Characterization of wildland-urban interfaces using LiDAR data to estimate the risk of wildfire damage

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Abstract: Galicia is a region in NW Spain which is usually affected by a high number of forest fires, and it should meet the current regulations regarding the distance between forests and buildings. This paper aims to identify and characterize woodlands and classify buildings according to their fire risk, for a 36 km^2 area in Forcarei (Pontevedra, Spain). We used LiDAR data to generate three spatial models (DTM: Digital Terrain Model, DSM: Digital Surface Model and nDSM: Normalized Digital Surface Model) and two statistics to characterize the forest stands (density of dominant trees per hectare and their average height). The identification of forested areas was performed using an object-based classification method using the intensity image, the height model and an orthophotograph of the area, and a kappa coefficient of 0.82 was obtained in the validation. The woodlands were reclassified according to the magnitude of a possible fire, based on the density and the average height of the woodlands. The forest stands were mapped according to the magnitude of a possible fire and it was found that 1.18 km^2 would be susceptible to a low magnitude fire, 3.75 km^2 to a medium magnitude fire and 2.25 km^2 to a fire of a high magnitude. Afterwards, it was determined whether the buildings in the area complied with the legislation relating to minimum distance from the forested areas (30 meters). For those that did not meet this distance, the risk of damage in case of a wildfire was calculated. The result was that 43.01% of buildings in the area complied with the regulations, 9.95% were located in a very low risk area, 25.74% in a low risk location, 12.37% in a medium risk area and 8.93% were in a high or very high risk area.

Key words: LiDAR, woodlands, buildings, forest fire, OBIA, PNOA.

Caracterización del interfaz forestal/urbano empleando LiDAR como herramienta para la estimación del riesgo de daños por incendios forestales

Resumen: Galicia (NO de España), afectada por alto número de incendios forestales, debería cumplir la normativa vigente en relación a la distancia entre masas forestales y edificaciones. Este trabajo tiene como objetivos identificar y caracterizar las masas forestales y clasificar las edificaciones en función del riesgo en caso de incendio para un área de 36 km^2 del municipio de Forcarei (Pontevedra). A partir de los datos LiDAR se obtuvo la imagen de intensidades, modelos espaciales (MDT: Modelo Digital del Terreno, MDS: Modelo Digital de Superficies y MANO: Modelo de Alturas Normalizadas de Objetos) y dos estadísticos para la caracterización de las masas forestales (densidad de pies dominantes por hectárea y altura promedio de dominantes). La identificación de las masas forestales se realizó con un método de clasificación orientado a objetos empleando la imagen de intensidades, el modelo de alturas y ortofotografía de la zona, obteniéndose coeficiente kappa de grado de correspondencia de 0,82 en la validación. Las masas forestales se reclasificaron en función de la magnitud de un posible incendio, basándose en la densidad y la altura promedio de la masa. Se generó la cartografía de las masas según la magnitud de un posible incendio, obteniéndose que 1,18 km^2 serían susceptibles de incendios de baja magnitud, 3,75 km^2 de magnitud media

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y 2,25 km² de elevada. Se determinó si las edificaciones de la zona cumplían la legislación relativa a los 30 metros de distancia mínima a la masa forestal, clasificando el riesgo de daños de aquellas que no cumplían en caso de incendio forestal. El resultado fue que el 43,01% de las edificaciones cumplía la normativa, el 9,95% situación de riesgo muy bajo, el 25,74% en riesgo bajo, el 12,37% en medio y que el 8,93% estaba en una situación de riesgo alto o muy alto.

Palabras clave: LiDAR, masas forestales, edificaciones, incendio, OBIA, PNOA.

1. Introduction

Galicia (NW Spain) was the Spanish region most affected by wildfires from 2001-2010, with 72423 fires, 68 of them were classified as large forest fires (more than 500 ha) (MAGRAMA, 2012). In addition to the frequent wildfires in Galicia, the scattered distribution of the settlements and the large number of buildings located in the wildland-urban interface, brings to light the need to identify the buildings which could be affected if there was a wildfire and to quantify their risk of damage in regards to their location.

The law applicable to this field in Galicia is determined by Title V of the Forestry Regulations for Galicia (Ley de Montes de Galicia), approved on 28th June 2012 (Xunta de Galicia, 2012), which tried to make the forest policy compatible with the urban development laws. These Forestry Regulations (Annex II) state that forests and buildings have to be, at least, 30 metres apart, regardless of whether the buildings are in a rural or an urban location.

The aim of this work was to identify the buildings and forests which do not meet these regulations, using LiDAR data and other cartographic tools. LiDAR was chosen as the main data source in this study due to the improvements in data acquisition (quicker and more efficient), the increase in precision and its lower cost (McRoberts & Tomppo, 2007), therefore more accurate and detailed maps can be obtained than in the past. LiDAR data was used also because the PNOA (Spanish National Plan for Aerial Orthophotography) has been registering these data from 2008 for most of the territory, with point densities of 4, 2, 1 and 0.5 points m⁻² (depending on the year and area). In Galicia, the flights took place in 2009 and 2011, with an average point density of 0.5 points m⁻².

LiDAR data have been widely used in forest inventory (Hyyppä *et al.,* 2008), forest variables estimation (González *et al.,* 2014), wildfire management (Alonso *et al.,* 2003) or modelling fuel variables in forest stands (Garcia *et al.,* 2014).

Moreover, they have been used with other remotely sensed data, as in Bujan *et al.* (2012), where LiDAR data and orthoimages were processed together to classify land cover in rural landscapes, or in Chen *et al.* (2009), where LiDAR data were combined with high spatial resolution imagery to characterize urban areas. The most common results in these applications are vector layers, raster data and statistics, which after their integration in Geographic Information Systems (GIS), increase the capability of the user to analyze, map and interpret this information for decision making (Martínez *et al.,* 2009), as well as its dissemination through Spatial Data Infrastructures (SDI).

2. Objectives

The objectives of this work are:

- Identify and characterize forested areas (from a wildfire point of view) using LiDAR data.

- Classify the buildings which are close to forested areas taking into account the risk of damage if a wildfire occurs.

3. Materials

3.1. Study area

The study location is a 36 km² area located in the municipality of Forcarei, in the province of Pontevedra (Galicia), in the NW of Spain (Figure 1). The study area is defined by a rectangle delimited by the following coordinates (in meters): ETRS89 UTM29 558000 4722000 and ETRS89 UTM29 552000 4716000. This location was chosen since it is representative of the Galician rural landscape, with forest lands (mainly oak, pine and

eucalyptus trees), farming areas, and also small settlements and scattered buildings.

3.2. LiDAR data

The LiDAR data used for this work were gathered as part of the PNOA in 2011, according to the technical specifications as described by the PNOA. For the study area the point density was 2 points m^{-2}, as it was for the whole province of Pontevedra.

These data are available for free for non-commercial use in the region of Galicia, and they were downloaded from http://visorgis.cmati.xunta.es/cdix/mapa.html in nine quadrants of 2 km×2 km. The files were in ".las" format and consisted of point clouds with the following data associated with each point: point number, X coordinate (m), Y coordinate (m), Z coordinate (m), Intensity, pulse number, return number and nadir angle. All data were downloaded in the coordinate reference system ETRS89 UTM Zone 29 (EPSG: 25829).

3.3. Cartographic reference data

The municipal and provincial boundaries were obtained as vector data through the Web Feature Service (WFS) of the Spatial Data Infrastructure of Galicia IDEGalicia: http://mapas.xunta.es/directorio-de-servizos-web/presentacion) at a scale of 1/25000.

In addition, the vector file with the building locations and geometry (named "Constru") was also downloaded for free from the Cadastre website (http://www.sedecatastro.gob.es/)

3.4. PNOA orthophotograph

The 2011 orthophotograph which covered the study area was downloaded from the (http://centrodedescargas.cnig.es/CentroDescargas/index.jsp) in the coordinate reference system ETRS89 UTM Zone 29 (EPSG: 25829). This image matches the map sheet number 153 of the National Topographic Map at a scale 1/50000 (MTN50) and provided spectral information in the visible region of the electromagnetic sprectrum.
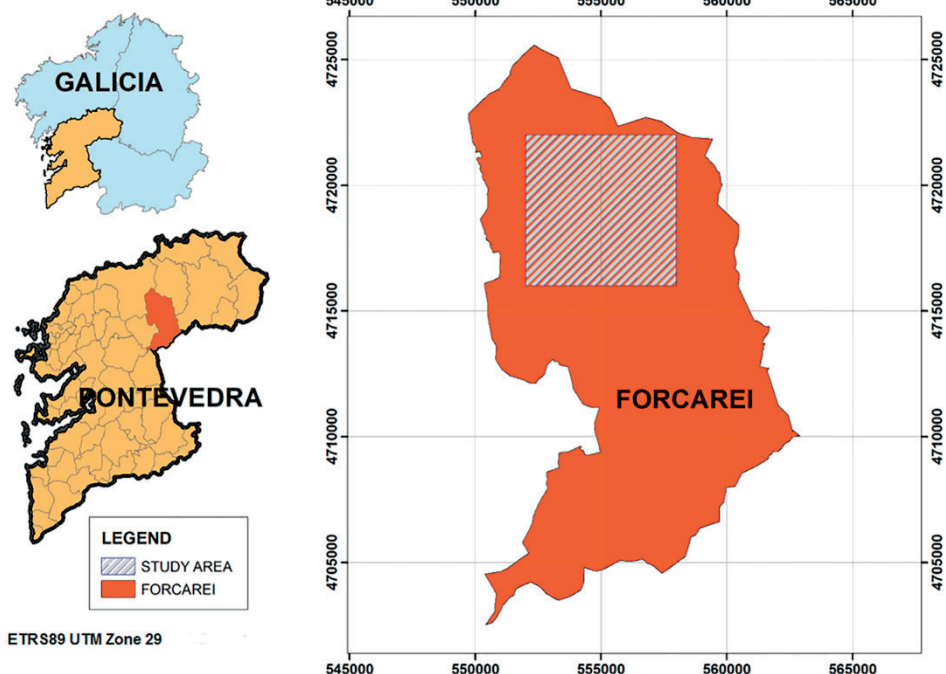

Figure 1. Study area location.

3.5. Software

Diverse software has been used to complete the different parts of this project. For the LiDAR data processing, we used FUSION 3.30 and ALDPAT 1.0; for the statistical analysis: R 3.1.0; for the image segmentation and classification tasks, eCognition 8.9.0; and for mapping and GIS analysis ArcGIS 10.1.

4. Methods

The workflow followed in this study is showed in Figure 2. First of all, the LiDAR data were used to create the intensity image; secondly the ground data were identified by a filtering algorithm and the digital terrain model (DTM) was obtained. Later the DTM and the digital surface model (DSM) were used to create the normalized digital surface model (nDSM). The next step was the identification and statistical characterization of the forest stands. Once the forests were classified according to the potential magnitude of a wildfire, a spatial analysis was carried out taking into account the proximity of the buildings to the forested areas.

4.1. Intensity image

In order to create the intensity image (Figure 3), we analyzed the histograms of the LiDAR intensity data for the different files that were gathered to cover the study area. It was noticed that 95% of the values were between 10 and 370. Therefore, these two values were chosen as thresholds in order to

adjust the histogram of the intensity image that was created to cover the whole area. This procedure was followed by McGaughey *et al.* (2007) and Bujan *et al.* (2012, 2013) for similar works. The pixel size of the resulting intensity image was set to 2 m×2 m. This step was a requirement that was needed in order to process the data using the software Fusion 3.30. The intensity image was also used in other processes which are described in the next sections.

4.2. Ground point filtering and validation

First of all the outliers and extreme values were eliminated from the data, so that they would not interfere in the next steps of the workflow. This task was performed using the tool "Filterdata" (McGaughey, 2014), available in Fusion 3.30, setting the multiple of the standard deviation to 2 and the window size to 150. Then, two different filtering algorithms were applied to extract the ground points: the iterative linear prediction method (Kraus y Pfeifer, 1998) and the adaptive triangulated irregular network model (Axelsson, 2000), implemented in Fusion 3.30 and Aldpat 1.0, correspondingly. The parameter values chosen for the linear prediction algorithms were: g:–2, w: 2.5, average: 5, and a cell size of 3×3 for the intermediate models. On the other hand, for the adaptive filter the values were: cell size: 1×1, elevation increase: 0.30, angle threshold: 0.20, triangulation size: 50, algorithm window: 150×150 and a buffer size of 20. The values were chosen
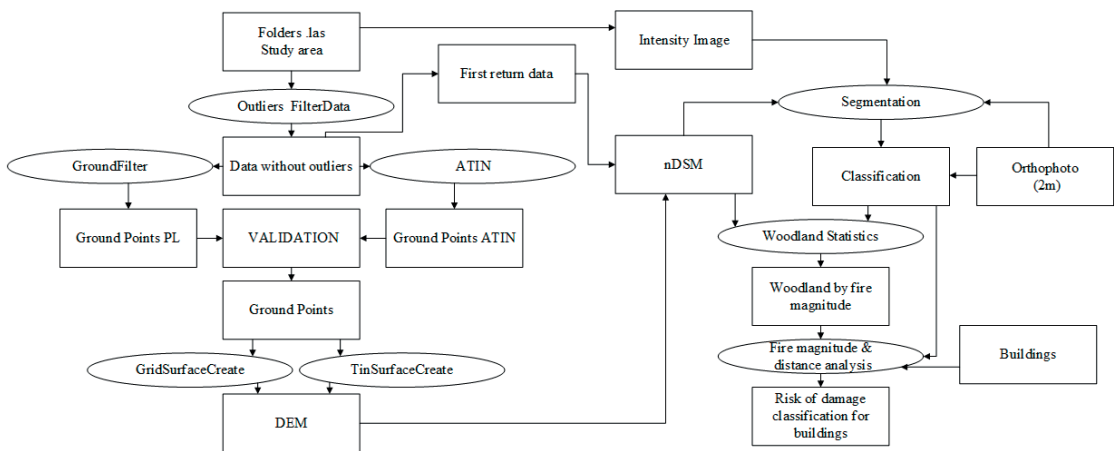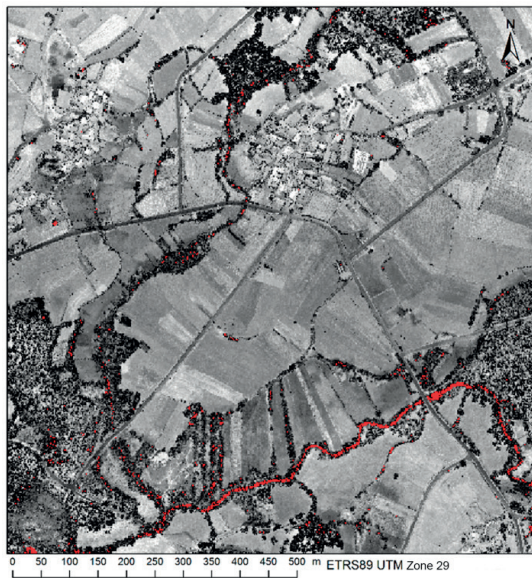

Figure 2. Workflow.

Figure 3. Intensity image.

taking into account the characteristics of the study area and considering previous works in similar locations, such as Bujan *et al.* (2012).

As a result of the filtering process, two ".las" files that contained ground data were obtained. The results were validated by calculating the omission and commission errors associated to each algorithm. This accuracy assessment was critical in deciding which ground data file would be used to obtain the DTM. The reference samples for the validation were selected from the LiDAR data files where the outliers had been already removed, using a random sampling. Afterwards, each sample point was assigned to the "Object" (O) or "Terrain" (T) classes, using the PNOA orthophotograph as a surrogate for the ground truth data. This orthophotograph was from the same year as the LiDAR data. Overall, 47 terrain and 28 object validation points were selected. The omission and commission errors were computed using R, therefore the results were validated from the point of view of the filtering methods applied. This process consisted of checking whether the reference points that were identified as terrain were in the filtered model or not, this process was repeated for the reference points that were identified as objects. To determine if a point was in the

filtered model, we calculated the distance between the reference points (terrain or object) and the filtered (ground) data, considering that any distance smaller or equal to 10 cm indicated that there was a coincidence between the reference point and the model. A distance of zero was not required, since some differences can be caused by the decimal places, and it could lead to an underestimation of the accuracy of the filtering method.

4.3. Digital terrain model (DTM)

Two different DTM were created using the ground data resulting from applying the most suitable filtering algorithm and two interpolations tools existing in Fusion 3.30: "GridSurfaceCreate" and "TINSurfaceCreate". Since accurate coordinates for a sample of ground points were not available, the selection of the most adequate interpolation method was based on determining the differences between both models. In case the differences were small, computational efficiency was the criterion. Thus, a normalized DTM was obtained, using the GRS80 ellipsoid as a reference. As for the intensity image, the cell size for the model was set to 2 m×2 m.

4.4. Normalized digital surface model (nDSM)

A digital surface model (DSM) is the result of creating a surface using the first returns of the point cloud, assuming that they belong to the top of the elements (objects) above the ground. The DSM was created using the first returns of the LiDAR data and the "CanopyModel" algorithm (McGaughey, 2014), available in Fusion 3.30.

In order to obtain the normalized digital surface model (nDSM), which consists of the normalized heights of the objects above the ground, it was necessary to add the DTM to the "CanopyModel" workflow. The resulting nDSM had a cell size of 2 m×2 m and one constraint was that the normalized height values were between 0 and 50 m. Figure 4 shows the DTM and nDSM for a section of the study area

4.5. Identification of the forested areas

The forest stands were identified using a supervised classification, following an object oriented approach. The fundamentals of an object based workflow are described in Benz *et al.* (2004). The input data were: the intensity image (section 4.1), the nDSM (section 4.4) and the PNOA Orthophotograph, while the software was eCognition 8.9.0.

The first step for the identification of the stands was a segmentation to obtain homogenous segments (objects). Regarding intensity and height, we weighed the intensity (2) to be double the weight of the height (1). We tested several values for the segmentation parameters, taking into consideration the experience from previous works (Álvarez Taboada, 2006; Fernández-Luque *et al.,* 2013, Fernández-Luque *et al.,* 2014), the final values we chose were a scale parameter of 30, a compactness of 0.50 and a shape value of 0.30. With the aim of extracting spectral information from the orthophotograph that would be suitable to identify the forested areas, the green ratio was computed on the segmented image (Equation I).

$$GR = \frac{G}{G+B+R} \qquad (I)$$

Where GR is the Green Ratio for a certain object, and G, B and R are the average values of the Green, Blue and Red band (respectively) for the pixels which belong to that object.

The segmented image was classified using a thresholding method. For the "forest" class the threshold values were established taking into account the values obtained from a sample of segments which were visually identified as forested. These values had a Green Ratio larger or equal to 0.35 and a normalized height larger than 1.5 meters. Once the image was classified following these criteria, the result was exported as a vector file, so it could be visualized in ArcGIS 10.1.

For the validation we used a stratified random sampling which covered the whole study area, 45 samples for forested areas and 34 for non-forested were obtained. The user's and producer's accuracies and Kappa were calculated, as well as the omission and commission errors (Jensen, 2005) with the corresponding confidence intervals at 95% (Sauro y Lewis, 2005). The forest stands were mapped in the study area as homogeneous polygons.

4.6. Classification of the forest stands regarding the magnitude of a possible wildfire

For the classification of the forest stands depending on the magnitude of a possible wildfire, it was necessary to characterize them using the LiDAR data. This process was carried out with the tools "Cloudmetrics" and "CanopyMaxima" (McGaughey, 2014), implemented in Fusion 3.30.
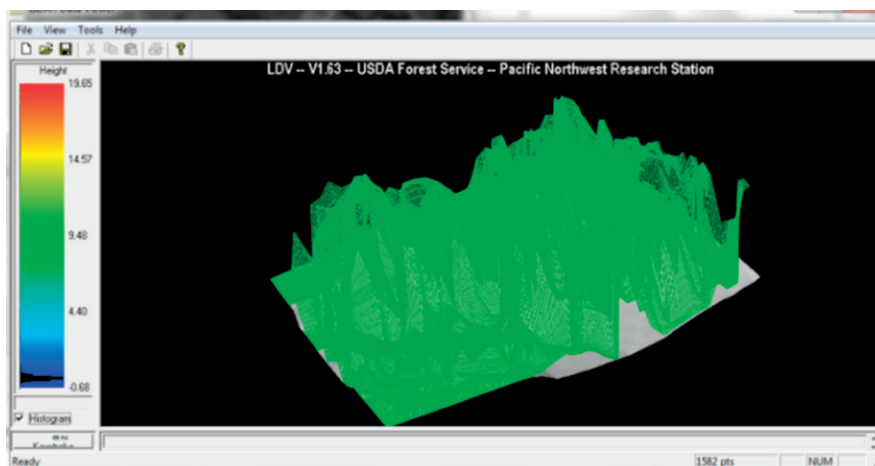

Figure 4. Visualization of the nDSM (green) and DTM (grey) with the LDV tool (Fusion 3.30).

"Cloudmetrics" provided the statistics which allowed the estimation of stand variables. On the other hand, "CanopyMaxima" supplied information about the location and height of the dominant and codominant trees in each forested polygon, using the nDSM as input data.

Once the statistics were processed, the derived forest information was linked to the corresponding polygon, and the stands were reclassified considering the dominant/codominant tree density per hectare and the average height of the dominant/codominant trees. Three levels of magnitude of a possible wildfire were established: Low, Medium and High, as showed in Table 1. One advantage of this classification approach is that it can be applied to all the species in the study area and that it depends only on variables derived from LiDAR data. The proposed classes were a generalization of the schema proposed by Fernandes (2009), where fire risk (characterized by variables as propagation, intensity or crown fire potential) was related to forest structure, defined by tree density and height. In the same direction is the work developed by Castedo *et al.* (2012), which shows that, in general and also in particular for maritime pine in Galicia, the higher the tree density, the lower the above ground fuel load (due to the shadowing effect of the trees on the understory), and therefore the fuel model would lead to wildfires of a lower magnitude. With respect to the height of the forest stand, in general, the higher the trees, the lower the probability of a fire reaching the crowns and propagating through them, increasing the magnitude of the wildfire, as Gómez-Vázquez *et al.* (2014) found for maritime pine.

After assigning the values of Table 1 to each polygon, the forest stands were mapped depending on the magnitude of a possible wildfire.

Table 1. Classification of the wildfire magnitude based on the stand density and the average dominant height. Ddom (trees /ha): dominant stand density; Hdom (m): average dominant height; L: Low; M: Medium; H: High.

D_{dom} (trees/ha)	H_{dom} (m)		
	<8	8-15	>15
<100	H	H	M
100-250	H	M	L
>250	M	L	L

4.7. Risk of damage to buildings in case of a wildfire

The first step in estimating the risk of damage to the buildings close to forested areas in case of a wildfire was to map all the buildings in the study area. In order to do that, we created a vector layer with the edifices and built-up areas that were already registered in the Cadaster file named "Constru", and the constructions which were found in the LiDAR intensity image and the PNOA orthophotograph and which were missing in the Cadaster file. The latter were digitized as polygons and added to the file.

Secondly, the radius defining the minimum distance between buildings and forest stands was set to 30 m, following the requirement of the Forestry Regulations for Galicia (Xunta de Galicia, 2012). The forested areas which did not meet the minimum distance from the built up structures were evaluated, and the risk of damage to each building in case of a wildfire was computed using Equation II.

$$R = \sum_1^n (A_P \cdot M_P) \qquad \text{(II)}$$

where R is the risk for a certain building, n the number of forest stand polygons within the 30 m buffer area, A_p is the intersected area of each forest polygon in the 30 m buffer area and M_p is the magnitude of the wildfire which could take place in each forest stand polygon. The magnitude classes defined in Table 1 were converted into numerical values, so the Low, Medium and High magnitudes corresponded to 1, 2 and 3 in this equation, respectively.

Finally, the constructions were classified regarding their risk, using the method of half the standard deviation to define the intervals (Slocum *et al.,* 2008).

5. Results and discussion

5.1. Intensity image

The intensity image (Figure 3) was created using a pixel size of 2 m×2 m, which was considered to be suitable since it decreased the number of pixels with no data (showed in red in the image) and it

also minimized the size of the image, with respect to a pixel size with a higher spatial resolution.

5.2. Ground filtering and validation

The selection of a suitable filtering algorithm to extract the ground points was crucial in the creation of the DTM and all the models derived from it, as well as the correct selection of the values for the parameters which define the algorithm. For the "GroundFilter" (McGaughey, 2014) tool, several cell sizes for the intermediate surface models were tested. A value of 5 provided results which led to miscalculations in the normalized heights, while a value of 1 caused errors in the nDSM in the built-up areas. Intermediate values were tested to balance these errors; in the end a value of 3 m×3 m as a pixel size was chosen. The results for the different values were visually tested using ArcGIS 10.1.

Two point clouds (LP and ATIN) were obtained from the two tested algorithms: the Linear Prediction method ("GroundFilter" tool, available in Fusion 3.30) and the adaptive triangulated irregular network model ("ATIN" tool, available in Aldpat 1.0), respectively. The results of the validation are showed in Table 2.

Table 2. Validation of the filtering algorithm (ground point identification)

	Errors (%)	
	Commission	Omission
ATIN	70,21	17,86
Groundfilter	75,00	2,13

Both models provided commission errors higher than 70%, because some points were classified as ground data points although they were not on the terrain. Ultimately, the model created using the GroundFilter tool was chosen, since it had a smaller omission error and the differences between the commission errors were not significant (smaller than 10%). These errors were taken in consideration in the next steps of this work, especially when discussing the results obtained for the land cover classification (forest/non-forest) and the risk of the building in case of a wildfire.

5.3. Digital terrain model (DTM)

As a result of the interpolation, two DTM were available: one created with the "GridSurfaceCreate" tool and another one with the "TINSurfaceCreate" method. In order to choose the most suitable model, the differences between them were calculated, being the values not very different. Since according to the data values it was irrelevant whether one model was chosen over the other, the computational efficiency of both tools was examined. The "TINSurfaceCreate" tool cannot process a large amount of data, so its use required splitting the ground point cloud in order to create the models, which then had to be assembled together again for the derived models. These steps are cumbersome and slow down the workflow. Therefore, we chose the "GridSurfaceCreate" method, which allows the automatization of the whole process and can work with the whole database.

An in-depth analysis of the DTM showed that it did not perform well in the treed areas, due to the low LiDAR point density in large and dense forested areas, where the laser pulse cannot reach the ground. This fact means that some points were classified as ground when they were not, which caused the MDT to be higher than what it should have been in those areas, and led to an unrealistic decrease in the values for the vegetation height.

Another source of error was detected, regarding the transition zones between bare soil and vegetated areas, since they showed irregularities due to abrupt changes in height between the points located in bare land and the points that were misclassified as terrain in the forested areas. With the aim to minimize this problem, we reduced the window size for the intermediate models which were created by the algorithms. The size of the window is set by considering the average size of the objects in the study area, so that if the window size is too small, large objects will be classified as ground points, and if it is too large, the ground points will be classified as objects. Likewise, it was verified that diminishing the size of the window used in the intermediate processes, made the buildings larger than the window size to be included in the DTM. To overcome these inconveniences, an intermediate widow size of 3×3 pixels (3 m×3 m) was considered, as suggested by Evans *et al.* (2007).

5.4. Normalized digital surface model (nDSM)

The Digital Surface Model (DSM) was created to visually assess the correct filtering of the first return data. After checking the correctness of the data in this model, the normalized digital surface model (nDSM) was computed. The nDSM showed that in the study area the heights of the objects varied between 0 m and 39.05 m. We confirmed that the highest values corresponded with the forested areas, where pines, oaks and eucalyptus trees were the dominant species.

5.5. Identification of the forested areas

The segmentation of the image provided 10801 elements in the study area. Their homogeneity regarding the land cover was tested visually. The classification was validated. The results are showed in Table 3. The forested areas were classified. The producer's accuracy of the classification was 84.44%, while the user's accuracy was 100% and it had an overall accuracy of 91.14%. 2432 segments were classified as forested areas, covering an area of 7.30 km^2.

The commission error of the DTM had an effect on the final classification, since for the points that were misclassified as terrain there was not a difference between the DTM and the DSM, and therefore the nDSM was 0. Since the nDSM was one of the variables used to identify the "Forest" class, the omission error for this class (15%) was larger than that for the "Non-forest" class (0%). This means that some of the forested areas were missing and that our model underestimated the risks of the buildings in case of a wildfire. Having

a more dense LiDAR point cloud available could help minimize this error, especially in areas with a dense canopy cover (Watt *et al.,* 2014).

5.6. Classification of the forest stands regarding the magnitude of a possible wildfire

The statistics obtained using "Cloudmetrics" did not characterize the forest stands properly. In the inner areas of the forest stands the DTM did not registered the ground correctly, thus the tree heights were reduce to value that were too low, and therefore the stand statistics derived from the elevation data were not correct (e.g. very low average heights).

The statistics obtained for individual trees were more accurate than for the stand approach. The "CanopyMaxima" tool detects the maximum values in the nDSM and uses those values to compute the statistics, excluding the other values of the nDSM from the calculations. The maximum values corresponded with the dominant and codominant trees, so the statistics were only representative of those trees. It should be taken into account that in the stands where the tree heights were very similar, the stand density was underestimated, since the algorithm had difficulties to find maximum values.

115232 dominant and codominant trees were found, distributed in 2346 forested polygons. This result means that for 77 polygons identified as forested, the differences in the tree heights were not large enough for the "CanopyMaxima" to identify dominant/codominant trees.

Table 3. Accuracy assessment of the classification to identify forested areas. The values in brackets for the accuracies and errors are the Adjusted Wald confidence intervals.

| | Class | Ground Truth | | | | |
		Forest	Not forest	Total	User's accuracy (%)	Commission Error (%)
Image Classification	Forest	38	0	38	100 (92.06-100.00)	0 (0-7.94)
	Not forest	7	34	41	81.40 (68.42-91.79)	17.07 (8.21-31.58)
	Total	45	34	79		
	Producer's accuracy (%)	84.44 (70.90-92.57)	100 (91.20-100.00)		Overall Accuracy (%): 91.14 (82.56-95.91)	
	Omission Error (%)	15.56 (7.43-29.10)	0 (0-8.80)		Kappa: 0.82	

LEGEND

Study Area
MAGNITUDE
LOW
MEDIUM
HIGH

0   500   1000   1500   2000 m

Figure 5. Classification of the forest stands in the study area, according to the magnitude of a possible wildfire.

Therefore these polygons (less than 4% of the total) were removed from the analyses. Figure 5 shows the forest stands in the study area, classified according to the magnitude of a possible wildfire (Table 1). 1.18 km² were covered by forest stands where the magnitude was low, 3.75 km² where it was medium and 2.25 km² were it was high.

When applying the proposed methodology, it should be taken into account that, although the threshold values chosen to define the magnitude of the wildfires are coherent with the fire behaviour models that were set as a reference (Fernandes 2009; Castedo *et al.*, 2012) and that they have been considered to be suitable for the study area, a different choice would have led to different results. The difficulty of setting these values lays in the fact that the fire behaviour models we used do not specify what is considered to be a dense or a tall stand, and therefore the user has to establish these values arbitrarily. It would be suitable to have empirical models available which relate these forest variables

and the magnitude of wildfires, so the threshold values can be verified or set.

5.7. Risk of damage to the buildings in case of a wildfire

The Cadaster data did not show all the existing buildings in the study area, which probably meant that the information was not up-to-date. 42 new polygons were digitized to complete the cadastral information. The total number of buildings in the study area was 1488. The results about the risk of damage to each building in case of a wildfire, showed that 640 (43.01%) constructions had a minimum risk, since they complied with the regulations. Table 4 shows the complete results of the risk of damages to the buildings in the study area, where more than 80% (83.67%) had a low, very low or minimum risk. As an example, Figure 6 and Figure 7 show the risk situation for some of the buildings in the study area, with regards to Article 6 of the Forestry Regulations for Galicia.

Table 4. Analysis the risk of damage to the buildings due to wildfire.

	Buildings	
Class	Count	%
Legal- Minimum risk	640	43.01
Very Low Risk	148	9.95
Low Risk	383	25.74
Medium Risk	184	12.37
High Risk	81	5.44
Very High Risk	52	3.49
TOTAL	1488	100.00

It should be taken into account that applying the proposed model to assign the risk of damage to a building (Equation II) involves the acceptance of several assumptions which have not been proved a priori, such as the risk linked to a high magnitude wildfire is three times the risk for a low magnitude one. Hence, the implementation of the proposed methodology would improve if there were available indices which measure the risk of damages and also the magnitude of a wildfire, and therefore we could establish an empirical relationship between the two variables.
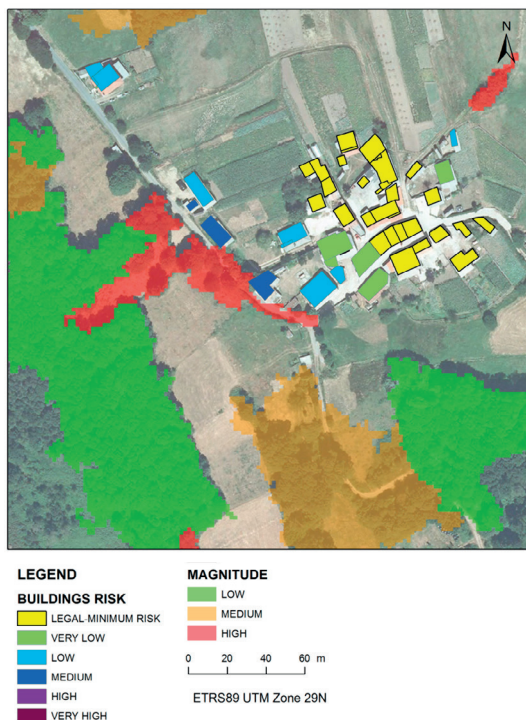
LEGEND

BUILDINGS RISK
- LEGAL-MINIMUM RISK
- VERY LOW
- LOW
- MEDIUM
- HIGH
- VERY HIGH

MAGNITUDE
- LOW
- MEDIUM
- HIGH

0   20   40   60 m

ETRS89 UTM Zone 29N

Figure 6. Risk situation for some of the buildings in the study area and magnitude of a possible wildfire.

LEGEND

BUILDINGS RISK
- LEGAL-MINIMUM RISK
- VERY LOW
- LOW
- MEDIUM
- HIGH
- VERY HIGH

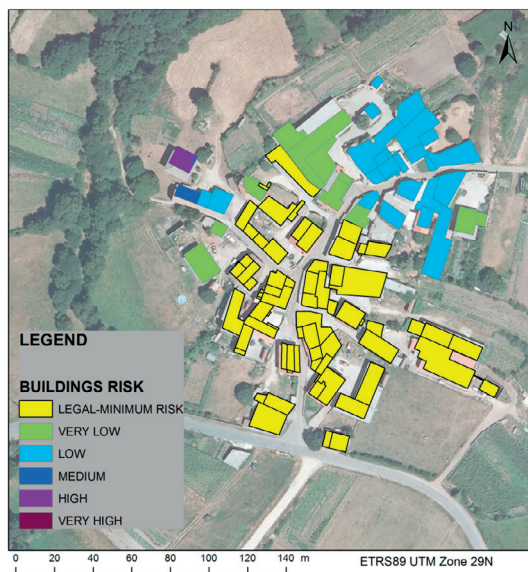0   20   40   60   80   100   120   140 m   ETRS89 UTM Zone 29N

Figure 7. Risk situation for some of the buildings.

6. Conclusions

The results of this work show that in some areas of Galicia it is advisable to have a more exhaustive control of the compliance with the Forestry Regulations, since more than half of the buildings are closer to the forested area than the required distance.

There is a need for a suitable LiDAR point density, since it affects the quality of the DTM and therefore the DSM and nDSM, and this reduces the opportunities for a multi-purpose use of the data and has an impact on works like this one.

The intensity image did not add any relevant information to help identify the forested areas, since it did not differentiate between the forested and built-up areas, but it can be useful in the segmentation process if there are not any updated orthophotographs for the area.

Using the cadastral information as a source to map land use/cover classes such as buildings can lead to several errors, not only due to the differences between the geometrical accuracy of the existing polygons, but also because of the out of date data, which do not represent the existing reality.

The data generated in this study can be a starting point for other works, like a detailed characterization of the forest stands. The created maps could be used when searching for suitable locations for new forest plantations, or to develop evacuation models in case of a wildfire.

This study did not have forest field data available, and it would be interesting to use them for the validation processes.

In the case of applying this methodology to a larger or different area, Fusion 3.30 allows the workflow to be semi-automated, although, as it has been explained before, the values of some parameters should be modified, since our values were set to optimize its performance in this study area.

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