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Generation of high-resolution fuel model maps from discrete airborne laser scanner and Landsat-8 OLI: A low-cost and highly updated methodology for large areas

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ABSTRACT

Wildfire risk is increasing in the context of global change, and the need for accurate fuel model maps in broader areas is becoming urgent to manage large wildfires. Among remote sensing technologies, Airborne Laser Scanner (ALS) is extremely useful for fuel mapping as it provides 3D information on vegetation distribution. A cost-effective methodology to obtain high-resolution fuel model maps in large forest areas from ALS data (1 pulse/m^2) and Landsat-8 OLI images is presented. A two-phase approach was used to generate the fuel model maps: i) ad-hoc vegetation classification derived from ALS and Landsat-8 OLI, and ii) fuel model assignment based on fuel complex structure from a limited number of ALS-derived metrics: fractional canopy cover, fuel height, and canopy relief ratio. Fuel model maps for the Canary Islands (Spain) were generated for two fuel classification systems, standard Northern Forest Fire Laboratory (NFFL) and specific Canarian fuel models (CIFM), at 25 m resolution (3678 km^2) according to decision rules based on ALS-derived metrics developed for each vegetation type. Fieldwork was used to validate the fuel model maps, obtaining an overall accuracy of 82% (kappa = 0.777) and 70% (kappa = 0.679) for the standard NFFL and CIFM fuel models respectively. Discrimination between fuel models associated to forests with and without understory was satisfactory, showing higher errors due to species composition classification rather than to ALS-derived fuel structure. Errors due to underestimation of ALS-derived fuel cover and height were more evident in mixed grassland and shrubland fuels. Results demonstrated the potential of combining imagery and ALS for fuel model mapping at a large scale from existing data sources, even with low laser pulse density and temporarily mismatched data sets. The proposed methodology may be applied for fuel mapping in other large areas provided that ALS information is available and that fuel model definition has explicit structure characteristics allowing decision rules based on ALS data. Once algorithms are defined for fuel model assignment, the low number of ALS-derived metrics and the semi-automated processing ensures that fuel model maps can be easily updated as new data sources become available providing managers with useful spatial information in large areas.

1. Introduction

Wildfire risk and occurrence is increasing in many forest areas due to the context of global climate change, which poses a major concern because of the environmental, societal and economic consequences (Moreira et al., 2011; Moritz et al., 2012; San-Miguel-Ayanz et al., 2013). In addition to climate, other factors such as ignition agents, length of the fire season, vegetation characteristics and human activities, such as fire management policies and landscape fragmentation, may greatly influence the fire regime in the next century (Flannigan et al., 2000). As in other parts of the world, the Canary Islands had a significant increase in the number and extent of forest fires during the last decade, showing the highest increasing tendency in wildfire occurrence in Spain (MAGRAMA, 2012). The situation is expected to worsen due to the predicted extreme fire weather increase according to future climate change scenarios, as longer fire intervals in conjunction with land abandonment and fuel accumulation would make these areas more vulnerable to catastrophic wildfires (Moritz et al., 2012; San-Miguel-Ayanz et al., 2013).

Fuel characterization is key to wildfire prevention as forest fuel is one of the primary factors affecting wildfire risk and behaviour. In the context of wildfires, vegetation is grouped into different large classes generally called "fuel types". These classes vary according to different classification schemes, which intend to summarize the main physical characteristics (live and dead biomass, particle size, etc.) related to

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forest fuel flammability (fire spread, intensity, etc.). The term "fuel model" is usually applied when referring to more detailed fuel types defined by a numerical description of the relevant physical properties of vegetation according to a particular fuel classification system (Anderson, 1982; Scott and Burgan, 2005).

Landscape-level fire behaviour simulation models, such as the widely-used FARSITE (Finney, 1998) and FlamMap (Finney, 2006) software, are becoming essential tools to support decision making. These fire behaviour models require spatial information on fuel characteristics in continuous layers as input data. The need for accurate and spatially-explicit information on existing forest fuels in broader areas is becoming urgent to prevent large forest fires and mitigate their negative effects (Erdody and Moskal, 2010; Seielstad and Queen, 2003). However, traditional fuel mapping is highly expensive and time consuming. Hence, managers often have to deal with old fuel model cartography, which hinders getting realistic wildfire risk predictions.

Although LiDAR (Light Detection and Ranging) has been used more recently in forest applications compared to other remote sensing methods (Arroyo et al., 2008; Lefsky et al., 2002), this type of data is proven to be extremely useful for forest fuel characterization (Andersen et al., 2005; Riaño et al., 2003; Seielstad and Queen, 2003). Airborne LiDAR, hereinafter referred to as ALS (Airborne Laser Scanner), can be used to directly measure the three-dimensional structure of vegetation across large spatial areas (Duncanson et al., 2014; Evans et al., 2009; Ferraz et al., 2012; Lefsky et al., 2002, 2005). The ability to detect vertical distribution of forest stands at a fine spatial scale is a significant improvement compared to other type of advanced remote sensing techniques (e.g. satellite and aerial imagery from hyperspectral sensors), which is making ALS an essential complementary tool to determine fuel metrics (Erdody and Moskal, 2010) and fuel models (García et al., 2011; Mutlu et al., 2008). ALS is particularly interesting to discriminate the presence of vertical fuel continuity, and thus to predict increased fire danger associated to crown fire potential in forest stands. Some studies have successfully estimated important fuel properties from ALS data, such as fuel height, vegetation cover and several canopy parameters (Andersen et al., 2005; Gonzalez-Ferreiro et al., 2014; Riaño et al., 2003, 2007). However, being able to translate fuel models into ALS-derived parameters requires an explicit characterization of vegetation structure that is not always straight-forward depending on the fuel classification system used.

Despite technological improvements have led to the possibility of gathering ALS data at high pulse densities (tipically considered above 1 point/m^2), acquisition costs still limit the availability of this kind of data in large areas (Jakubowksi et al., 2013a). In Spain, free ALS data are provided for all the country at a low pulse density (0.5 points/m^2) by PNOA (Spanish National Plan for Aerial Orthophotography). Despite the fact that higher laser pulse density is expected to improve accuracy, previous studies (Gonzalez-Ferreiro et al., 2014; Jakubowksi et al., 2013a) suggest that relatively low density ALS is sufficient to accurately retrieve the required metrics for fuel mapping. ALS data can be used to model canopy fuel properties, and obtain geo-referenced raster files on detailed fuel characteristics that can be periodically updated (Gonzalez-Ferreiro et al., 2014).

Imagery data is useful for species identification, land cover and coarse fuel-type classification, but is not suitable to estimate canopy fuel structure and understory vegetation (Erdody and Moskal, 2010; Falkowski et al., 2005; Riaño et al., 2002). García et al. (2011) used a Support Vector Machine (SVM) classification of the basic fuel types (grassland, shrubland and trees) as the input for a second phase classification of fuel models according to the Prometheus scheme that relies on fuel height and cover (European Commission, 1999). These authors used a combination of ALS data to derive fuel vertical distribution and multispectral imagery to better characterize vegetation composition and structure. More detailed fuel classification systems require users not only to discriminate tree stands from shrubland and grassland, but also vegetation composition as fuel load can significantly vary among species (Lydersen et al., 2015). In forest stands, understory composition is particularly difficult to discern by remote sensing techniques, either by ALS or passive sensors. Imagery could be used to provide this information on sparse tree stands, but not in a multi-layer forest structure with dense canopy closure where only species composition in the dominant overstory layer could be detected. Moreover, the more detailed the classification scheme is, the more difficult is to discriminate between fuel models. Considering similar spatial resolution and methodological approaches, fuel model assignment errors are more likely to occur when using a specific fuel classification system (e.g. Scott and Burgan, 2005) compared to standard classification systems (e.g. Northern Forest Fire Laboratory -NFFL, Prometheus).

Costs are generally a trade-off of accuracy. Although the integration of ALS and optical data would generally improve fuel model maps (Mutlu et al., 2008), some studies found only small increases in estimation accuracy when fusing ALS data with imagery and/or LiDAR intensity compared to ALS alone (Erdody and Moskal, 2010; Jakubowksi et al., 2013b). Erdody and Moskal (2010) highlight that cost analysis should be taken into consideration when asking if it is necessary to use two different sensors for a marginal increase in accuracy when using just one (ALS) gives excellent results.

Previous research on fuel mapping from ALS data are mainly focused on relatively small extent areas (García et al., 2011; Mutlu et al., 2008; González-Olabarria et al., 2012; Jakubowksi et al., 2013b). At a broader scale, i.e. national or continental, there are also some studies that have used spaceborne LiDAR data to indirectly account for vegetation height in order to classify fuel types at low spatial resolution (Pettinari et al., 2014). The main objective of the present work is to obtain fuel model maps from ALS data and Landsat-8 OLI imagery at a high spatial resolution in the Canary Islands. The specific objectives are: (a) to develop a cost-effective methodology to characterize forest fuels in large geographical areas (regional scale) that could be easy to update; and (b) to compare the performance of ALS data for fuel mapping with different fuel classification systems: specific fuel models adapted to the Canarian vegetation vs standard NFFL fuel models. For this purpose, a two-phase approach is proposed to generate the fuel model maps: i) vegetation classification from ALS and Landsat-8 OLI to obtain ad-hoc groups according to basic fuel types and species composition; and ii) fuel model assignment based on fuel structure derived from ALS data and decision rules specifically developed for the fuel classification systems used.

2. Material and methods

2.1. Study area

The study area comprised the five islands with presence of forest lands in the Canary Islands archipelago, Spain (Fig. 1). These volcanic islands are located in the Atlantic Ocean, in front of the northern African coast, from 27°37′N to 29°25′N, and 13°20′W to 18°10′W. A total of 3678 km^2 are included in this work, covering grassland, shrublands and tree stands, which represents on average the 74% of the area in the islands (Table 1). Important protected natural environments, like Teide National Park (Tenerife Island), Garajonay National Park (La Gomera Island) and Caldera de Taburiente National Park (La Palma Island), were included. Concerning topography, 31% of the study area has steep slopes of over 30%. The general climate is subtropical but with a high local variability depending on altitude (ranging from 0 to 3718 m above sea level) and north-south exposure, which results in a wide variety of vegetation types (Fernandez-Palacios, 1992).

Among the forest stands, the most representative tree species is the endemic Canary pine (*Pinus canariensis* C.Sm. ex DC.). It is found in pure stands or mixed with other pine species (e.g. *P. radiata* D.Don) or evergreen trees (tree heath, *Erica arborea* L., and wax myrtle, *Myrica faya* Ait.). Another important forest ecosystem characteristic of more humid climate is the laurel forest (called *laurisilva*), composed of *Laurus azorica* (Seub.) Franco, *Persea indica* (L.) Spreng. or *Ilex canariensis* Poir.,