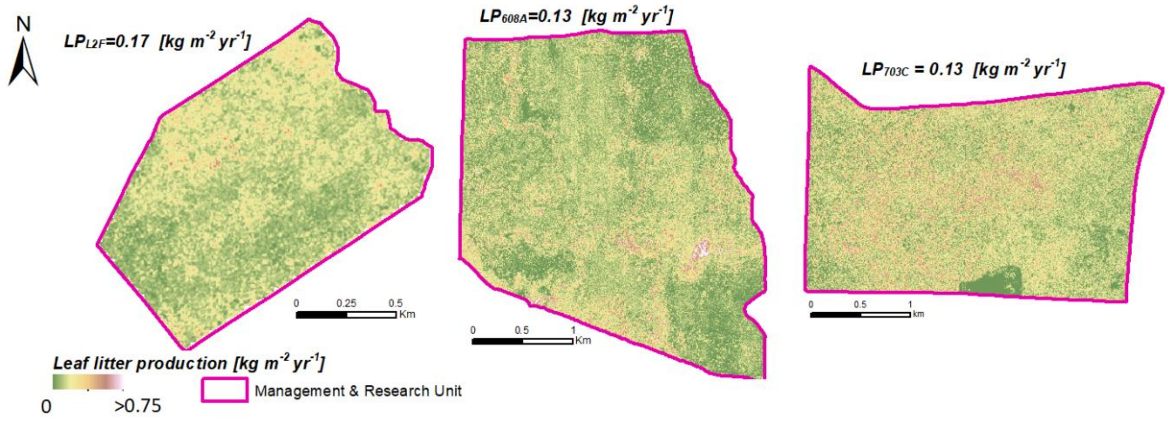

Figure 4. Annual litterfall [kg m^{-2} yr^{-1}] at the L2F, 608A, and 703C management units.

Average actual evapotranspiration within Eglin AFB was 714 mm, and the average decomposition rate was 0.13 [kg yr^{-1}]; therefore, the expected time necessary to reach 90% of the accumulation based on the Olson model was ~17 years. Average estimated litter loads at the L2F unit after 3 YSF was 0.38 [kg m^{-2}], and 0.26 and 0.35 [kg m^{-2}] at the 608A and 703C units after 2 YSF (Figure 5).

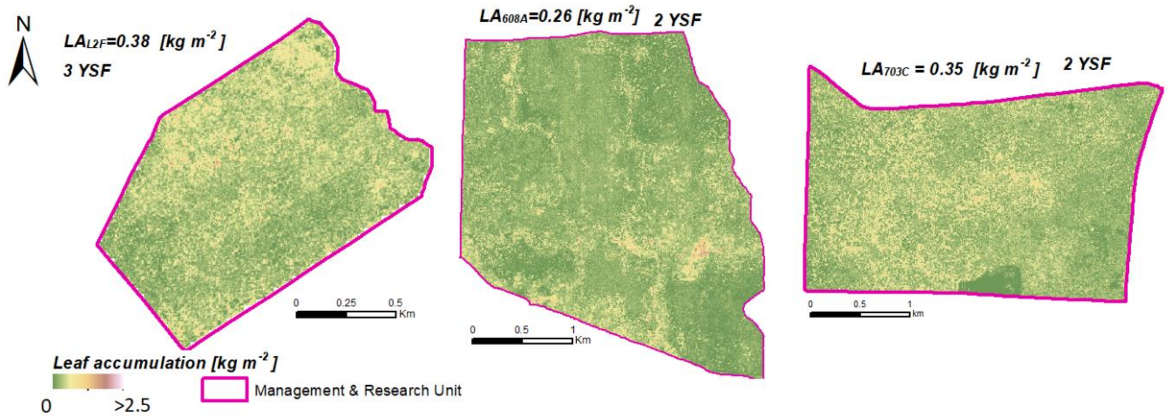

Figure 5. Litter loads at the 608A and 703C management units after 2 years since fire and after 3 years at L2F unit.

Table 2. R Pearson's correlation (R), RMSD, and BIAS of the litter biomass observed (Y_i) in the clip plots (0.25-1 m^2) sampled pre-fire at the L2F, 608A, and 603C units and the estimated ($\hat{Y}_i$) litter biomass corresponding with the cell value spatially intersecting the center of the field litter clip plot (0.25-1 m^2); n indicates the number of clip plot measurements evaluated at each time

Unit	**n**	$\frac{1}{n}\sum_{i=1}^{n}(Y_i)$ **[kg m^{-2}]**	$\frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i)$ **[kg m^{-2}]**	**R**	**RMSD [kg m^{-2}]**	**BIAS [kg m^{-2}]**
L2F	66	0.48	0.43	0.58	0.27	-0.05
608A	60	0.34	0.35	0.63	0.20	0.01
703C	40	0.33	0.42	0.32	0.24	0.09

Overal RMSD and BIAS were 0.24 and 0.004 [kg m^{-2}]. By unit, RMSD and BIAS were 0.27 and -0.05 [kg m^{-2}] at the L2F unit, 0.20 and 0.01 [kg m^{-2}] at the 608A unit, and 0.24 and 0.09 [kg m^{-2}] at the 703C unit. Accuracy assessment revealed a moderate R Pearson correlation between predicted ($\hat{Y}_i$) and observed (Y_i) litter loads (R=0.52) (Figure 6), which was expected given the large variability observed on the field data (Table 1). The correlation was higher at the L2F and 608A units (R=0.63, and 0.58) compared to the 703C (R=0.32), where the number of field samples was lower (n=40) (Table 2).

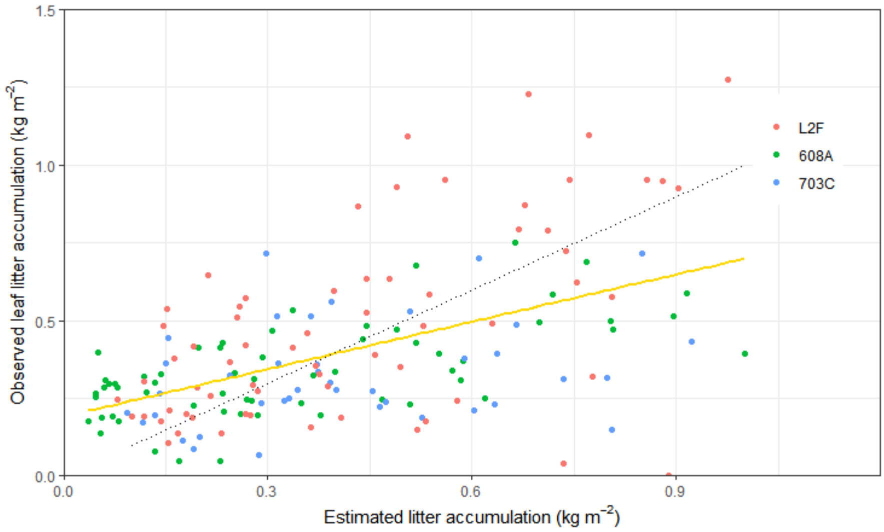

Figure 6. Litter biomass observed on the 166 litter clip plots (0.25-1 m^2) sampled pre-fire at Eglin AFB (y axis) and estimated litter biomass corresponding with the cell value of the litter accumulation map (25 m^2) spatially intersecting the center of the field litter clip plot (x axis). In each case, the spatially explicit implementation of the Olson's model was run for the same YSF observed on the units at the time of the data collection. The yellow line represents the best fit of the linear model between estimated and observed values, and the grey dashed line represents the 1:1 relationship.

5. Discussion

We mapped litter accumulation at high spatial resolution (5 m), developing a conceptual approach to estimate annual litterfall patterns at the tree level using 3D remotely sensed data and using the fire-driven Olson accumulation model to subsequently estimate litter loads. Our results support our initial hypothesis that, on these frequently burned forest ecosystems and up to 3 YSF, tree leaf litter accumulation and its distribution over the forest floor are mainly driven by tree foliar biomass and YSF, as indicated by the relatively good agreement between predicted and observed accumulated litter loads (R=0.52) (Figure 6). While it is a moderate correlation, it is relevant considering the large heterogeneity of litter loads observed over the forest floor at the local scale (Table 1), and the difference in size of the litter clip plots (0.25-1 m^2) and the pixel size of the leaf litter map (25 m^2).

The methodology can be transferred to other study sites and ecological regions where ALS data and the time since fire are known. Nevertheless, further research is needed to assess the performance on the model over a longer term (> 3 YSF). Our methods provide a realistic means to map the continuity of the litter layer conditioned on overstory tree crowns, thus overcoming the limitation of traditional ecological landscape models to account for spatial heterogeneity. This high-resolution map of litter loads will have further value as input to physics-based fire behavior and spread models and to improve the spatially explicit characterization of the duff layer.

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