Estimating canopy fuels across Europe with satellite data and allometric equations

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Keywords: remote sensing, geospatial data, forest structure analysis, vegetation monitoring, fire modelling, wildfire risk assessment

Abstract:

This study presents results regarding the estimation of two critical variables for modelling fire behaviour and fire danger: the canopy base height (CBH) and the canopy bulk density (CBD). Both variables have been mapped as raster datasets at a 100-meter spatial resolution across Europe, harmonizing data for all EU countries. Therefore, these canopy fuels are subsequently used for further processing regarding the identification of fire danger assessment, being a key input for forest fire prevention actions. A more in-depth analysis of these findings has been submitted to a journal and is currently in a revision phase. We present here a summary of the results and ideas for future developments. The overall study consists of estimating CBH and CBD using Earth observation products combined with artificial intelligence and species-specific allometric equations, applied geo-spatially using a tree species map of Europe encompassing the 16 most important tree species. Validation was carried out by comparing the results with higher-accuracy sampling methods, combining LiDAR data and field measurements in different European latitudes, typically applied on a smaller scale and with greater detail. Results show, as expected, a higher level of uncertainty than local methods, but they are still applicable to the European scale for which they were implemented. The accuracies reported in our study, when considering aggregated data on the 7 areas in Portugal were the following: R = 0.75, RMSE = 0.890 m, and MAPE = 54% for the mean CBH, and R = 0.93, RMSE = 0.020 kg m^{-3}, and MAPE = 57% for the mean CBD.

1. Introduction

Wildfires are influenced by biophysical variables such as climate conditions, vegetation distribution and structure (fuel), and topography (Meigs et al., 2020; Wasserman and Mueller, 2023). These factors primarily drive fire ignitions and fire behaviour (Ganteaume et al., 2013), as well as fire occurrence, spread, and severity (Zin et al., 2022). Fire danger is predominantly caused by dry, hot, and windy weather conditions, which increase the occurrence of fires (Venäläinen et al., 2014). Ignitions are caused mostly by human activities, and according to Kolanek et al. (2021), human activities cause up to 90% of forest fires in the world. In Europe, wildfires are a major hazard, causing significant economic damage, ecological impacts, loss of human lives, and destruction of infrastructure (Galizia et al., 2022). Recent analyses show that fire events are increasing in frequency, intensity, and extension (Grünig et al., 2023; Giannaros and Papavasileiou, 2023), particularly in southern Europe, where the number, size, and frequency of forest fires have shown an increasing trend (Turco et al., 2019; Dupuy et al., 2020). Each year in Europe, over half a million hectares of forest resources are affected (Khabarov et al., 2016). Therefore, enhancing fire prevention is crucial to mitigating the trend of extreme wildfire events across Europe.

For effective fire suppression planning, it is crucial to characterize canopy fuels and analyse the transition from surface to crown fire spread (Mitsopoulos and Dimitrakopoulos, 2007). This characterization primarily involves two attributes, such as the canopy base height (CBH) and the canopy bulk density (CBD). The CBH refers to the vertical distance from the ground to the bottom of the crown (Mišić et al., 2024), while the CBD represents the dry mass of available canopy fuel per unit of canopy volume (Maltamo et al., 2020; Willis et al., 2024). Accurately measuring these attributes is challenging due to the high variability of vegetation within the same area. However, precise data on CBH and CBD are essential for simulating forest fire behaviour in different software such as FARSITE (Finney, 2004), FlamMap (Finney, 2006), Wildfire Analyst (Monedero et al., 2019) or Cell2Fire (Pais et al., 2021). Therefore, these softwares, through the geospatial data available, can provide simulation outputs, including the rate of spread, fire intensity, or flame length, among other outputs (e.g., Wu et al., 2022; Kudláčková et al., 2023). Despite this, there is a significant information gap at the pan-European level, where harmonized and operationally available data are needed for all EU-countries.

Remote sensing can play a crucial role in providing accurate data on canopy fuels. Different sensors, active and passive, can be combined to provide the variables of CBH and CBD in local areas and to extrapolate to large scales (*e.g.*, Garcia et al., 2017). Several studies were carried out using LiDAR data to provide CBH and CBD at different forest stands, which is a reliable approach for estimating canopy fuel attributes since LiDAR can penetrate the canopy and provide sub-canopy information (Chamberlain et al., 2021). Other works have been carried out at the pan-European level to determine canopy fuels. For example, Aragoneses et al. (2024) used the Global Ecosystem Dynamics Investigation (GEDI), which is a full-waveform lidar instrument that produces detailed 3D structures from the Earth surface, creating datasets on forest canopy features (Dubayah et al., 2020). The results by the authors were satisfactory to estimate the canopy height, canopy cover, and CBH, but the spatial resolution was coarse (1 km), making it difficult to use for operative purposes.

The aim of this study was to integrate remote-sensing-derived products with allometric equations and artificial intelligence, and add spatial information regarding tree species, to predict canopy fuel attributes, such as CBH and CBD, at a pan-European level, reaching a spatial resolution of 100 m and co-registering in the same reference system. This data will be available on an operational scale to support countries lacking the necessary information to simulate forest fire behaviour.

2. Materials

2.1 Study area

The study area covers all the pan-European continent, in the sense that all EU countries and the UK are included, as shown in Figure 1. Due to the availability of LiDAR data on forest inventory plots, we only used four countries (Portugal, Greece, Italy, and Norway) for the validation phase.

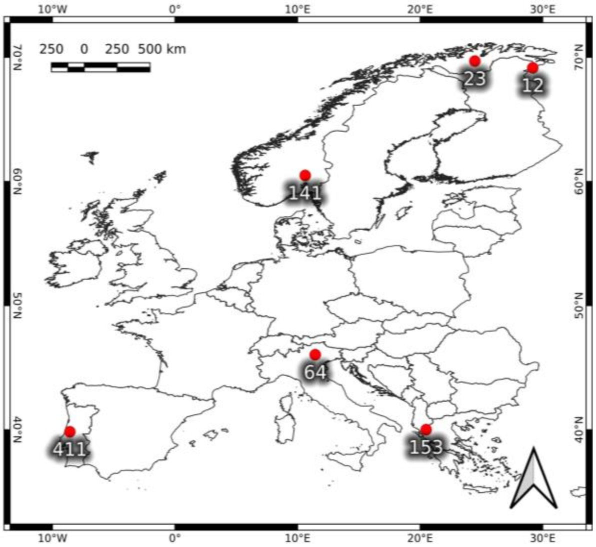

Figure 1. Study area with validation plots in red dots. The number indicates the number of plots per validation area.

3. Methods

3.1 Canopy base height and canopy bulk density

Canopy base height is the first dependent variable to be assessed, as it is then used to estimate canopy bulk density along with tree height, canopy volume, and the foliage fraction. Tree height was an available earth observation product from the work by Lang et al. (2023), while canopy volume and foliage fraction were estimated as products through allometric models. These models were species-dependent, so knowledge of the tree species in each 100-m cell is important. For this, a 30 m resolution European tree species map was used (Bonannella et al., 2022). This map does not represent the actual present species, but the probability of the presence of the following 16 tree species: *Abies alba* Mill., *Castanea sativa* Mill., *Corylus avellana* L., *Fagus sylvatica* L., *Olea europea* L., *Picea abies* L.H. Karst., *Pinus halepensis* Mill., *Pinus nigra* J.F Arnold, *Pinus pinea* L., *Pinus sylvestris* L., *Prunus avium* L., *Quercus cerris* L., *Quercus ilex* L., *Quercus robur* L., *Quercus suber* L., and *Salix caprea* L. This map provided the realized distribution of these 16 tree species using 300 variables as independent covariates to feed an AI framework using spatiotemporal machine learning, including a total of three million points to train different algorithms.

Species-specific allometric equations were developed to estimate two specific variables: the CBH and the foliage fraction that is necessary for the CBD map. It should be noted that CBH depends not only on the species but also on the silvicultural management, age, and biosocial status of the tree at a specific stand density (Maltamo et al., 2018). Foliage fraction is also correlated with the above-mentioned factors, with tree species explaining a lot of the variance in the models, but they are not the only covariate. The CBD also depends on the amount of overlap between crowns in the vertical canopy profile and tree height and crown ratios (Ex et al., 2016). Mapping microclimatic and local ecological factors are also partly correlated to foliage fraction, but mapping such values at the pan-European scale is out of the scope of this work. It would add unnecessary complexity, and the foreseen improvement of the model is marginal. The model thus focusses on using solely tree species, which explain a large part of the variance of foliage fraction values.

$$\text{CBH} = f \left| \begin{array}{ll} \text{Canopy Heights} & \text{(Lang et al., 2023)} \\ \text{Species} & \text{(Bonannella et al., 2022)} \end{array} \right. \tag{1}$$

$$\text{CBD} = f \left| \begin{array}{ll} \text{CBH} & \text{(see equation 1)} \\ \text{Species} & \text{(Bonannella et al., 2022)} \\ \text{AGB} & \text{(Pirotti et al., 2023)} \\ \text{DBH} & \text{Allometry from canopy heights (Lang et al., 2023)} \end{array} \right. \tag{2}$$

3.2 Validation

The validation was carried out using seven LiDAR-based canopy fuel maps from surveys carried out in the same year as the CBH and CBD maps and on 804 ground plots distributed in four countries in Europe. Figure 1 shows the position of the plots.

The seven LiDAR-derived canopy fuel maps with CBH and CBD values were located in Portugal. CBH and CBD were estimated using field samples and LiDAR data with a flight between 2020 and 2021 (Mihajlovski et al., 2023). Field measurements from the forest inventory in the same period were used to calibrate the models for the estimation of CBH and CBD. Final raster maps have a 25 m cell resolution. These areas represent a mapped estimation of CBH and CBD based on calibration using ground plots and thus are a reliable source for validation of our results.

The 804 ground plots were selected from Greece (153 plots), Italy (64 plots), Norway (176 plots), and Portugal (411 plots). The surveys were done in different years, between 2010 and 2020. The difference between the time of the modelled CBH and CBD maps and the surveys was taken into consideration by removing the parts that had suffered some kind of forest loss. We used the Hansen et al. (2013) canopy cover loss map as a mask to remove any pixels that were detected as having had a canopy loss between the years 2000 and 2020.

https://doi.org/10.5194/isprs-archives-XLVIII-3-2024-279-2024

For each validation site, we calculated the root mean square error (RMSE), the relative error with the mean absolute percentage error (MAPE), and the coefficient of correlation R using the Pearson method.

3.3 Uncertainty

It is worth noting that error propagation is important to establish the sensitivity of the model and final uncertainty. This is also calculated in this work using two methods: for CBH the chain rule is used, as the model is relatively simple, whereas for CBD Monte Carlo simulations are used to infer the distribution of the uncertainty to each cell in the map. We assessed the number of runs for the Monte Carlo simulations as a function of the target accuracy.

$$N = Z_{ci} \cdot \frac{\sigma}{\epsilon} \tag{3}$$

where N is the number of iterations needed, σ is the estimated standard deviation of the output, ε is the desired margin of error, and Z_{CI} is the critical value of the normal distribution for a specific confidence interval, *i.e.*, the z value such that the area of the right-hand tail in a normal distribution is α/2 where α is.

4. Results

The following two tables report respectively the accuracy metrics from the seven LiDAR-derived canopy fuel maps and the ground plots, while Figure 2 shows some details regarding the final canopy fuel maps of CBH and CBD near the ground plots. An overall view of the pan-European map is given in Figure 3.

	ACCURACY METRICS 7 AREAS	
Canopy Fuel	CBH	CBD
RMSE	0.890	0.020
MAPE	54%	57%
R	0.749	0.937

Table 1. Results from the 7 areas in Portugal with LiDAR derived fuel maps.

	ACCURACY METRICS PLOTS			
Canopy Fuel	**CBH**		**CBD**	
Forest Cover	Fc > 0%	Fc>80%	Fc > 0%	Fc>80%
N	804	322	486	225
RMSE	3.9	3.8	0.109	0.090
MAPE	61%	50%	77%	56%
R	0.445	0.524	0.309	0.412

Table 2. Results from the 804 ground plots, compering different fraction cover.

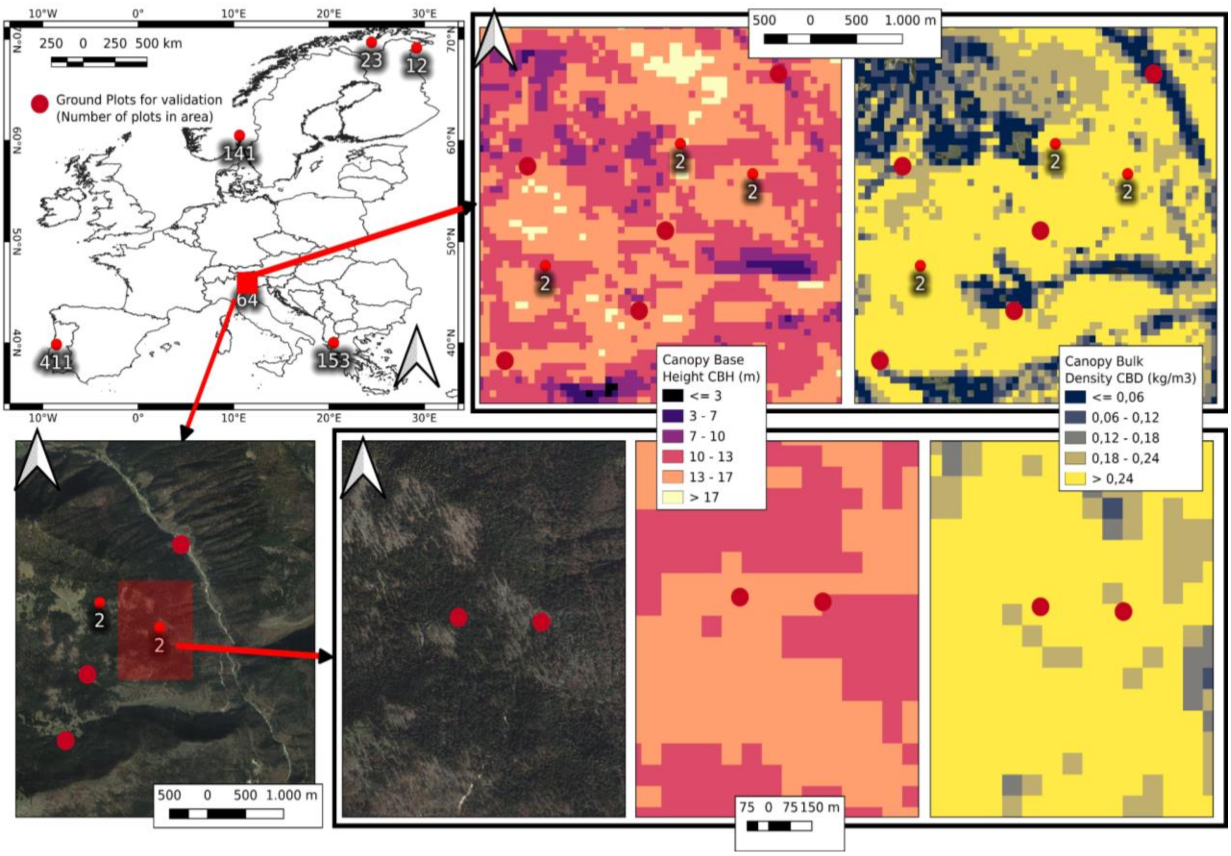

Figure 2. Details of the validation area in Italy with results of CBH and CBD at various scales.

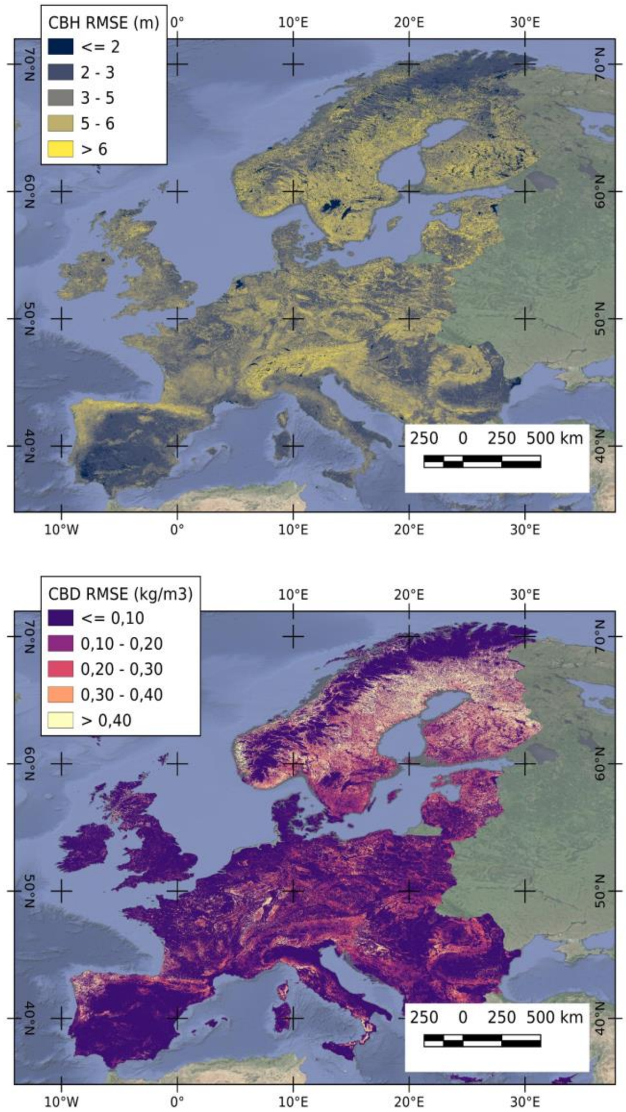

Figure 3. Pan-European canopy fuel maps for CBH (top) and CBD (bottom).

Specific scatter plots for the seven LiDAR-derived CBH and CBD maps are given in Figure 4 and Figure 5. The CBH and CBD values of the 804 plots were compared with estimated CBH and CBD values in Figure 6 and Figure 7, respectively. A partial subset of the 804 plots is represented in Figure 6 and Figure 7, as only fully forested areas were chosen (>80% canopy cover). This was done to harmonize the data as plot values consisted in the mean of the canopy measurements, whereas our method takes into consideration a cell of 100 m x 100 m area (larger than the plot size). If the plot is in a partially forested area, the CBH and CBD values of the cell will be averaged and thus lower than the plot values. Taking into account only cells with a complete canopy cover (or close to a total canopy cover) mitigates this problem and makes the data more comparable. It should be noted that the number of cells with a canopy cover of 80% or more are 322 and 255, respectively, for CBH and CBD. This difference is due to not having CBD values for all the plots; thus, the number of plots for CBD is lower than for CBH.

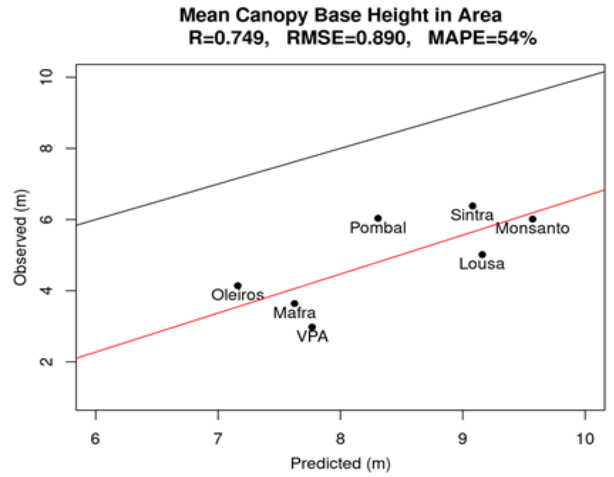

Figure 4. Scatterplot of predicted values in the pan-European map and observed values aggregated for each area in the LiDAR-derived CBH maps.

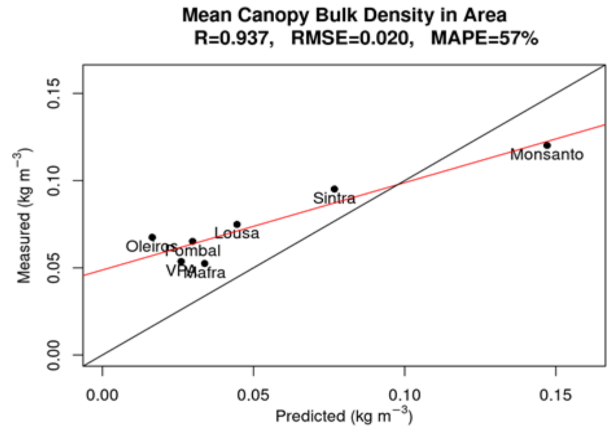

Figure 5. Scatterplot of predicted values in the pan-European map and observed values aggregated for each area in the LiDAR-derived CBD maps.

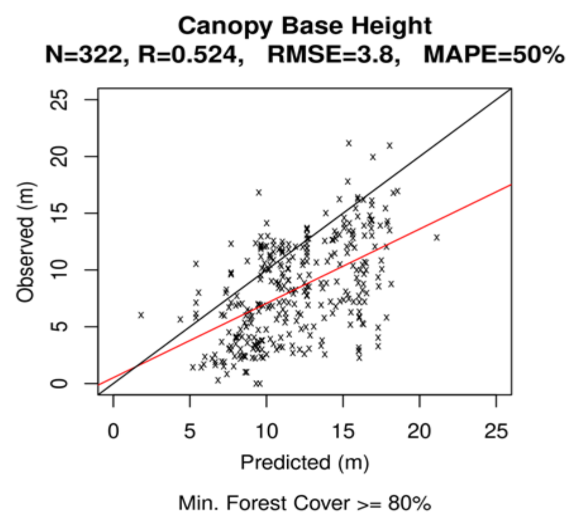

Figure 6. Scatterplot of predicted CBH values in the pan-European map and observed values at a subset of the 804 plots, where canopy cover was above 80%.

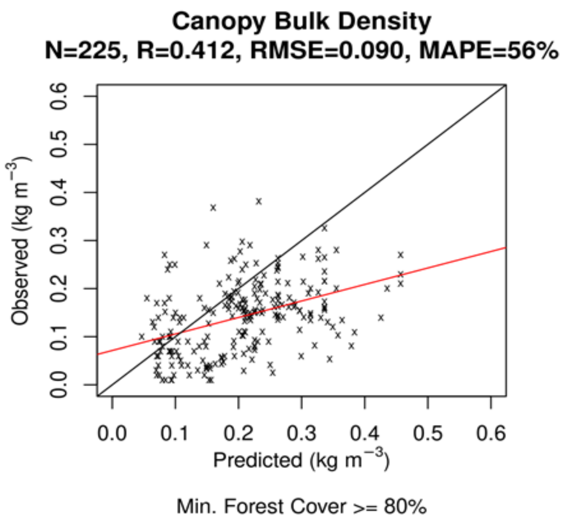

Figure 7. Scatterplot of predicted CBD values in the pan-European map and observed values at a subset of the 804 plots, where canopy cover was above 80%.

5. Discussion

Our innovative method, which combined different remote sensing-derived products with allometric equations and artificial intelligence, utilized harmonized data, which was provided by other authors. First, the probabilistic tree species map provided by Bonannella et al. (2022) specified the spatial distribution of the main 16 European tree species. This information was crucial to determining the use of the species- specific allometric equation at a specific pixel location. Therefore, this information was used to apply the species- specific equations to determine the CBH based on several datasets that predict the height branch insertion and the hamonized biomass models at tree components provided by Forrester et al. (2017), helping to extract the foliage biomass and thus determine the CBD. However, testing the accuracy of the canopy fuels related to our method is a challenging task due to the different uncertainties accumulated through the use of different rasters, mainly related to the canopy height (Lang et al., 2023), aboveground biomass (Pirotti et al., 2023), and the uncertainty of identifying the right tree species at the pixel location, considering that several tree species can be found in a pixel of 30 m of spatial resolution (Bonannella et al., 2022). In addition, the species- specific allometric equations to predict the height branch insertion and the specific foliage biomass also provide uncertainties that are added to the uncertainties that already come from the remote sensing derived-products. On the other hand, variables such as CBH and CBD may represent a large amount of variability in their values at the individual tree level, in which, in a reduced area, some trees can have different crown dimensions and distributions, making it difficult to extract a representative value at the pixel level.

Despite the uncertainties mentioned above concerning the inputs used in the canopy fuel maps. The results presented reasonable accuracy metrics, considering that 804 plots were well-distributed and precisely measured with LiDAR data, and field measurements were used as independent data for validation. It is important to note that ground plots only cover a small fraction of the pixel size, which normally area areas between 250 and 1,000 m^2 in most of the conventional forest inventories (*e.g.*, Botequim et al., 2019; Mihajlovski et al., 2023) and in exceptional cases larger plots (1 ha) can also be measured (*e.g.*, Chávez-Durán et al., 2024), but with a limited number of samples. In our case, the pixel size of the canopy fuel maps was about 100 x 100 m, which can be mixed by different CBH and CBD scenarios. However, covering such large areas for measuring CBH and CBD as ground-truth data is quite time-consuming and expensive, being an unfeasible alternative for a more robust validation process.

However, in spite of the limitations of the presented study, that showed clear overestimation in CBH and underestimation in CBD. There are not many studies that have attempted to harmonise these two important variables to simulate forest fire behaviour outputs at the pan-European scale. Aragoneses et al. (2024) produced through GEDI data a pan-European map, but only for the CBH variable. The results by the authors using GEDI data were satisfactory, obtaining low CBH map uncertainties (RMSE - m). These authors included a robust validation using airborne laser scanning (ALS) observations over forest inventory plots as reference data in different locations around Europe, including 6,587 forest inventory plots distributed in three countries (Germany, Spain, and Slovenia), but Spain was the only country with CBH reference data. However, this CBH map has the limitation of the coarse spatial resolution (1 km), not being suitable for operational uses. On the other hand, to our knowledge, there are no CBD maps available at a pan-European level, which is another crucial layer to complete the geospatial data needed to run the forest fire behaviour simulations.

6. Conclusions

The primary objective of this study was to estimate the two fundamental canopy fuel variables using remote sensing-derived products combined with allometric equations and artificial intelligence. The allometric relationships were derived from open data and field data collection within the FIRE-RES project. The final rasters were produced at a spatial resolution of 100 m and were updated to the year 2020. Accuracy metrics for both rasters were validated using two independent datasets: one LiDAR-derived maps of CBH and CBD and one set of 804 ground-truth plots located in Portugal, Greece, Italy, and Norway. The plots provided CBH and CBD values by integrating LiDAR data with field measurements. The resulting canopy fuel maps cover the entire pan-European territory with harmonized data, which is essential for modelling forest fire behaviour. Due to limited space, an overview of results was given. A more in-depth report is under peer-review at a scientific journal. We believe that these new inputs with reasonable accuracy are valuable information for countries lacking such data, as they can support the development of mitigation plans to reduce the potential damage from extreme wildfire events.

Acknowledgements

This work was funded by the European Union's Horizon 2020 Research and Innovation Programme by the project entitled "Innovation technologies & socio-ecological-economic solutions for fire resilient territories in Europe - FIRE-RES" under grant agreement Nº101037419. Dr. Erico Kutchartt was supported by Fondazione Cassa di Risparmio di Padova e Rovigo (CARIPARO), while Dra. Núria Aquilué was supported by a Juan de la Cierva fellowship of the Spanish Ministry of Science and Innovation (FCJ2020-046387-I).

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