Lin et al. Fire Ecology (2024) 20:58
https://doi.org/10.1186/s42408-024-00287-7

Fire Ecology

ORIGINAL RESEARCH

Open Access

Use of airborne LiDAR to predict fine dead fuel load in Mediterranean forest stands of Southern Europe

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Abstract

Background Mediterranean forests are increasingly threatened by wildfires, with fuel load playing a crucial role in fire dynamics and behaviors. Accurate fuel load determination contributes substantially to the wildfire monitoring, management, and prevention. This study aimed to evaluate the effectiveness of airborne Light Detection and Ranging (LiDAR) data in estimating fine dead fuel load, focusing on the development of models using LiDAR-derived metrics to predict various categories of fine dead fuel load. The estimation of fine dead fuel load was performed by the integration of field data and airborne LiDAR data by applying multiple linear regression analysis. Model performance was evaluated by the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE).

Results Through multiple linear regression models, the study explored the relationship between LiDAR-derived height and canopy cover metrics and different types of fine dead fuel load (1-h, 10-h, 100-h fuel loads, and litter). The accuracy of these models varied, with litter prediction showing the highest accuracy (R^2 = 0.569, nRMSE = 0.158). In contrast, the 1-h fuel load prediction was the least accurate (R^2 = 0.521, nRMSE = 0.168). The analysis highlighted the significance of specific LiDAR metrics in predicting different fuel loads, revealing a strong correlation between the vertical structure of vegetation and the accumulation of fine dead fuels.

Conclusions The findings demonstrate the potential of airborne LiDAR data in accurately estimating fine dead fuel loads in Mediterranean forests. This capability is significant for enhancing wildfire management, including risk assessment and mitigation. The study underscores the relevance of LiDAR in environmental monitoring and forest management, particularly in regions prone to wildfires.

Keywords Fuel load prediction, LiDAR, Forest, Fuel management, Wildfire regression model

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Resumen

Antecedentes Los bosques del Mediterráneo están siendo crecientemente amenazados por incendios forestales, con los combustibles finos jugando un rol crucial en la dinámica del fuego. Este estudio tiene por objetivo evaluar la efectividad de datos del LiDAR (Light Detection and Ranging), para estimar los combustibles finos muertos dentro de esos ecosistemas. EL foco estuvo puesto en el desarrollo de modelos usando medidas derivadas del LiDAR para predecir varias categorías de carga de combustible fino muerto, crucial para entender y manejar el riesgo de incendio. La estimación de la carga de combustible fino muerto fue realizada mediante la integración de datos de campo y de datos LiDAR, aplicando un análisis de regresión linear múltiple. La performance del modelo fue evaluada mediante el coeficiente de determinación (R2), la raíz del error cuadrático medio (RMSE) y el error medio absoluto (MAE).

Resultados A través de modelos de regresión múltiple, este estudio exploró las relaciones entre medidas de altura y cobertura del dosel derivadas del LiDAR y diferentes tipos de carga de combustibles muertos (de 1 h, 10 h, 100 h, y 1000 h, y mantillo o broza). La exactitud de esos modelos varió, con la predicción de la broza dando la exactitud más alta ((R^2 = 0.569, nRMSE = 0.158). En contraste, la predicción de los combustibles de 1 h fue el menos exacto (R^2 = 0.521, nRMSE= 0.168). El análisis subrayó la significancia de las medidas del LiDAR en la predicción de las diferentes cargas de combustibles, revelando una fuerte correlación entre la estructura vertical de la vegetación y la acumulación del combustible fino muerto.

Conclusiones Los resultados demuestran el potencial de los datos LiDAR en la estimación exacta de las cargas de combustibles finos muertos en los bosques mediterráneos. Esta capacidad es significativa para mejorar el manejo del fuego incluyendo la determinación y mitigación del riesgo. El estudio subraya la relevancia del LiDAR en el monitoreo y manejo de bosques, particularmente en regiones proclives al fuego.

Background

Over the past decades, the frequency and severity of wildfires have been increasing throughout the Europe (Cardíl et al. 2023; Nolè et al. 2022; Regos et al. 2023; Vieira et al. 2023). The consequences of wildfire have a significant impact on ecosystems, resulting in soil degradation and greenhouse gas emissions (Gajendiran et al. 2024). Therefore, early fire prevention and suppression are urgently required. Fuel load is the critical factor in assessing fire characteristics such as flame length, fuel consumption, and severity and is also an essential input for fire behavior models (Li et al. 2021). Generally, fuel load, defined as the fuel dry mass per unit area, quantifies the amount of both live and dead biomass available for ignition and combustion (Alonso-Rego et al. 2020). It is considered a key characteristic of fuel and is the only component related to fire that can be modified (Gale et al. 2021). Furthermore, fuel load plays a crucial role in assessing the carbon cycle and predicting fire emissions (Jiménez et al. 2013; Lasslop and Kloster 2015). Therefore, accurately estimating fuel load on forest floors is essential for effective fuel management and wildfire prevention to mitigate wildfire's adverse effects.

However, quantifying the forest fuel load is challenging due to its spatial and temporal variability (Lydersen et al. 2015). Traditional fuel load estimation methods are mainly based on field surveys, which are labor-intensive, time-consuming, and limited in spatial coverage (D'Este et al. 2021; Stefanidou et al. 2020). Therefore, exploring alternative methods for fuel load estimation becomes crucial.

Remote sensing technology has been widely used to estimate fuel load as it offers numerous benefits over field-based approaches of fuel load assessments, including the ability to provide high-resolution data and cost efficiency over large areas in remote or inaccessible regions (Gale et al. 2021). A great variety of previous studies have attempted to use passive remote sensors to estimate the fuel loads (Jin and Chen 2012; Franke et al. 2018; Santos et al. 2023). For example, Arellano-Pérez et al. (2018) used multispectral Sentinel-2 to estimate surface fuel load in even-aged pine stands in northwest Spain (12% of accuracy). Li and He (2022) combined optical data (Landsat 7 ETM+) and spaceborne synthetic aperture radar data to estimate above-ground live forest fuel loads in northern Sweden using a semi-empirical retrieval model, achieving reasonable performance with 64% or higher accuracy. Li et al. (2021) employed satellite data including Landsat Enhanced Thematic Mapper Plus (ETM +) and Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band Synthetic Aperture Radar (PALSAR) data to estimate the above-ground forest fuel loads in Sweden. The models demonstrated high accuracy, with performance ratings of 76% for stem fuel load, 81% for branch fuel load, and 82% for foliage fuel load.

Other authors (Labenski et al. 2023; Urbazaev et al. 2018), recently, have emphasized some limitations of the passive remote sensors as they are poorly capable of providing estimates for each horizontal and vertical fuel layer of the forest stand. In this regard, active remote sensors, such as the Light Detection and Ranging (LiDAR) scanners can fill these gaps by actively capturing three-dimensional information of vegetation layers (Giannico et al. 2016). Several previous studies have examined the potential of LiDAR data in fuel load estimation (Alonso-Rego et al. 2020; Chen et al. 2017; Heisig et al. 2022; Hudak et al. 2016; Lin et al. 2021; Mauro et al. 2021; Price and Gordon 2016). Lopes Queiroz et al. (2020) demonstrated a novel approach that using optical imagery combined with an infra-canopy vegetation-index layer from multispectral aerial LiDAR to estimate and map coarse woody debris in Alberta's boreal forest, with a coefficient of determination (R^2, the proportion of the variation in the dependent variable that is predictable from the independent variable) value of 62% and a root mean square error (RMSE, the quadratic mean of the differences between the observed values and predicted ones) of 0.224 compared to field data. Marino et al. (2022) used low-density LiDAR point cloud data to estimate main canopy fuel attributes such as canopy base height, canopy fuel load, and bulk density in a pine-dominated forest in Spain, with an adjusted R^2 of 68% and RMSE of 0.14. Bright et al. (2022) combined multitemporal airborne LiDAR and Landsat-derived fire history metrics to predict and map canopy and surface fuels across the landscape of the northern Arizona in the USA, with the R^2 of 50%, 39%, 59%, and 48% for canopy fuel, 1- to 1000-h fuels, litter and duff, and total surface fuel, respectively. However, few previous studies have specifically focused on fine dead fuel load estimation using airborne LiDAR data. Fine dead fuel load significantly influences the occurrence and behavior of wildfires (Zhang and Tian 2024). Due to its low moisture content, fine dead fuel load dries out quickly, facilitating the easy ignition and rapid spread of wildfires. Therefore, fine dead fuel load is considered as the primary source of ignition and propagation of wildfires (Nguyen et al. 2024). Thus, an accurate assessment of fine dead fuel load is crucial for effective wildfire management, as well as for ecological and environmental considerations.

To address the literature gap in the use of airborne LiDAR for fine dead fuel load prediction, the main objective of this research was to investigate the potential use of airborne LiDAR in predicting four different fine dead fuel load parameters (i.e., 1-h, 10-h, and 100-h fuel load, litter) in the Mediterranean forest. We employed multiple linear regression analysis to examine the contribution of vegetation vertical structure metrics obtained from airborne LiDAR to the reliable prediction of each individual fine dead fuel load type in the Apulia region of southern Italy, where is strongly affected by wildfires. This study intends to increase the ability to regularly estimate fine dead fuel load across large areas by using LiDAR-derived metrics, which would benefit to the fire risk assessment and fuel load management.

Method

Study area

The Apulia region, situated in southern Italy's peninsular area, lies between 39°50′ and 41°50′ N latitude and 15°50′ and 18°50′ E longitude (Fig. 1). Encompassing 19,345 square kilometers, the region is divided into six provinces. The region's orography consists of 53% plain, with hills and low mountains in the northwest, where the highest point reaching 1155 m above sea level. The climate is typically Mediterranean with hot, dry summers and mild, rainy winters. The annual mean rainfall varies between 450 mm and 650 mm. The mean annual temperature ranges from 12 °C in mountainous areas to 19 °C in southern coastal areas (D'Este et al. 2021).

Forests in the Apulia region are mainly represented by various tree species including *Quercus ilex* L., *Q. pubescens* Willd, *Q. cerris* L., *Q. coccifera* L., *Carpinus betulus* L., *Carpinus orientalis* Mill, *Fagus sylvatica* L., *Pinus halepensis* L., *Pinus pinea* L., *Phillyrea* spp., *Ruscus aculeatus* L., *Pistacia lentiscus* L., *Asparagus acutifolius* L., *Cistus monspeliensis* L., *C. incanus* L., *C. salvifolius* L., *Fraxinus ornus* L., *Prunus spinosa* L., and *Paliurus spina-christi* Mill (Elia et al. 2015).

According to the European Forest Fire Information System (EFFIS) annual fire reports, from 2011 to 2022, over 50,000 hectares were burned in more than 4500 recorded fire events in the Apulia region. Typically, fire season occurs from May to September, with a significant increase in fire events peaking in August. Apulia is among the Italian regions that the most frequently affected by wildfires. For this reason, we selected the Apulia region as the pilot area for our study.

Field Data

The field data were collected during 2018 and 2019. 104 plots across the Apulia region were randomly selected to assess the fine dead fuel load. The sample areas identified in Apulia present different forest formations including coniferous forest, broadleaf forest, mixed forest, areas with Sclerophyllous vegetation, and areas with bushes and shrubs.

Fuel load sampling was conducted using the method developed by the US Department of Agriculture Forest Services (Brown et al. 1982). The field sampling protocol is demonstrated in Figs. S1 and S2. Firstly, circular plots with a diameter of 10 m each were identified using GPS-registered geographical coordinates. Within each plot, a 15-m transect length was established to sample the

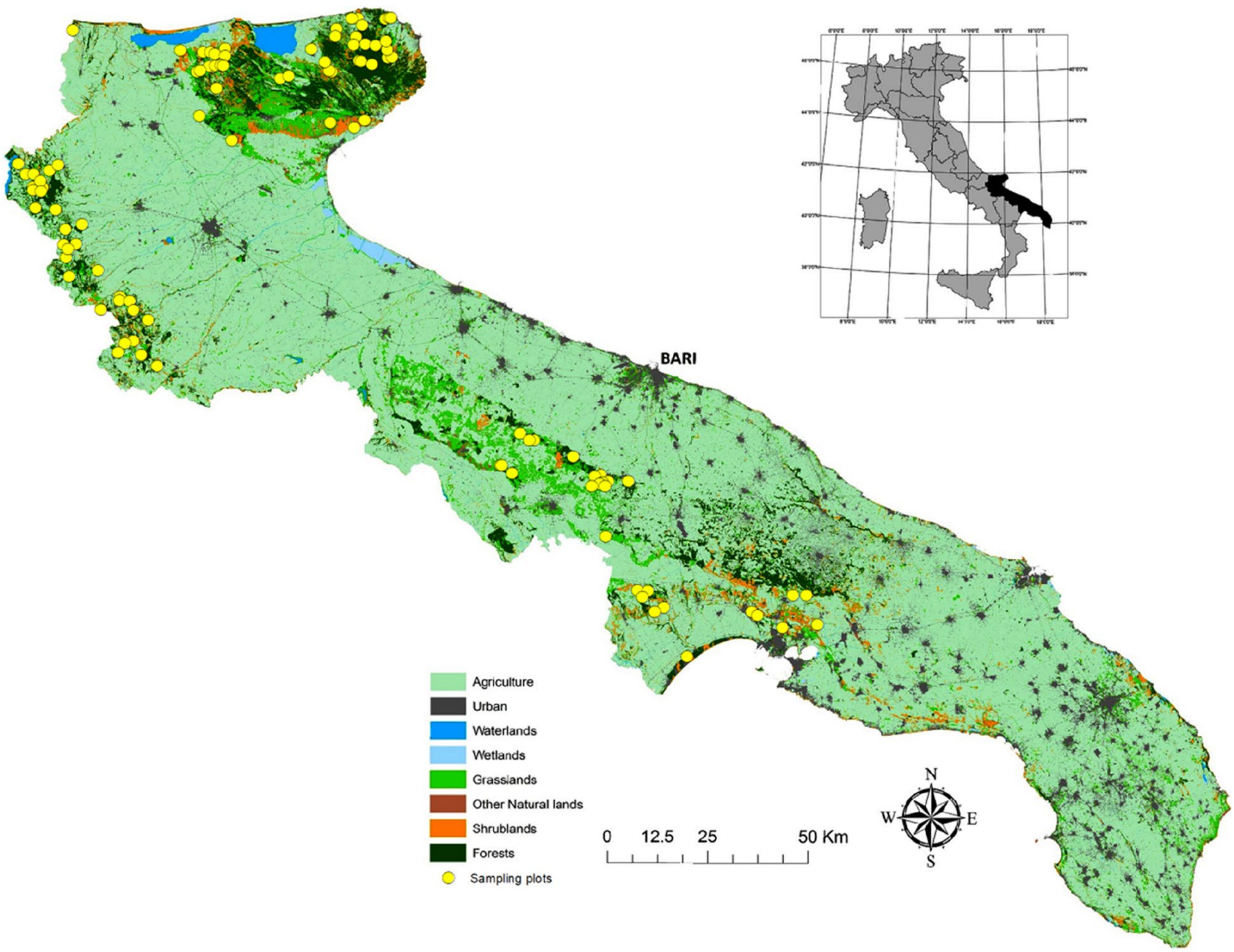

Fig. 1 Location of the Apulia region in Italy and 104 field plots across the Apulia region

dead woody material in the form of small dead branches, stems, fallen or lying shrubs, and tree trunks.

A measuring tape is placed on the ground, extending 7.5 m in each direction from the sampling center, forming a 60° angle with the northward sampling plane. The objective is to record the number of woody pieces on the ground that intersect the tape. Only pieces whose central axes intersect with the transect are counted. If a curved piece intersects the transect at multiple points, each intersection is recorded according as specified by the method developed by Brown et al. (1982). In this survey, dead woody materials were classified into three time-lag classes (1-h, 10-h, and 100-h) based on the diameter measured by the caliper at the point of intersection with the transect (Lydersen et al. 2015). The 1-h fuel load mainly consisted of needles, leaves, and small twigs with a diameter of less than 0.65 cm. The 10-h fuel load included dead twigs and foliage with a diameter between 0.65 and 2.5 cm. The 100-h fuel load was large branches and large pieces of bark with a diameter ranging from 2.5 to 7.5 cm. The collection of litter, which was composed of plant residues on the ground was conducted by placing a 30 × 60 cm rectangular plot within a square area of 2.5-m sides, which was positioned 5 m away from the center of the sampling plane along the transect. From within each plot, a sample of litter was obtained and placed in sealed bags and put in an oven at 105 ℃ for 24 h to exclude the moisture content from the fuel load and then calculated the dry mass of litter.

LiDAR Data

Airborne LiDAR (Light Detection and Ranging) technology was used in this study to gather high-resolution data reflecting the structure of the forest vegetation. LiDAR data was derived from "Ministero dell'Ambiente e della Tutela del Territorio e del Mare". The LiDAR data were acquired with ALTM Gemini and ALTM 3100EA laser-scan sensors from the Canadian company Optech. The LiDAR data was mainly obtained in 2013 and the resolution was three points per m^2.

LiDAR point cloud data processing was conducted using LAStools (Isenburg, 2014). The LiDAR point-cloud data were initially classified into ground and non-ground points, and normalized z values of height above ground for each return to eliminate the effect of varying elevation on vegetation structure calculations. Once each point cloud was suitably georeferenced and normalized, any points below zero were removed, and the heights of all remaining points classified as vegetation that is 0.4 m above the ground were calculated. These procedures involved the use of various LAStools (i.e. lasground, lasheight, and lasclassify) (Isenburg, 2014). Finally, we clipped a buffer zone with a radius of 10 m, ensuring that the LiDAR metrics were extracted specifically within predefined areas. These 10-m radius plots correspond to the areas where field surveys were conducted to measure fine dead fuel loads.

A set of LiDAR metrics were extracted directly and calculated using “lascanopy” function (Table 1). These metrics were grouped into three main categories. The height characteristics include variables that are commonly used, such as maximum height, minimum height, mean height, and height percentiles. Variables that are grouped into the height variability categories include simple descriptions of point height distribution such as kurtosis, skewness, and standard deviation. The point cloud cover was described based on the percentage of return. The percentage of the first return was described as canopy cover and the percentage of all returns was described as canopy density (Giannico et al. 2016, 2022).

Fine dead fuel load prediction

Because of the relatively low number of observations in this study, multiple linear regression was applied using the LiDAR-derived metrics (Table 1) for the development of models predicting the fine dead fuel load (i.e., litter, 1-h, 10-h, and 100-h fuel load). Prior to analysis, outliers in the multiple linear regression models were assessed through visualizing residual plots. First, we initialized a multiple linear regression model incorporating all available features. Then we removed the outliers based on the Cook’s distance method, which any point that was more than 3× the mean of all the distances was identified as outliers and excluded. This procedure was repeated until the model achieved a relatively good fit for the majority of the dataset.

Due to the large number of the LiDAR metrics to be considered as potential predictive variables, we used stepwise regression to select the most significant ones in terms of correlation with fine dead fuel load and predictability. Stepwise regression is the step-by-step iterative construction of a regression model that involves the selection of variables to be used in a final model, through adding (forward) or removing (backward) variables in succession (Smith 2018). In this study, we did both forward and backward selection at each step. Through the use of the Akaike Information Criterion (AIC), the number of variables was optimized by removing the least significant variable one at a time with the highest AIC until the model with the lowest AIC was identified. The selected variables for each type of fuel load after stepwise regression were used to perform the multiple linear regression analysis, as shown in the following equation (Park 2020):

$$y = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{x}_1 + \boldsymbol{\beta}_2\boldsymbol{x}_2 + \cdots + \boldsymbol{\beta}_n\boldsymbol{x}_n + \varepsilon \quad (1)$$

where y is the fine dead fuel load measured in the field survey; x_1, x_2, ..., x_n are the selected variables from LiDAR data; β_0, β_1, β_2, ..., β_n are the estimated regression parameters; $\boldsymbol{\varepsilon}$ is residuals.

Model performance

To assess the stability of the best model after the stepwise procedure, the dataset was split into an 80% training set and 20% testing set. This random partitioning was repeated five times to obtain five random subsamples, ensuring a robust validation of the model against

Table 1 Descriptions of selected LiDAR metrics derived from the point cloud as explanatory variables

Category	Metrics	Code
Height characteristics	Maximum height	max
	Minimum height	min
	Mean height	avg
	Percentile of height distribution	p10, p25, p50, p75, p90
Height variability	Standard deviation of height	std
	Skewness of height	ske
	Kurtosis of height	kur
Cover	Percentage of first return > 1.37 m in height	cov
	Percentage of all returns > 1.37 m in height	dns

overfitting. Using each one of the subsamples, the optimal multiple linear regression model with the correct number of variables was calibrated using a training set and validated using a testing set.

The performance of the multiple regression model was evaluated based on three standard goodness-of-fit metrics, including the normalized root mean squared error (nRMSE), mean absolute error (MAE), and the coefficient of determination (R^2). The formulas for these metrics are as follows (D'Este et al. 2021):

$$nRMSE = \frac{\sum (y_i - x_i)^2}{\sum {x_i}^2} \tag{2}$$

$$MAE = \sum_{\mathbf{i}=1}^{\mathbf{n}} \frac{|\mathbf{y_i} - \mathbf{x_i}|}{\mathbf{n}} \tag{3}$$

$$\boldsymbol{R}^2 = 1 - \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (x_i - \overline{y_i})^2} \tag{4}$$

where y_i is the predicted value, x_i is the observed value, and $\overline{y_i}$ is the mean of the observed value.

Result

Field measurements summary statistics

Table 2 presents the statistics of fine dead fuel load collected from field plots. The 1-h fuel load ranged from 0 to 4.10 t/ha and averaged 0.68 t/ha, 10-h fuel load ranged from 0 to 7.14 t/ha with an average value of 1.54 t/ha, 100-h fuel load ranged from 0 to 12.01 t/ha and averaged 1.24 t/ha, and litter ranged from 0 to 260.83 t/ha and averaged 73.33 t/ha. From a total of 104 plots, nine plots, representing 8% of the total plots, were removed as outliers based on the method mentioned before.

Multiple regression model prediction for fine dead fuel load

Principle component analysis based on the correlation matrix was used to detect the presence of potential collinearity in the multiple regression analysis. The condition number was calculated by the square root of the largest eigenvalue divided by the smallest eigenvalue, which was used to suggest collinearity. The condition number larger than 30 was indicated as collinearity (Næsset 2002). The selected models for further analysis were those fulfilled the requirement of condition number smaller than 30.

In general, the result presented in Table 3 showed that R^2 values ranging from 0.521 to 0.569 (0.110–0.169 nRMSE) could be achieved by the multiple linear regression model developed with LiDAR-derived metrics for the 1-h, 10-h, 100-h fuel load and litter. The accuracy of estimation varied across different models. Among four different fuel types, litter was the most accurately estimated, with the model yielding an R^2 of 0.569 and 0.158 nRMSE. In particular, the accuracy of the prediction between 10-h fuel load and litter was very close, with an R^2 of 0.568 and 0.569 and nRMSE of 0.169 and 0.158, respectively. The model with the lowest predictive accuracy was the 1-h fuel load. Fifty-two percent of the 1-h fuel load variance was explained with an nRMSE of 0.168. The models' fits to the field-measured fine dead fuel load values were not very close to the hypothetical 1:1 relationship (Fig. 2), indicating the limitation of using multiple linear regression analysis to predict the fine dead fuel load.

The developed models for each fuel type were evaluated by implementing the independent test set. The cross-validation confirmed the robustness of the multiple linear regression model (Table 4). The calculation for 5 subsamples of train and test sets showed similar MAE, nRMSE, and R^2 values, demonstrating that there was no overfitting in the final model.

Relationship between LiDAR-derived metrics and fine dead fuel load

The multiple linear regression analysis conducted on various fine dead fuel load types revealed significant relationships between LiDAR-derived variables and fine dead fuel load including litter, 1-h, 10-h, and 100-h fuel load, each exhibiting distinct associations with the predictors (Table 5).

In the case of metrics from the cover category, measured as the percentage of returns greater than 1.37m, were less consistently significant across the models but showed some influence in 10-h fuel load and litter. Specifically, dns, which represented the canopy density,

Table 2 Summary of the field-measured fine dead fuel load

Fuel type	Fine dead fuel load statistical measures (t/ha)			
	Min	Max	Mean	Std
1-h fuel load	0.00	4.10	0.68	0.63
10-h fuel load	0.00	7.14	1.54	1.56
100-h fuel load	0.00	12.01	1.24	2.20
Litter	0.00	260.83	73.33	58.48

Table 3 Performance metrics of multiple linear regression model for each fuel type. Each standard goodness-of-fit metrics summarized with coefficient of determination (R^2), normalized root mean squared error (nRMSE), and mean absolute error (MAE)

Fuel type(T/ha)	R^2	nRMSE (%)	MAE
1-h fuel load	0.521	0.168	0.275
10-h fuel load	0.568	0.169	0.728
100-h fuel load	0.549	0.110	0.720
Litter	0.569	0.158	27.958

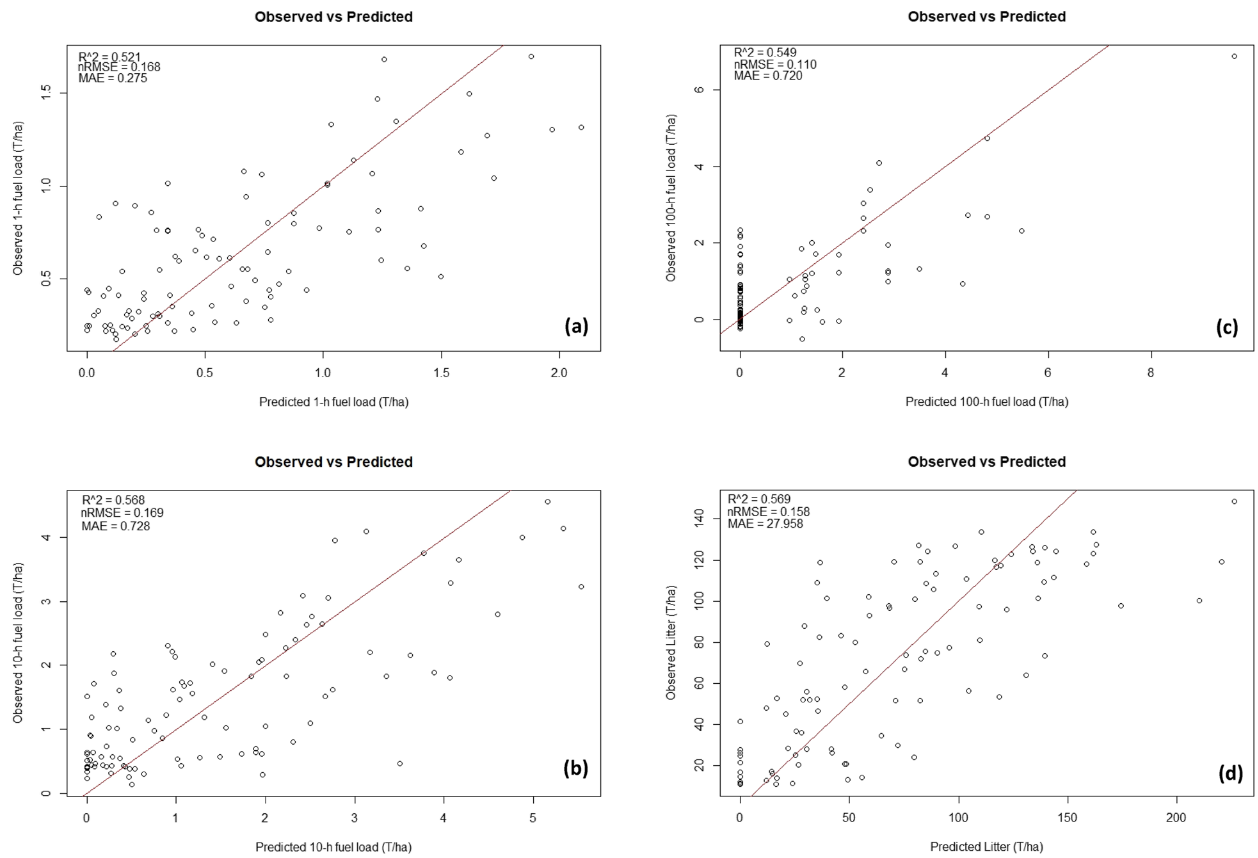

Fig. 2 The observed versus predicted plots for the prediction of **a** 1-h fuel load (R^2 = 0.521), **b** 10-h fuel load (R^2 = 0.568), **c** 100-h fuel load (R^2 = 0.549), and **d** litter (R^2 = 0.569) through the multiple linear regression analysis (The red line is the 1:1 line). Each standard goodness-of-fit metrics summarized with coefficient of determination (R^2), normalized root mean squared error (nRMSE), and mean absolute error (MAE). These results refer to the models produced with the use of LiDAR-derived metrics

was positively correlated with litter in the model, indicating that denser canopies contribute to more surface litter.

Regarding height variability, the standard deviation of height (std) consistently demonstrated a negative relationship with both 1-h, 10-h, and 100-h fuel loads, suggesting that greater height variability decreased overall fuel load. This could imply that uniform forest canopies could accumulate more fuel. Skewness of height (ske) and kurtosis of height (kur) revealed significant dynamics, with skewness of height showing a significant negative coefficient in th 100-h fuel load model while kurtosis of height displayed a positive correlation, particularly in the 10-h fuel load model, underscoring the impact of the shape of the height distribution on fuel accumulation.

For the height characteristics, minimum height (min) consistently exhibited a positive correlation across fuel load models, particularly in the 100-h fuel load model. The percentile metrics provided insight into the distribution of canopy height and their relation to fuel loads. Notably, lower percentiles such as 10 percentile height (p10) and 25 percentile height (p25) and higher percentiles such as 75 percentile height (p75) and 90 percentile height (p90) exhibited both negative and positive influences across 1-h, 10-h, and 100-h fuel load models, reflecting their complex roles in fuel accumulation dynamics.

Discussion

In this study, multiple linear regression analysis was implemented for the prediction of various fine dead fuel loads (i.e., litter, 1-h, 10-h, and 100-h fuel load) using airborne LiDAR data. Height and canopy cover metrics derived from LiDAR were used as potential independent variables for the development of four regression models, with different predictors for each fine dead fuel load parameter. Following the cross-validation approach, the evaluation performance statistics showcased that there was no overfitting in the calibrated model. Overall, the results demonstrated that multiple linear regression models based on the airborne LiDAR-derived metrics describing forest structure have the potential to predict

Table 4 Prediction performance of the multiple linear regression model in 5 training and testing subsamples of 1-h fuel load; 10-h fuel load; 100-h fuel load; litter. Each standard goodness-of-fit metrics summarized with coefficient of determination (R^2), normalized root mean squared error (nRMSE), and mean absolute error (MAE)

Fuel type		MAE	nRMSE	R^2
1-h fuel load	Subsample 1	0.283	0.217	0.535
	Subsample 2	0.237	0.236	0.510
	Subsample 3	0.274	0.201	0.507
	Subsample 4	0.279	0.203	0.525
	Subsample 5	0.234	0.222	0.536
10-h fuel load	Subsample 1	0.703	0.190	0.583
	Subsample 2	0.784	0.179	0.609
	Subsample 3	0.736	0.207	0.601
	Subsample 4	0.798	0.196	0.571
	Subsample 5	0.818	0.199	0.588
100-h fuel load	Subsample 1	0.978	0.330	0.621
	Subsample 2	0.909	0.292	0.590
	Subsample 3	0.938	0.281	0.605
	Subsample 4	0.903	0.275	0.607
	Subsample 5	0.940	0.314	0.597
Litter	Subsample 1	29.803	0.184	0.599
	Subsample 2	27.220	0.223	0.588
	Subsample 3	27.275	0.182	0.547
	Subsample 4	25.848	0.192	0.554
	Subsample 5	29.941	0.210	0.559

MAE Mean absolute error; *nRMSE* Normalized root mean squared error; R^2 Coefficient of determination

Table 5 Results of variable selection to each fuel type by stepwise regression, each variable summarized with: kurtosis of height (kur), skewness of height (ske), minimum height (min), standard deviation of height (std), percentage of first return > 1.37m in height (cov), percentage of all returns > 1.37m in height (dns), 10 percentile height (p10), 25 percentile height (p25), 50 percentile height (p50), 75 percentile height (p75), 90 percentile height (p90)

Fuel type	Variable	Coefficient	Std. error	*p* value
1-h fuel load	(Intercept)	0.217	0.066	< 0.01**
	kur	0.588	0.151	< 0.001***
	std	− 3.299	0.980	< 0.01**
	min	0.973	0.386	< 0.1*
	p10	− 4.027	1.065	< 0.001***
	p25	2.274	0.614	< 0.001***
	p75	− 2.727	0.851	< 0.001**
	p90	3.501	0.931	< 0.001***
10-h fuel load	(Intercept)	0.416	0.204	< 0.1*
	cov	− 0.028	0.016	> 0.1
	dns	0.023	0.015	> 0.1
	kur	2.502	0.708	< 0.001***
	std	− 7.356	2.462	< 0.01**
	min	2.372	1.022	< 0.1*
	p10	− 9.370	2.573	< 0.001***
	p25	5.457	1.978	< 0.01**
	p50	− 2.932	1.515	> 0.1
	p90	4.316	1.378	< 0.01**
100-h fuel load	(Intercept)	− 0.058	0.213	> 0.1
	dns	0.023	0.009	< 0.01**
	ske	− 5.684	1.949	< 0.01**
	std	− 8.110	2.824	< 0.01**
	min	4.694	1.154	< 0.001***
	p10	− 10.529	2.259	< 0.001***
	p50	3.946	1.813	< 0.1*
	p75	− 7.986	2.874	< 0.01**
	p90	9.638	2.691	< 0.001***
Litter	(Intercept)	8.516	6.453	> 0.1
	dns	1.464	0.127	< 0.001***

*$p < 0.1$; **$p < 0.01$; ***$p < 0.001$

fine dead fuel load in the Mediterranean forest stands with moderate accuracy.

According to the results of the regression analysis, the fine dead fuel load explained by the models varied in their accuracy (R^2 values) ranging from 0.521 to 0.569 and nRMSE values between 0.110 and 0.169. Our result in general exceeds those from previous studies. For example, Stefanidou et al. (2020) found that a multiple linear regression model including LiDAR height distribution metrics explained 48% in litter load, 58% in 1-h fuel load, and 48% in 10-h fuel load in the forest located in central Greece. Similarly, Jakubowksi et al. (2013) also predicted each type of surface fuel load through combining multiple linear regression, additive regression, and support vector machine algorithms. Their results showed that the model of the 1-h, 10-h, and 100-h fuel load and litter all yielded very poor correlation coefficients. Moreover, Alonso-Rego et al. (2021) used both airborne laser scanning (ALS) and terrestrial laser scanning (TLS) metrics to estimate surface fuel loads. The results showed that with models based on ALS metrics, in the case of downed woody debris load and litter and duff load variables, the R^2 were 0.4069 and 0.1049, respectively. As with models based on the combination of ALS and TLS metrics, the R^2 was 0.4894 for the downed woody debris load model and 0.4311 for litter and duff load model.

In our study, the highest accuracy was observed in estimating litter (R^2 = 0.569, nRMSE = 0.158). This could be attributed to the fact that litter typically remains on the surface, unlike larger woody fuels that may be buried, making it more detectable by LiDAR. In contrast, the 1-h fuel load was predicted with the lowest accuracy (R^2 = 0.521, nRMSE = 0.168). The potential reason could be that 1-h fuel load varies at millimeter scales, influenced by the micro-topography of the forest floor, the presence of herbaceous plants, and the accumulation of dead needles and fine twigs under fallen branches. This heterogeneity might not be fully captured by the airborne LiDAR data (Labenski et al. 2023). The final multiple linear regression models showed that the height metrics were mostly used for fine dead fuel load estimation, indicating that although airborne LiDAR cannot directly measure fine dead fuel load, it effectively characterizes stand structure and the canopy conditions correlating with fine dead fuel load characteristics.

With respect to the LiDAR metrics within each model, several previous studies have incorporated the relevant metrics related to canopy height and cover into their models. For instance, Giannico et al. (2016) utilized a combination of LiDAR-derived height metrics, finding that the 95th percentile of height distribution was one of the best predictors for estimating forest stand volume and above-ground biomass. D'Este et al. (2021) applied multiple algorithms, such as multiple linear regression, using remote sensing predictors, including LiDAR data, to estimate the 1-h fuel load. The results indicated that LiDAR variables, such as the Canopy Height Model and Canopy cover, played a crucial role in fuel estimation. Leite et al. (2022) used GEDI-derived vegetation structure metrics, including relative height at the 98th height percentile and canopy cover fraction, to predict fuel load components. In our research, in the case of height metrics, minimum height (min) showed a significant positive correlation with fuel loads, especially in the 100-h fuel load model compared to the 1-h and 10-h fuel load models. This suggested that shorter vegetation, including shrubs and undergrowth, also contributed to fuel loads. Analysis of height percentiles showed negative coefficients for lower percentiles (e.g., 10 percentile height) and positive coefficients for higher percentiles (e.g., 90 percentile height) across 1-h, 10-h, and 100-h fuel load models, illustrating the complexity of forest structure in influencing fuel loads. Lower forest strata, represented by lower percentiles, likely accumulated less fuel due to moisture retention and reduced light penetration. In contrast, upper layers were exposed to more environmental stress and sunlight, leading to more frequent shedding of combustible materials like dead branches and leaves, contributing to increased fuel loads on the forest floor. Concerning height variability, the standard deviation of height (std) displayed a consistent negative correlation with the models of 1-h, 10-h, and 100-h fuel loads. This might result from the heterogeneity forest structure, which could disrupt the spatially continuous of fuel loads (Chávez-Durán et al. 2022). Kurtosis of height (kur) was included in the 1-h and 10-h fuel load model as an important predictor. High kurtosis values were frequently associated with dense underbrush areas, indicating a substantial accumulation of fine fuels. The presence of skewness of height (ske) only in the model as an important variable for predicting 100-h fuel load suggested an asymmetry in height distribution that was relevant for this fuel load type. Canopy density (dns) was the only significant predictor of litter, showing a positive correlation with it. Dense canopies typically result from a higher density of trees and larger crowns, which leads to more leaves, twigs, and small branches falling to the forest floor, thereby contributing to the litter layer. In addition, trees shed parts of themselves during the natural life cycles, which contribute to litter accumulation. Dense canopies create a humid environment on the forest floor, which can slow down the rate of decomposition of organic matter, resulting in the accumulation of organic materials like fallen leaves and wood (Wallace et al. 2018).

Even though the multiple linear regression models in our study demonstrated the potential of using LiDAR-derived height metrics to predict underlying fine dead fuel load, there was still room for improvement. Firstly, the moderate accuracy of our result indicated that fine dead fuel loads are not always correlated with forest stand attributes, factors such as topography, wind, temperature, and humidity also play significant roles. Therefore, incorporating these abovementioned variables could notably enhance the accuracy of the fine dead fuel load prediction model. In addition, the observed versus predicted discrepancies underscored the limitations of multiple linear regression in accurate fine dead fuel load estimation, suggesting the need for more sophisticated models such as machine learning techniques to improve accuracy (Cilli et al. 2022). Moreover, the predictive models developed in this research could not be transferred to other forest ecosystems. Although the models showed a reliable predictive performance in our area, variations in vegetation composition, topography, and sensor characteristics could alter the relationship between the response and LiDAR-derived predictive variables, thus influencing the results. Fine dead fuel load estimation in different forested areas would require new reference data collection and the development of alternative regression models. In the future, even less field data, which are time- and cost-consuming, would be needed with the advancements of knowledge and technologies. Nevertheless, we argued that the employed methodology provides a robust framework for fine dead fuel load estimation using airborne LiDAR data.

Implications for fuel load management

By achieving moderate accuracy from the outputs of models in predicting fine dead fuel load, this research indicated that LiDAR could be a valuable tool for forest managers to monitor and predict fine dead fuel loads. The variable accuracy across different fine dead fuel load types suggested a need for adaptive management strategies. For instance, while LiDAR data in this study could be reliably used for managing fine dead fuel load with larger diameter, finer fuels such as 1-h fuel may require additional estimation methodologies such as using a mobile laser scanner and more frequent management interventions. In addition, the results could contribute to more comprehensive fire risk mapping by revealing the spatial distribution of the fuel load, which allows for more targeted and efficient fuel load management strategies, such as prescribed burns, mechanical removal, or other fire prevention measures, especially in critical areas.

Focusing on LiDAR metrics used to estimate fine dead fuel loads in this study, different metrics exhibited either positive or negative correlations with each fine dead fuel load type. Moreover, each fine dead fuel load type had several significant predictors determined by the variable importance. Understanding the relationship between forest structure and fuel load accumulation, as indicated by LiDAR metrics, can guide forest thinning or other treatment operations, focusing on structural characteristics like changing canopy cover or altering tree heights to manage the accumulation of specific fine dead fuel load type effectively.

Ultimately, the utilization of airborne LiDAR data alongside field surveys for fine dead fuel load estimation presents a valuable approach for fuel data collection. The remotely derived point clouds can consistently predict the fine dead fuel load without many tree-level measurements, enabling data collection over larger areas and with higher sampling densities than traditional methods that rely on field measurements alone. This method is applicable in high-profile areas as well as in actively managed forests.

Conclusion

The present paper focused on the estimation of various fine dead fuel loads (i.e., 1-h, 10-h, 100-h fuel load, and litter) in the Mediterranean forest stands of the Apulia region in southern Italy by employing airborne LiDAR data. The fine dead fuel loads were predicted by multiple linear regression models, which were developed using LiDAR-derived height and canopy cover metrics as potential independent variables. A stepwise regression process was applied to compare the developed models in terms of accuracy.

The research findings indicated that the predictive accuracy of these models varies among different fuel types, with the explained variance (R^2) between 0.521 and 0.569 (normalized root mean square error (nRMSE) 11–16.9%). The study also revealed the significant role of specific LiDAR-derived metrics in predicting different types of fine dead fuel loads. The importance of these metrics reflected the intricate relationship between vegetation vertical structure and fine dead fuel load accumulation.

In general, the results demonstrated a promising approach in estimating fine dead fuel loads with moderate accuracy, providing a robust framework for fine dead fuel load estimation using airborne LiDAR data, which contributes to the forest fire management. Considering the limitations of the present study, future research should incorporate additional variables such as topography, wind, and temperature and employ more sophisticated modeling techniques like machine learning to improve the accuracy of fine dead fuel load estimation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-024-00287-7.

Supplementary Material 1: Fig S1. The field sampling plot is demonstrated. Fuel data were measured in the 10-m diameter plot; Fallen dead woody material was sampled along the 15 m transect; Litter were collected within 30 × 60 cm rectangular plot. Table S1. Models were fitted by multiple linear regression and selected based on the Akaike information criterion (AIC). Models are ranked from worst to best fitting, with the best-fitting model highlighted in bold; wi are the Akaike weights computed considering the difference in AIC between each model and the best-fitting model in the candidate set. Abbreviations of the variable names are described in Table 1.

Authors' contributions

Lin Di: writing — original draft, investigation, and formal analysis; Vincenzo Giannico: writing — review and editing, methodology, conceptualization; Raffaele Lafortezza: writing — review and editing; Giovanni Sanesi: writing — review and editing, funding acquisition; Mario Elia: writing — review and editing, conceptualization, supervision.

Funding

This study was carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1032 17/06/2022, CN00000022). This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them.
This study was carried out within the PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) Missione 4 "Istruzione e Ricerca" - Componente C2 Investimento 1.1, "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)" - FIRE-BOX – Essential tools for wildland fire risk management in Italy (P2022MXRK9). This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them.
V.G. (Corresponding author) was supported by the project "Approcci innovativi per la caratterizzazione degli effetti del cambiamento climatico sulla perdita di biodiversità negli habitat forestali a rischio (AppForBio)", action co-funded by Programma Operativo (PON) Ricerca E Innovazione 2014–2020—Azione IV.6 "Contratti di ricerca su tematiche Green" (CUP H95F21001390006).

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Received: 1 February 2024 Accepted: 26 May 2024
Published online: 04 July 2024

References
Alonso-Rego, C., S. Arellano-Pérez, C. Cabo, C. Ordoñez, J.G. Álvarez-González, R.A. Díaz-Varela, and A.D. Ruiz-González. 2020. Estimating Fuel Loads and Structural Characteristics of Shrub Communities by Using Terrestrial Laser Scanning. *Remote Sensing* 12: 3704. https://doi.org/10.3390/rs12223704.
Alonso-Rego, C., S. Arellano-Pérez, J. Guerra-Hernández, J.A. Molina-Valero, A. Martínez-Calvo, C. Pérez-Cruzado, F. Castedo-Dorado, E. González-Ferreiro, J.G. Álvarez-González, and A.D. Ruiz-González. 2021. Estimating Stand and Fire-Related Surface and Canopy Fuel Variables in Pine Stands Using Low-Density Airborne and Single-Scan Terrestrial Laser Scanning Data. *Remote Sensing* 13: 5170. https://doi.org/10.3390/rs13245170.
Arellano-Pérez, S., F. Castedo-Dorado, C. López-Sánchez, E. González-Ferreiro, Z. Yang, R. Díaz-Varela, J. Álvarez-González, J. Vega, and A. Ruiz-González. 2018. Potential of Sentinel-2A Data to Model Surface and Canopy Fuel Characteristics in Relation to Crown Fire Hazard. *Remote Sensing* 10: 1645. https://doi.org/10.3390/rs10101645.
Bright, B.C., Hudak, A.T., McCarley, T.R., Spannuth, A., Sánchez-López, N., Ottmar, R.D., Soja, A.J., 2022. Multitemporal lidar captures heterogeneity in fuel loads and consumption on the Kaibab Plateau. fire ecol 18, 18. https://doi.org/10.1186/s42408-022-00142-7
Brown, J.K., Oberheu, R.D., Johnston, C.M., 1982. Handbook for inventorying surface fuels and biomass in the Interior West (No. INT-GTR-129). U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station, Ogden, UT. https://doi.org/10.2737/INT-GTR-129
Cardíl, A., V.M. Tapia, S. Monedero, T. Quiñones, K. Little, C.R. Stoof, J. Ramirez, and de-Miguel, S.,. 2023. Characterizing the rate of spread of large wildfires in emerging fire environments of northwestern Europe using Visible Infrared Imaging Radiometer Suite active fire data. *Nat. Hazards Earth Syst. Sci.* 23: 361–373. https://doi.org/10.5194/nhess-23-361-2023.
Chávez-Durán, Á.A., M. Olvera-Vargas, B. Figueroa-Rangel, M. García, I. Aguado, and J.A. Ruiz-Corral. 2022. Mapping Homogeneous Response Areas for Forest Fuel Management Using Geospatial Data, K-Means, and Random Forest Classification. *Forests* 13: 1970. https://doi.org/10.3390/f13121970.
Chen, Y., X. Zhu, M. Yebra, S. Harris, and N. Tapper. 2017. Development of a predictive model for estimating forest surface fuel load in Australian eucalypt forests with LiDAR data. *Environmental Modelling & Software* 97: 61–71. https://doi.org/10.1016/j.envsoft.2017.07.007.
Cilli, R., M. Elia, M. D'Este, V. Giannico, N. Amoroso, A. Lombardi, E. Pantaleo, A. Monaco, G. Sanesi, S. Tangaro, R. Bellotti, and R. Lafortezza. 2022. Explainable artificial intelligence (XAI) detects wildfire occurrence in the Mediterranean countries of Southern Europe. *Sci Rep* 12: 16349. https://doi.org/10.1038/s41598-022-20347-9.
D'Este, M., M. Elia, V. Giannico, G. Spano, R. Lafortezza, and G. Sanesi. 2021. Machine Learning Techniques for Fine Dead Fuel Load Estimation Using Multi-Source Remote Sensing Data. *Remote Sensing* 13: 1658. https://doi.org/10.3390/rs13091658.
Elia, M., R. Lafortezza, R. Lovreglio, and G. Sanesi. 2015. Developing Custom Fire Behavior Fuel Models for Mediterranean Wildland-Urban Interfaces in Southern Italy. *Environmental Management* 56: 754–764. https://doi.org/10.1007/s00267-015-0531-z.
Franke, J., A.C.S. Barradas, M.A. Borges, M. Menezes Costa, P.A. Dias, A.A. Hoffmann, J.C. Orozco Filho, A.E. Melchiori, and F. Siegert. 2018. Fuel load mapping in the Brazilian Cerrado in support of integrated fire management. *Remote Sensing of Environment* 217: 221–232. https://doi.org/10.1016/j.rse.2018.08.018.
Gajendiran, K., S. Kandasamy, and M. Narayanan. 2024. Influences of wildfire on the forest ecosystem and climate change: A comprehensive study. *Environmental Research* 240: 117537. https://doi.org/10.1016/j.envres.2023.117537.
Gale, M.G., G.J. Cary, A.I.J.M. Van Dijk, and M. Yebra. 2021. Forest fire fuel through the lens of remote sensing: Review of approaches, challenges and future directions in the remote sensing of biotic determinants of fire behaviour. *Remote Sensing of Environment* 255: 112282. https://doi.org/10.1016/j.rse.2020.112282.
Giannico, V., R. Lafortezza, R. John, G. Sanesi, L. Pesola, and J. Chen. 2016. Estimating Stand Volume and Above-Ground Biomass of Urban Forests Using LiDAR. *Remote Sensing* 8: 339. https://doi.org/10.3390/rs8040339.
Giannico, V., M. Stafoggia, G. Spano, M. Elia, P. Dadvand, and G. Sanesi. 2022. Characterizing green and gray space exposure for epidemiological studies: Moving from 2D to 3D indicators. *Urban Forestry & Urban Greening* 72: 127567. https://doi.org/10.1016/j.ufug.2022.127567.
Heisig, J., E. Olson, and E. Pebesma. 2022. Predicting Wildfire Fuels and Hazard in a Central European Temperate Forest Using Active and Passive Remote Sensing. *Fire* 5: 29. https://doi.org/10.3390/fire5010029.
Hudak, A.T., B.C. Bright, S.M. Pokswinski, E.L. Loudermilk, J.J. O'Brien, B.S. Hornsby, C. Klauberg, and C.A. Silva. 2016. Mapping Forest Structure and Composition from Low-Density LiDAR for Informed Forest, Fuel, and Fire Management at Eglin Air Force Base, Florida, USA. *Canadian Journal of Remote Sensing* 42: 411–427. https://doi.org/10.1080/07038992.2016.1217482.
Isenburg, M., 2014. LAStools, "Efficient LiDAR processing software."
Jakubowksi, M.K., Guo, Q., Collins, B., Stephens, S., Kelly, M., 2013. Predicting Surface Fuel Models and Fuel Metrics Using Lidar and CIR Imagery in a Dense, Mountainous Forest. photogramm eng remote sensing 79, 37–49. https://doi.org/10.14358/PERS.79.1.37
Jiménez, E., J.A. Vega, A.D. Ruiz-González, M. Guijarro, J.G. Alvarez-González, J. Madrigal, P. Cuiñas, C. Hernando, and J.M. Fernández-Alonso. 2013. Carbon emissions and vertical pattern of canopy fuel consumption in three Pinus pinaster Ait. active crown fires in Galicia (NW Spain). *Ecological Engineering* 54: 202–209. https://doi.org/10.1016/j.ecoleng.2013.01.039.
Jin, S., and S.-C. Chen. 2012. Application of QuickBird imagery in fuel load estimation in the Daxinganling region. *China. Int. J. Wildland Fire* 21: 583. https://doi.org/10.1071/WF11018.
Labenski, P., M. Ewald, S. Schmidtlein, F.A. Heinsch, and F.E. Fassnacht. 2023. Quantifying surface fuels for fire modelling in temperate forests using airborne lidar and Sentinel-2: potential and limitations. *Remote Sensing of Environment* 295: 113711. https://doi.org/10.1016/j.rse.2023.113711.
Lasslop, G., and S. Kloster. 2015. Impact of fuel variability on wildfire emission estimates. *Atmospheric Environment* 121: 93–102. https://doi.org/10.1016/j.atmosenv.2015.05.040.
Leite, R.V., C.A. Silva, E.N. Broadbent, C.H.D. Amaral, V. Liesenberg, D.R.A.D. Almeida, M. Mohan, S. Godinho, A. Cardil, C. Hamamura, B.L.D. Faria, P.H.S. Brancalion, A. Hirsch, G.E. Marcatti, A.P. Dalla Corte, A.M.A. Zambrano, M.B.T.D. Costa, E.A.T. Matricardi, A.L.D. Silva, L.R.R.Y. Goya, R. Valbuena, B.A.F.D. Mendonça, C.H.L. Silva Junior, L.E.O.C. Aragão, M. García, J. Liang, T. Merrick, A.T. Hudak, J. Xiao, S. Hancock, L. Duncason, M.P. Ferreira, D. Valle, S. Saatchi, and C. Klauberg. 2022. Large scale multi-layer fuel load characterization in tropical savanna using GEDI spaceborne lidar data. *Remote Sensing of Environment* 268: 112764. https://doi.org/10.1016/j.rse.2021.112764.
Li, Y., and B. He. 2022. A Semi-Empirical Retrieval Method of Above-Ground Live Forest Fuel Loads by Combining SAR and Optical Data. *Remote Sensing* 15: 5. https://doi.org/10.3390/rs15010005.
Li, Y., X. Quan, Z. Liao, and B. He. 2021. Forest Fuel Loads Estimation from Landsat ETM+ and ALOS PALSAR Data. *Remote Sensing* 13: 1189. https://doi.org/10.3390/rs13061189.
Lin, C., S.-E. Ma, L.-P. Huang, C.-I. Chen, P.-T. Lin, Z.-K. Yang, and K.-T. Lin. 2021. Generating a Baseline Map of Surface Fuel Loading Using Stratified Random Sampling Inventory Data through Cokriging and Multiple Linear Regression Methods. *Remote Sensing* 13: 1561. https://doi.org/10.3390/rs13081561.
Lopes Queiroz, G., G. McDermid, J. Linke, C. Hopkinson, and J. Kariyeva. 2020. Estimating Coarse Woody Debris Volume Using Image Analysis and Multispectral LiDAR. *Forests* 11: 141. https://doi.org/10.3390/f11020141.

Lydersen, J.M., B.M. Collins, E.E. Knapp, G.B. Roller, and S. Stephens. 2015. Relating fuel loads to overstorey structure and composition in a fire-excluded Sierra Nevada mixed conifer forest. *Int. J. Wildland Fire* 24: 484. https://doi.org/10.1071/WF13066.

Marino, E., J.L. Tomé, C. Hernando, M. Guijarro, and J. Madrigal. 2022. Transferability of Airborne LiDAR Data for Canopy Fuel Mapping: Effect of Pulse Density and Model Formulation. *Fire* 5: 126. https://doi.org/10.3390/fire5050126.

Mauro, F., A.T. Hudak, P.A. Fekety, B. Frank, H. Temesgen, D.M. Bell, M.J. Gregory, and T.R. McCarley. 2021. Regional Modeling of Forest Fuels and Structural Attributes Using Airborne Laser Scanning Data in Oregon. *Remote Sensing* 13: 261. https://doi.org/10.3390/rs13020261.

Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sensing of Environment* 80: 88–99. https://doi.org/10.1016/S0034-4257(01)00290-5.

Nguyen, T.H., S. Jones, K.J. Reinke, and M. Soto-Berelov. 2024. Estimating fine fuel loads in Eucalypt forests using forest inventory data and a modelling approach. *Forest Ecology and Management* 561: 121851. https://doi.org/10.1016/j.foreco.2024.121851.

Nolè, A., A. Rita, M.F. Spatola, and M. Borghetti. 2022. Biogeographic variability in wildfire severity and post-fire vegetation recovery across the European forests via remote sensing-derived spectral metrics. *Science of The Total Environment* 823: 153807. https://doi.org/10.1016/j.scitotenv.2022.153807.

Park, T. 2020. Potential Lidar Height, Intensity, and Ratio Parameters for Plot Dominant Species Discrimination and Volume Estimation. *Remote Sensing* 12: 3266. https://doi.org/10.3390/rs12193266.

Price, O.F., and C.E. Gordon. 2016. The potential for LiDAR technology to map fire fuel hazard over large areas of Australian forest. *Journal of Environmental Management* 181: 663–673. https://doi.org/10.1016/j.jenvman.2016.08.042.

Regos, A., S. Pais, J.C. Campos, and J. Lecina-Diaz. 2023. Nature-based solutions to wildfires in rural landscapes of Southern Europe: let's be fire-smart! *Int. J. Wildland Fire*. https://doi.org/10.1071/WF22094.

Santos, M.M., A.C. Batista, E.H. Rezende, A.D.P. Da Silva, J.N. Cachoeira, G.R. Dos Santos, D. Biondi, and M. Giongo. 2023. Estimating the Surface Fuel Load of the Plant Physiognomy of the Cerrado Grassland Using Landsat 8 OLI Products. *Remote Sensing* 15: 5481. https://doi.org/10.3390/rs15235481.

Smith, G. 2018. Step away from stepwise. *J Big Data* 5: 32. https://doi.org/10.1186/s40537-018-0143-6.

Stefanidou, A., Z. Gitas, and I., Korhonen, L., Georgopoulos, N., Stavrakoudis, D.,. 2020. Multispectral LiDAR-Based Estimation of Surface Fuel Load in a Dense Coniferous Forest. *Remote Sensing* 12: 3333. https://doi.org/10.3390/rs12203333.

Urbazaev, M., C. Thiel, F. Cremer, R. Dubayah, M. Migliavacca, M. Reichstein, and C. Schmullius. 2018. Estimation of forest aboveground biomass and uncertainties by integration of field measurements, airborne LiDAR, and SAR and optical satellite data in Mexico. *Carbon Balance Manage* 13: 5. https://doi.org/10.1186/s13021-018-0093-5.

Vieira, D.C.S., P. Borrelli, D. Jahanianfard, A. Benali, S. Scarpa, and P. Panagos. 2023. Wildfires in Europe: Burned soils require attention. *Environmental Research* 217: 114936. https://doi.org/10.1016/j.envres.2022.114936.

Wallace, K.J., D.C. Laughlin, B.D. Clarkson, and L.A. Schipper. 2018. Forest canopy restoration has indirect effects on litter decomposition and no effect on denitrification. *Ecosphere* 9: e02534. https://doi.org/10.1002/ecs2.2534.

Zhang, Y., and L. Tian. 2024. Predicting Fine Dead Fuel Load of Forest Floors Based on Image Euler Numbers. *Forests* 15: 726. https://doi.org/10.3390/f15040726.

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