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Pan-European fuel map server: An open-geodata portal for supporting fire risk assessment

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ABSTRACT

Canopy fuels and surface fuel models, topographic features and other canopy attributes such as stand height and canopy cover, provide the necessary spatial datasets required by various fire behaviour modelling simulators. This is a technical note reporting on a pan-European fuel map server, highlighting the methods for the production and validation of canopy features, more specifically canopy fuels, and surface fuel models created for the European Union's Horizon 2020 "FIRE-RES" project, as well as other related data derived from earth observation. The aim was to deliver a fuel cartography in a findable, accessible, interoperable and replicable manner as per F.A.I.R. guiding principles for research data stewardship. We discuss the technology behind sharing large raster datasets via web-GIS technologies and highlight advances and novelty of the shared data. Uncertainty maps related to the canopy fuel variables are also available to give users the expected reliability of the data. Users can view, query and download single layers of interest, or download the whole pan-European dataset. All layers are in raster format and co-registered in the same reference system, extent and spatial resolution (100 m). Viewing and downloading is available at all NUTS scales, ranging from country level (NUTS0) to province level (NUTS3), thus facilitating data management and access. The system was implemented using R for part of the processing and Google Earth Engine. The final app is openly available to the public for accessing the data at various scales.

1. Introduction

Recently, the analysis and integration of vegetation fuel data have become a critical issue for understanding and preventing the impacts of wildfires since they are an important input for various fire simulators used in Europe, USA, South America and Australia [9]. Notable forest fire simulation software includes FARSITE [16], FlamMap [32], Prometheus [8], Wildfire Analyst [33], and Cell2Fire [34], among other alternatives. Accessing comprehensive geo-spatial data for fuel conditions and expected fire behaviour, and risk assessment is thus of prime necessity, especially when all these layers are combined to inform wildfire management agencies on decisions needed to be taken for

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prevention and suppression purposes. To address this need, few data servers have been developed in the past at regional and national levels to provide the necessary geospatial data functionality that is capable of predicting potential fire behaviour. Krsnik et al. [26] have created a data server for Catalonia that helps to evaluate fuel hazards and fire behaviour to mitigate the negative impact of wildfires under different meteorological scenarios. Rollins [40] developed the LANDFIRE, which provides the current state of vegetation, wildland fuel, and fire regimes across the United States at 30 m raster grids. In addition, GIP ATGeRi in France is maintaining a 30 m resolution fuel map for spatial planning and risk management. The above-mentioned open servers have proved their value in supporting decision-making and preventing and managing forest fires. However, there is an information gap regarding data availability on a continental scale, especially in Europe, where data needs to be harmonized and delivered on a single open access server for large scale landscapes.

Nowadays, a wide range of remote sensing derived products can be used to assess the terrain and vegetation characteristics using passive and active sensors [22]. These new sensors can feed models to spatially map with high accuracy the main fire drivers, identified by three components, namely, topography, weather, and fuels [25]. Remote sensing derived products at the global scale are already available. Topography variables (elevation, slope, and aspect) were produced by ALOS World 3D [43], canopy features, such as canopy height maps were recently provided at high spatial-resolution by Tolan et al. [46] using a convolutional network trained on GEDI observations, while canopy cover fraction was generated originally by Hansen et al. [20] based on Landsat data and then by Liu et al. [31] using MODIS observations. Topography, canopy cover and canopy height are accessible and available for download at worldwide scale. Other key input variables for fire behaviour modelling and fire risk assessment are less available at continental scale, and sparse data is far to be harmonised through the same methods and spatial resolution. Specifically, two other canopy features (CBH and CBD) and the surface fuel model maps are partially available in Europe and globally (e.g., [1,37]), but with a coarse spatial resolution, being incapable for use at operational purposes that require a finer scale of analysis and accuracy. Aragoneses et al. [2] provided a pan-European raster for the canopy base height (CBH) at 1 km as target resolution. Information on canopy bulk density (CBD) is difficult to estimate due the complexity of extracting the foliage biomass from the satellite sensors (see Table 1). The same team that generated the CBH model, produced a surface fuel map at the same spatial resolution (1 km) [3].

The aim of this work is to provide a coherent set of raster datasets (Table 1) to better characterise the fire hazard, behaviour, and risk based on assessment analyses at a pan-European level, organized at different administrative divisions according to the nomenclature of territorial units for statistics - NUTS. The second goal was to share such data as per F.A.I.R. guiding principles [14] for research data stewardship (Findability, Accessibility, Interoperability, and Reusability). These raster datasets are the necessary inputs needed to run many forest fire simulation models. They are provided as open data available at an harmonized spatial resolution of 100 m to the public. End-users can access a user-friendly interface for downloading specific areas of interest autonomously, or the entire pan-European datasets.

2. Datasets provided on the fuel map open server

Current operational models that estimate fire behaviour require geospatial data in grid format [9]. This data is usually a set of N raster layers that are commonly used to model fire behaviour in any study area of interest. Some variables that we provide in this server were already generated and provided in other geo-portal servers by other authors in raster format at different spatial resolutions (see Table 1). However, here, we share the estimations of the most challenging input variables to be produced at the pan-European level: two canopy fuel layers (CBH and CBD) and the surface fuel model layer (see Fig. 1).

Table 1
Description of the inputs of required geospatial data for running forest fire simulations. They are co-registered in the same reference system and cell resolution.

Variable	Description raster file
Topography	Topographical information regarding **elevation** (m), **slope** (°), and **aspect** (°) was derived using a global digital surface model (DSM) originally at 30 m resolution that was created using the Panchromatic Remote-sensing Instrument for Stereo Mapping, which was onboard the Advanced Land Observing Satellite launched by the Japan Aerospace Exploration Agency, see Tadono et al. [43].
Biomass	**Aboveground biomass** (AGB; Mg/ha) data was derived using an ensemble of machine learning algorithms. The algorithms were trained on 49 covariates derived from remote sensing products (e.g.,[42,48,29]), employing a stratified sampling approach. The training was based on a biomass map initially developed by the European Space Agency (ESA) in 2018, but the biomass map was predicted and updated to 2020 by Pirotti et al. [38] with its own methodology in order to keep updating this input for the next years.
Canopy features	**Tree canopy cover** (%) refers to the proportion of the ground surface area obstructed by the vertical projection of tree crowns and is commonly obtained through satellite data [20]. **Tree canopy height** (m) is the vertical distance from the ground to the top of the trees, which was developed using a Deep Learning (DL) model combining GEDI and Sentinel−2 data [29]. **Canopy base height** (CBH; m) refers to the vertical distance from the ground to the lowest continuous layer of live crown fuel. **Canopy bulk density** (CBD; kg/m^3) is the ratio of foliage biomass to canopy volume. Both canopy fuel raster datasets (CBH and CBD) were developed using remote sensing-derived products, artificial intelligence, and species-specific allometric equations.
Fuel model	The surface **fuel model** is a categorization/codification/classification of fuel typologies originally developed by Scott and Burgan [24] to predict the potential fire behavior characteristics, which organize fire data geo-spatially by the vegetational structure, height, and moisture content.

Table 1 describes the raster datasets that are available in the WebGIS portal that were resampled at approximately 100 m. The original spatial resolution of the topography variables and canopy cover was 30 m, while the canopy height was at 10 m. The aboveground biomass, the canopy fuels, and the fuel model were generated by the authors at 100 m. Some of these data sources come from different years. Topographic features were estimated using stereo imagery from satellite across several years (2006–2011). It is assumed that the terrain surface does not change significantly in such a short period, especially considering the scale and accuracy of the dataset (see Table 1). The AGB map was estimated for the year 2020, and also the canopy features are calculated for the year 2020. Regarding fuel model, information comes from two years, 2018 (Corine land cover) and 2020 (ESA World Cover). The year of reference is not that critical in canopy features, unless there is a modification by management practices or natural disturbances (e.g., [10,18,39]). The fuel layers ideally should be updated frequently to account for land-cover changes. This would allow to run proper forest fire simulations with recent canopy feature conditions. This can be done in a future scenario where the workflow pipeline is replicated automatically, and the fuel map updated accordingly. This is not the case at the moment, but users, if necessary, can add their own processing to fix the data and update it. This is only necessary if the area of interest has been significantly changed by natural or man-induced disturbances, as mentioned.

In the presented open-data server, we integrate the geospatial data required to support fire modelling. This data aims to characterise the terrain topography (point 1 in Table 1), and the vegetation that may be consumed by a fire (points 2–4 in Table 1). Overall, all 11 layers (3 topographic, 6 vegetation/fuel and 2 uncertainty raster datasets in canopy fuels) were loaded at the four European NUTS levels suggested

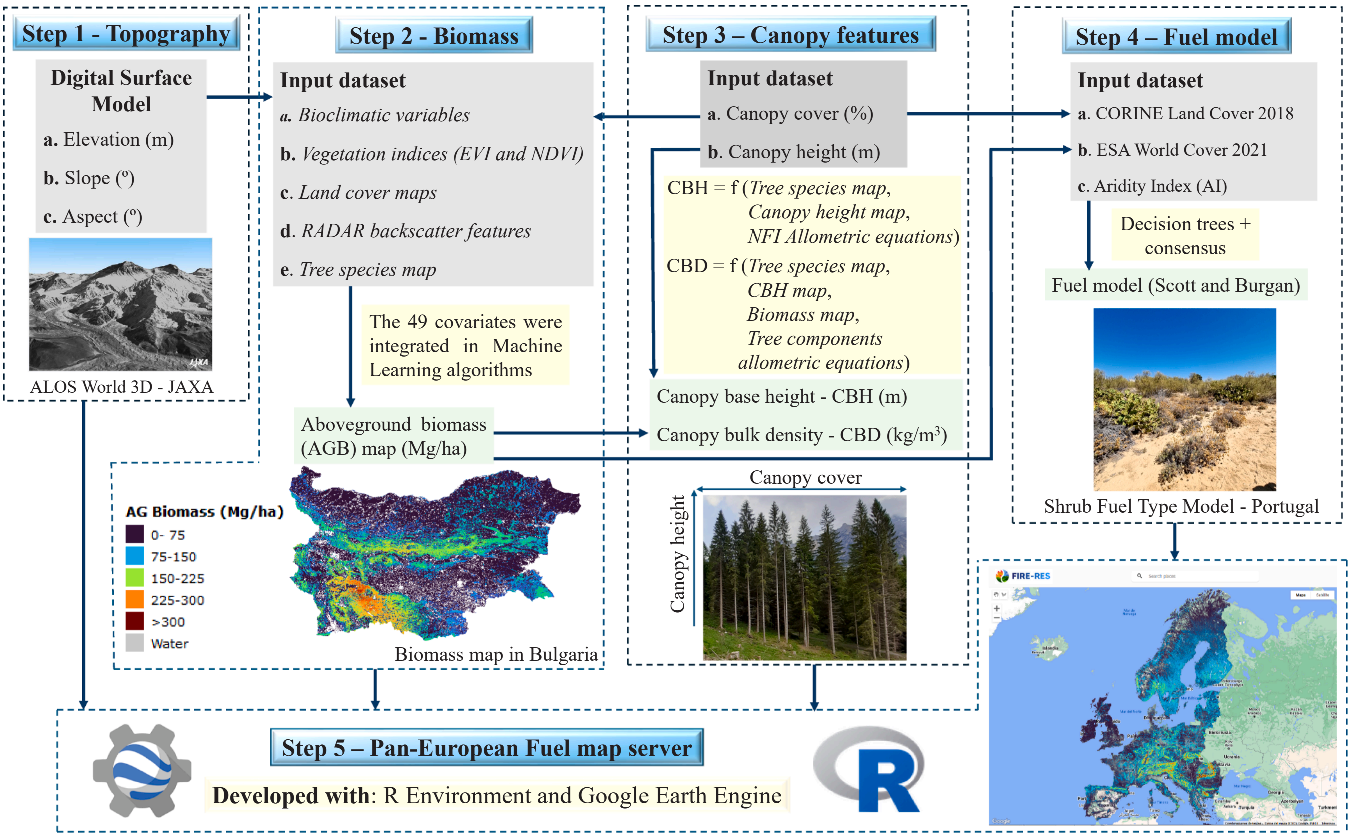

Fig. 1. The flow chart shows step by step how the data was obtained (grey), the process (yellow), and the outcomes (green) in the Pan-European fuel map server. The step 1 shows how the topography variables were obtained from the ALOS world 3D data; the step 2 shows the aboveground biomass (AGB) map produced by authors combining satellite data and machine learning algorithms; the step 3 shows the two canopy features, cover and height raster datasets that were obtained by previous authors; meanwhile, the canopy fuel raster datasets were produced by authors combining different derived remote sensing products with species- specific allometric equations. In case of the CBH, allometric equations were fitted based on data from different National Forest Inventories and local studies, while the CBD was estimated by a European compendium of allometric equations published by other authors (Forrester et al. [17]). Step 4 shows how authors produced the fuel model based on a tree-decision process by the consensus of different land cover maps, and finally, step 5 shows the Pan-European fuel map server developed through the R language environment and Google Earth Engine app.

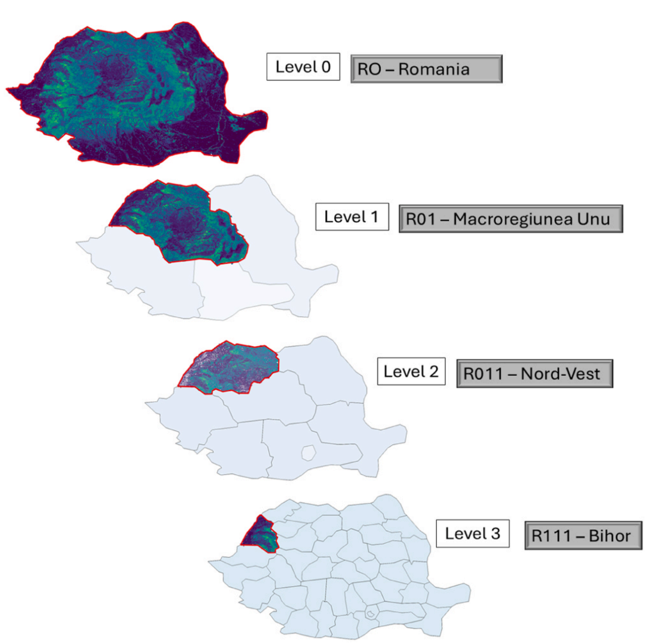

Fig. 2. A demonstration of the layer levels available at the pan-European fuel server at all the NUTS levels from 0 to 3, for the case of Romania.

by the EUROSTAT [13] at the pan-European scale (Fig. 2).

2.1. *Canopy feature raster layers*

All raster layers were co-registered in the WGS84 geographic coordinate reference system (CRS) defined in the EPSG database version 10.008 with EPSG code 4326 with approximately 100 m cell size (8.983° x 10^{-4}). It should be noted that this implies that cells will have different sizes according to the latitude of the cell, but the values in the cell node refer to a 100 m x 100 m area. We will therefore refer to pixel ground sampling distance as 100 m.

As indicated in Table 1, most of the layers in the geospatial data for fire simulators exist and were simply resampled at ~100 m and co-registered in the common reference frame and extent. In the framework of the H2020 "FIRE-RES" project, three specific layers were produced and delivered: CBH, CBD and surface fuel models. Also, the relative uncertainty maps for CBH and CBD were calculated and provided in the server. The pipeline to produce these layers starts with the estimation of aboveground biomass (AGB) using artificial intelligence and a set of predictors that include bioclimatic variables, vegetation indices from Sentinel-2, and radar backscatter from Sentinel-1 and ALOS. A detailed explanation of the method is provided in Pirotti et al. [38]. Novel aspects regarding biomass estimation are found in segmenting the European area in several tiles to train independently with stratified samples to cover in a balanced way the range of biomass variability available in each tile. An ensemble of machine learners was thus trained and used for mapping AGB over Europe for the reference year 2020. The framework used was the H2O library cluster [30] accessed by the R environment, and the training and testing data came from an existing aboveground biomass map [41]. In total, thirteen models were created with training data in each of the 19 tiles distributed across Europe, stratifying the sample and using around 200,000 locations for the training and testing process through the staked ensembles of models, which identifies the optimal prediction combination algorithms [38].

The AGB map was then used for extracting the CBD, which is the amount of thin biomass in the trees - i.e., highly flammable fuel. Bulk density refers to the amount of thin biomass per unit volume of the canopy (Fig. 3). Thin biomass is mostly leafing biomass (mostly leaves and small twigs), thus AGB without trunk and branch biomass (Fig. 3). To estimate the thin biomass, allometric models were used to infer the fraction of foliage biomass from the total AGB. Species- specific models were used to estimate the foliage biomass according to the compendium equations provided by Forrester et al. [17]. The value of the fraction is species-specific and depends on the size and age of the tree, but also on the forest management plans in case of forest plantations. To account for the former, we used a map of tree species probability [7], while tree size and age were estimated by using the canopy height map by Lang et al. [29] and inverse allometric models to derive diameter. Therefore, a set of biomass equations at tree components provided the fraction of thin biomass (foliage) for different tree species based on diameters as an explanatory-variable [17].

Once the biomass of the thin fuel components is determined, it is possible to determine the density using canopy volume as the denominator. Canopy volume was determined using tree height and the estimated canopy base height (CBH). Subtracting CBH from total tree height provided the canopy volume (Fig. 2). Therefore, canopy fuels are fundamental variables considering that fire usually starts from the ground and increases in intensity and spread rate if it can reach the crown easily, especially when it is near the ground (understory fuels). Therefore, the procedure included three main raster maps, such as tree species, canopy height, and aboveground biomass that were combined with different species -specific allometric equations. We used the 16 tree species available in Bonannella et al. [7] for predicting the branch insertion height and foliage biomass. The species map's uncertainty can lead to the assignment of an erroneous equation in the selected pixel, as a single pixel can host multiple tree species. Here, it is important to note that the information on the tree species map comes from a probabilistic model including the most representative tree species in Europe, but it excludes other regional-dominant species such as *Pinus pinaster* Aiton, *Quercus pyrenaica* Willd., *Pinus radiata* D. Don or *Eucalyptus globulus* Labill that are located in high fire-prone areas around Europe (e.g., [15, 36]). Thus, in order to minimise the uncertainty of matching the right tree species with the real species – specific allometric equation used in our model, the occurrence probability was used as a weight after normalisation.

2.2. Fuel model raster layer

The fuel model categories by Scott and Burgan [24] divide fuels in three main burnable categories i.e., timber, shrub and grasslands, plus some non-burnable categories like urban areas, water, and snow. Fuel model classes were determined according to the estimation of available fuel load and climate conditions (i.e. humid vs. dry environments). The fuel models were assessed and assigned to each cell through a consensus among different land cover maps to define the main categories at first. As in Aragoneses et al. [3], several land cover maps are used together. The method differs in the number of land cover maps used and in the final attribution of categories. The following available datasets were used in the process: the CORINE 2018 at 100 m resolution, the Copernicus global land cover (GLC) at 100 m resolution, and the ESA World Cover 2021 v200 at 10 m resolution (based on Sentinel-1 and Sentinel-2 data). Respectively, the overall thematic accuracies of these maps are $>$ 85%, ~80%, ~75%. The minimum mapping unit of the CORINE land cover is 25 ha. This means that usually features smaller than this size are clustered together, even if this is not a hard limit [19]. The canopy height, canopy cover and the AGB maps were used for assigning the final fuel model category through a decision tree process. The criteria

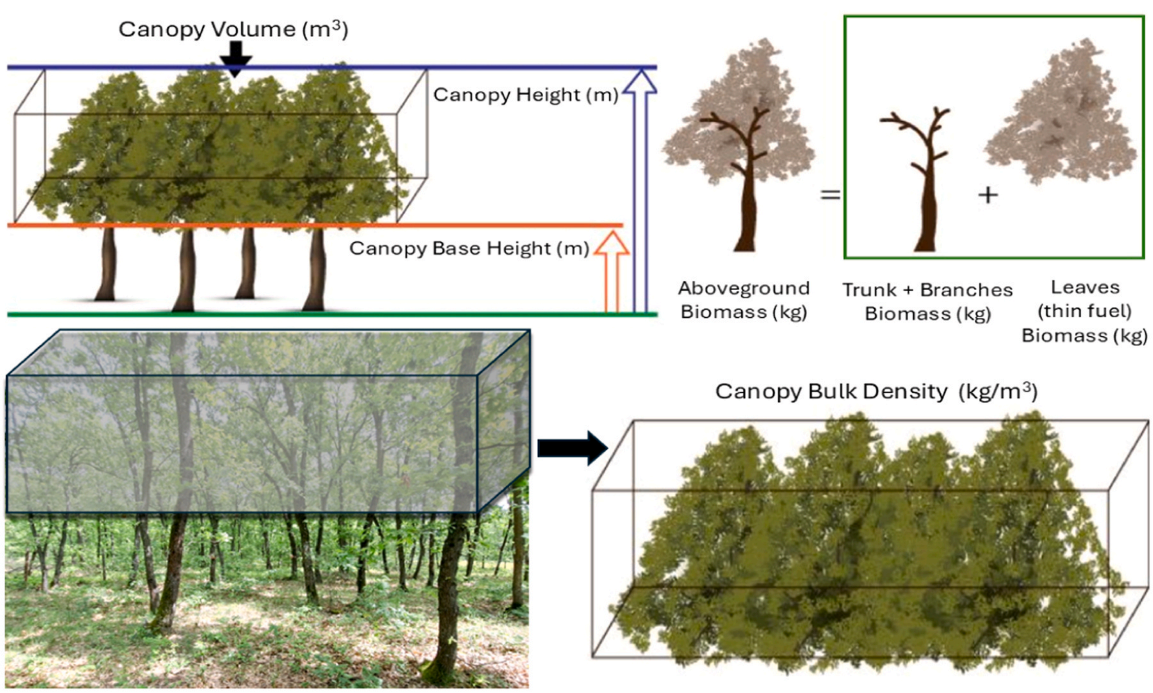

Fig. 3. Clockwise from top left: schema depicting the relation between canopy volume, canopy base height and canopy height; Top right: schema of AGB with respect to trunk, branches, and thin biomass; Bottom right: depicts only the foliage biomass component; Bottom left: is a geotagged image captured for validation to show how CBD is interpreted in the field.

regarding this step is that these three maps contain information related to grass/shrub/forest and the amount of such class in each cell. Therefore, they can be cross-checked with the CORINE land cover class to further improve accuracy. For example, a cell that is in class "coniferous forest" in the CORINE will be modified to grass or shrub class if there is very low biomass, canopy cover and/canopy heights. The canopy height is used to cross-check that timber, shrub and grassland main categories have consensus (*e.g.*, forests must have canopy heights > 2 m). It further uses canopy cover to provide a weight to cells that might have multiple land cover categories. The method provides a stack of rasters, one for each category in Aragoneses et al. [3] with respective weights. A final map with the category is provided by selecting the category with the maximum weight from the stack for each cell. The final fuel map uses the Scott and Burgan [24] categories that divide general grass/shrub/timber classes further depending on low/moderate/high/very high load. The load refers to biomass availability and is inferred using the biomass map as input. The final categories were assigned to dry or wet subcategory by calculating the aridity index (AI) map. The AI maps were estimated from bioclimatic data (precipitation, minimum average and maximum temperature, and solar irradiation) at 1 km spatial resolution from Hijmans et al. [23]. Climatic rasters were used to estimate evapotranspiration using the Hargreaves/Samani equation [21] and final aridity from dividing precipitation by evapotranspiration. Six classes of AI (hyper--arid, arid, semi-arid, dry sub-humid, humid, and hyper-humid) as per FAO-UNEP classification were assigned to each cell. A final fuel model category was assigned to dry (arid to semiarid climate - rainfall deficient in summer) or humid (subhumid to humid climate - rainfall adequate in all seasons) subcategories as per Scott and Burgan [24] according to the average AI value during the summer months. The final fuel model map was tested, and feedback was provided from living labs and in particular from experts involved in the project that used the data as input for fire behaviour simulations. Specifically, both static and dynamic fire simulations were conducted. The static simulation incorporated variables such as crown type, fireline intensity, rate of spread, flame length, and spotting distance. In contrast, the dynamic simulations were focused on burn probability and conditional flame length probabilities. The fire simulations performed satisfactory results, aligning well with the expected ranges.

2.3. Uncertainty layers of CBH and CBD maps

The procedures described above include multiple estimation steps through modelling, which naturally will propagate the uncertainty of the original data and of the estimations along the pipeline of the workflow. It was therefore important to map an uncertainty layer for each final product and thus provide a further informative layer to the users. Two different approaches were used to carry out uncertainty analysis: the chain rule and Monte Carlo simulations [27]. The former was used when the equations were relatively simple and were expected to have normally distributed values, such as the CBH map. The allometric model is a linear regression model so the expected error from the independent variable can be tracked. When functions become more complex like in the case of CBD, or require multiple steps like the fuel model map, then the Monte Carlo method is a more suitable tool. This method uses random samples of the input variables of interest extracted from an expected frequency distribution, described with an average and standard deviation, thus simulating the expected error.

It should be noted that error propagation takes into account the uncertainty of the original input data and then uses a method to calculate or estimate, depending on the approach, how the original arrives at the final product. Maps with categories like CORINE provide information on error using the well-known confusion matrix to extract class-wise expected accuracy; in this case we used weighted f1 score, with weights given by the relative area of each category. Recall and precision used to calculate f1 score are inferred from the provided confusion matrices in the validation report of CORINE documentation [11]. Map with quantitative values, such as CBH and CBD, use standard deviation of original data as uncertainty metric to propagate to the final maps. Arithmetically, also the standard deviation of the used models is also used to add the uncertainty derived from the estimation. For example, the CBH and CBD require the tree species information, which inherently has a determined uncertainty, and also the models used are trained and tested and provide an added expected error that must be accounted for. Specific final uncertainties for CBH and CBD are provided in [27].

2.4. Pan-European fuel map server

Google Earth Engine (GEE) provided the big-data infrastructure to organize all raster layers used and created in the project and also provided the means to share them through an app that was published online as the pan-European fuel map server (Fig. 4). The GEE environment allows linking data layers, loaded as GEE assets, to the web-based portal thus providing the necessary user-friendly interface for interacting with the data layers. R language environment was also used for some processing steps, such as training and applying the AI framework for estimating biomass for 2020 and for sub-setting the grid data at pan-European scale to the NUTS levels up to level 3. At the end of this last process, more than 1800 raster files are generated and stored for user download. The pan-European fuel maps server allows users to easily find and access each single layer of geospatial data. Visualization is provided as a styled raster layer. An interactive user query can extract all information from the raster layers at a user-defined location by selecting a location with the left mouse button. Further interaction consists in downloading the layers or the whole stack at the user-selected area at the chosen NUTS level. This increases the accessibility of the data, as analysis and decisions are usually made at specific administrative levels, with respective boundaries, such as states, provinces or regions. The replicability of the process is assured through the documented methodology, and both the R code and the GEE code for the server are available upon request to the authors.

All the raster data available in the server is at 100 m spatial resolution. The definition of the spatial resolution primarily stemmed from the constraints imposed by certain input datasets at a minimum geometric accuracy of 100 m, which were considered significant variables. The land cover map through CORINE was used for the fuel model at 100 m [11,35,47], while the AGB map was also used at 100 m to extract the foliage biomass and then to compute the CBD raster dataset [38,41,5]. Although some input datasets, such as topography and canopy cover (30 m resolution) and canopy height (10 m resolution), were available at finer spatial scales, the harmonization process involved resampling these datasets to 100 m. This resampling resulted in a loss of information in certain raster inputs, which in turn affected the accuracy of the final forest fire simulations. However, with the potential availability of new high-resolution land cover maps from the Copernicus program and the ESA WorldCover (the latter reaching a 10 m resolution [12]), significant improvements in spatial resolution are expected in the near future. Incorporating these new datasets will enhance the spatial resolution of fuel raster data. This is an important remark, considering that several studies have demonstrated that the fire behaviour model outputs are strongly affected by the spatial resolution from the data inputs [4,44,45].

2.5. Ground validation

The pan-European fuel maps server allows users to view and interact with the data. An important part of creating and sharing geodata is the accuracy of the information. In this case, the challenge is the large area considered. This encompasses a high variability among different countries, with marked contrasts from the Mediterranean vegetation in the south to the boreal forests of northern Europe.

To address how reliable can be the raster files available on the server, a solution that uses crowd-sourced imagery is under development for

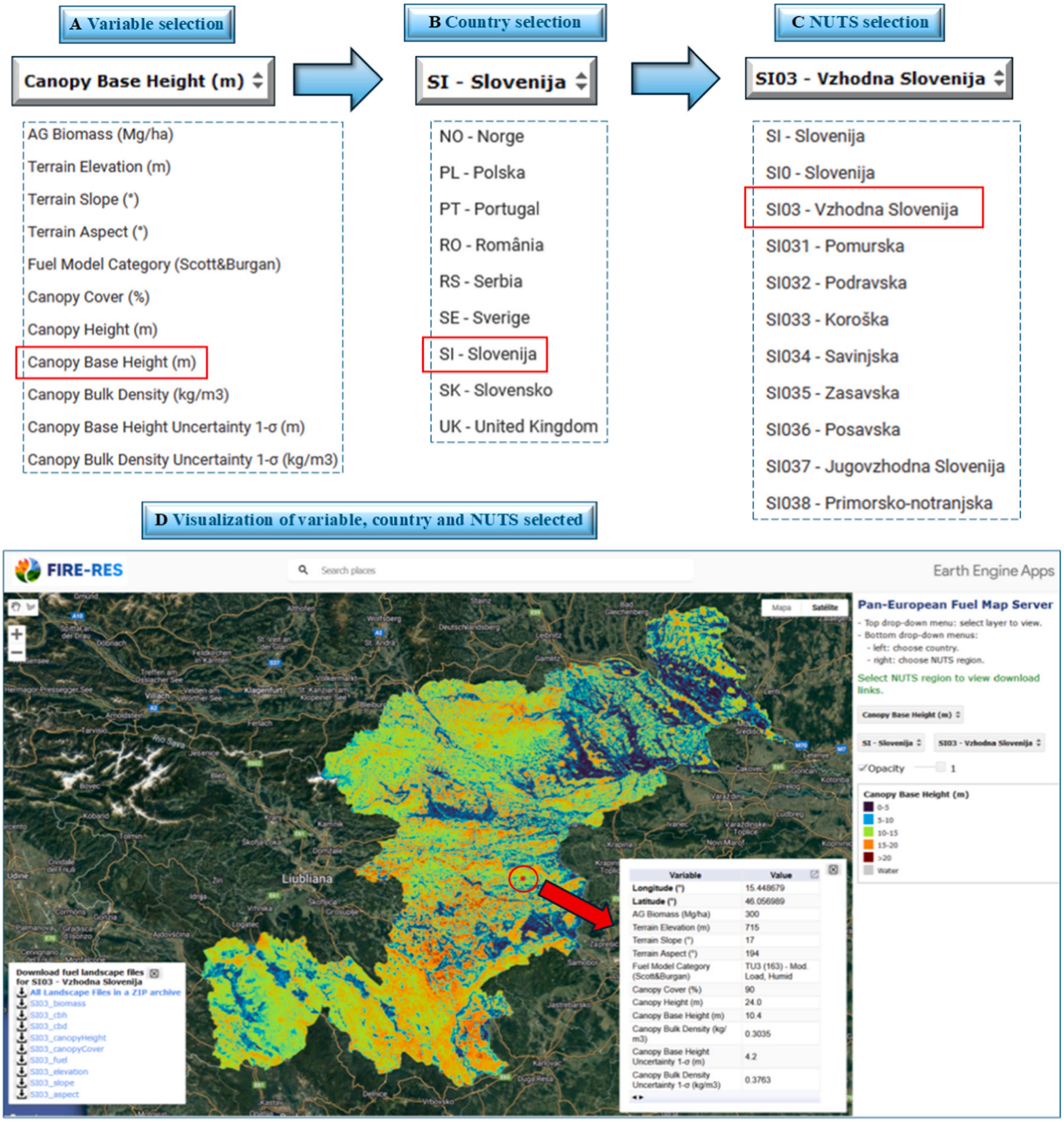

Fig. 4. An overview of the workflow on how to download the raster data: a) selecting the variable, b) selecting the country, and c) the NUTS level. Once the variable and geographical area is defined, d) a visualization will appear with the variable, country, and NUTS chosen, where a box appears with the option to download all raster files in a zipped folder or single raster files is provided. In addition, the raster file can be queried at any pixel, once the user clicks on it, a red dot will appear and a table will be opened with the values of the eleven variables offered, including the nine raster layers available, and the two uncertainty layers reported for the CBH and CBD. R and Google Earth Engine were used together to provide the work pipeline. Fundamentally all input layers are uploaded to GEE as assets. The R environment provides, via the *rgee* package [6], access to the GEE framework and the necessary interoperability between R and GEE objects. Resampling and alignment of the raster in GEE were done by keeping as reference the biomass map and aligning all input rasters to that map. This means that the final layers will all have the same origin, extents and cell resolution. This is an important factor to consider and further calculations of the downloaded data will require that rasters are aligned. Misaligned rasters would provide further uncertainty by mixing overlapping neighbouring pixels, and this was mitigated by aligning all inputs to a single reference. The alignment uses nearest neighbour values to assign final cell values, whereas when resampling smaller pixels to larger pixels, the average value of cells falling inside larger call was calculated.

improving the accuracy of the maps in the server, especially considering that better spatial resolution maps are expected in the near future. A smartphone application was developed in parallel with the pan-European fuel mapping server to support validation as follow-up research [28]. This app, called the FIRE-RES Geo-Catch app, differs from other photo-collecting apps as it is based on a very simple interface and uses a Progressive Web App (PWA) framework and thus can be accessed via a web-browser and/or be quickly installed in user's smartphones. It collects user photos as images with a specific EXIF tag enriched with geo-location, along with its accuracy, and camera orientation at the time the picture is taken. Thus, for a specific location, one or more images of the landscape with the direction of the line-of-sight becomes available in real-time after the user takes the picture. This supports validation at the corresponding cell at that location in the pan-European fuel maps server. Kutchartt et al. [28] show a depiction of a geotagged and orientated image captured by the FIRE-RES Geo-Catch app and show future development that will label images with categories of fuel models and other information. This step will be followed by training an AI model that will automatically predict a fuel model category for all the images. To this date 7000 + images have been collected throughout Europe.

3. Conclusions

This technical note reports on the role of geomatics for reaching two main goals, i.e., the creation of mapped products for decision support related to fire-risk management and sharing these data through a pan-European fuel maps server as per the F.A.I.R. guiding principles for research data stewardship. The geospatial data for fire simulations is used to refer to the co-registered set of gridded data that provides stakeholders key information to define fire prevention plans and other data-driven decisions as it is used by many fire behaviour models. Academia, public administrations, agencies and common citizens can find, query, and access the data at various scales to make informed decisions. Further research will focus on downscaling the fuel model and canopy fuel rasters at an even more operational scale, likely 30 m or less of ground sampling distance along with applying validation methods using LiDAR data and forest inventory plots as ground truth values.

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CRediT authorship contribution statement

Erico Kutchartt: Conceptualization, Investigation, Formal analysis, Data curation, Methodology, Writing - original draft. **José Ramón González-Olabarria:** Conceptualization, Methodology, Supervision. **Núria Aquilué:** Conceptualization, Writing - review & editing. **Jordi Garcia-Gonzalo:** Conceptualization, Resources. **Antoni Trasobares:** Funding acquisition, Supervision, Resources, Project administration. **Brigite Botequim:** Conceptualization. **Marius Hauglin:** Data curation, Validation. **Palaiologos Palaiologou:** Conceptualization, Data curation, Validation. **Vassil Vassilev:** Conceptualization, Validation. **Adrian Cardil:** Conceptualization, Writing - review & editing. **Miguel Ángel Navarrete:** Data curation, Validation. **Christophe Orazio:** Conceptualization. **Francesco Pirotti:** Methodology, Data curation, Formal analysis, Software, Validation, Writing - original draft.

Declaration of Competing Interest

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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Data availability

All the data are available in the pan-European fuel maps server, where the nine raster files can be visualised, queried, and downloaded at different NUTS levels for the whole pan-European region. In addition, the uncertainties of the canopy base height (CBH) and the canopy bulk density (CBD) maps are also available. The open server was implemented via Google Earth Engine app in the following link: www.cirgeo.unipd.it/fire-res/app.

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