Snowpack depth modelling and water availability from LIDAR measurements in eastern Pyrenees

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ABSTRACT:

In order to evaluate water reserves in mountain watersheds the Institut Geològic de Catalunya (IGC) jointly with Institut Cartogràfic de Catalunya (ICC) have begun a project to model snowpack depth distribution at the study site of Vall de Núria (38 Km^2 basin located in eastern Pyrenees). Remote sensing airborne LIDAR (*Light Detection and Ranging*) survey and field work validations were performed to make this calculation. Modelling snowpack distribution is a complex task because of its spatial variability. Despite being a recently developed technique, LIDAR has become a useful method in snow sciences because it has the advantage to offer dense point data and to cover wide areas with little economic and field work effort. The new methodology presented combines LIDAR data with field work, the use of Geographical Information Systems (GIS) and the stepwise regression tree (SRT), as extrapolation technique has allowed us to map snowpack depth distribution with high spatial resolution. Extrapolation is necessary because raw LIDAR data is only obtained from part of the study area in order to make the technique as affordable as possible. Promising results show low differences of total snow volume calculated from modeled snowpack distribution and total snow volume from LIDAR data only differ 1.4%.

KEYWORDS: snowpack depth, stepwise regression tree, LIDAR, GIS, Pyrenees

1 INTRODUCTION

Mediterranean climate is characterized by a high precipitation variability. As a result of this variability the Iberian Peninsula, and Catalonia as part of it, are affected by frequent and serious droughts that alter the availability of water supply. Hydric resources are not only concerned by natural fluctuations, but social pressure must also be taken into consideration. Catalonia's internal fluvial basins (those, whose responsibility is the local Government) occupy 52% of total Catalonia's surface but houses the 92% of the total population (Sangrà, 2008) which increases hydric stress. As a consequence of particularities mentioned above it is necessary to quantify hydric resources stored as snow.

High snowpack variability (Elder, 1995) and sparse snow depth data make it difficult to model snow cover. For this reason remote sensing is essential when modelling wide areas.

The use of airborne LIDAR (*Light Detection and Ranging*) to model snow depth has the advantage of covering large areas with high resolution at a relatively low economic cost. The application of LIDAR to model snow depth is possible due to the high accuracy it provides, vertical error of 15 cm in ideal conditions, as several studies have shown (Hopkinson, 2001; Fassnacht, 2005; Deems, 2006)

The present study, *Use of LIDAR to evaluate water reserves stored as snow in mountain watershed,* is carried out by Institut Geològic de Catalunya (IGC) jointly with Institut Cartogràfic de Catalunya (ICC). The project is composed of several stages with the final aim being to model water availability in mountain watersheds. First of all, snow depth volume was modeled and the results of this first stage are presented here.

A pilot study site at Vall de Núria (fig. 1) has been set up in order to validate LIDAR technique and to establish a valid methodology to model snow depth over large areas.

The valley itself covers an area of 38 km^2 with altitude ranging between 1950m at Núria Sanctuary and 2910m at the summit of Puigmal peak. Most part of the surface is above timberline with meadows and rocky soil covering most of the area that makes drifting snow really frequent.

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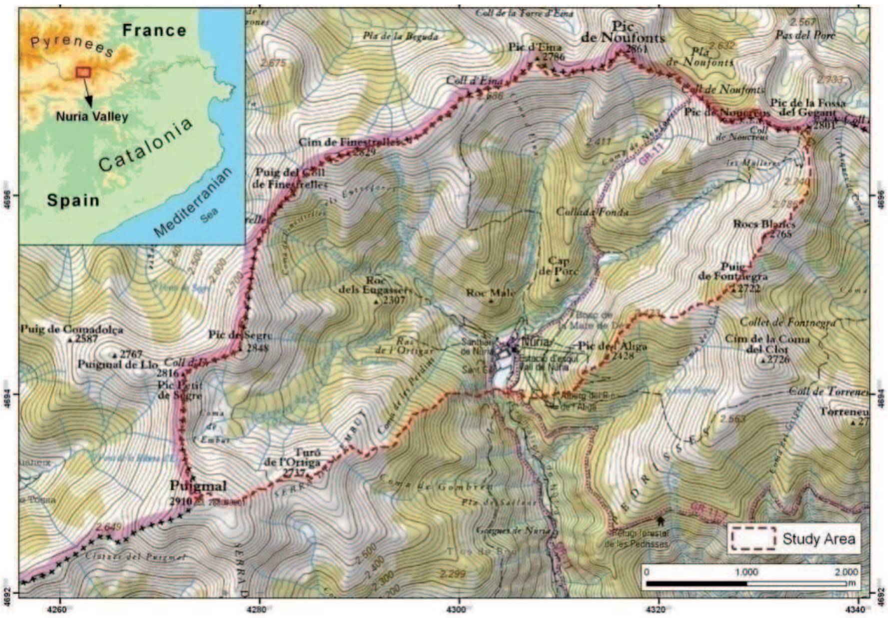

Figure 1. Vall de Núria location map.

2 DATA AND METHODS

As pointed out before, two LIDAR flights were necessary to obtain snow depth data. LIDAR flight with snow coverture was done on 9-3-2004. Covering the same area, a flight without snow was done on 9-8-2006. On both flights laser utilized was Optech ALTM3025.

Once flights were concluded, raw data was processed with specialized TerraScan® software to generate two high resolution, 1m cell size, *Digital Elevation Models (*DEM). Afterwards, subtraction of both models was done to obtain snow depth and distribution.

In order to validate snow depth calculated from LIDAR data (more than 1 point m^2 is obtained), a simultaneous field work was made to collect ground observations of snow depth. To achieve this purpose two teams equipped with submetric GPS systems were formed and distributed throughout different creeks. Due to means of transport (backcountry skis) and time necessary to get an accurate GPS position (exceeding 30 minutes per measure) only 19 data points were acquired. This sparse data made it difficult to validate snow depth LIDAR data, so indirect methods were used in the validation process, such as field work photography.

Once LIDAR snow depth data was processed and validated, modelling was carried out through extrapolation. In reality at Vall de Núria extrapolation was not necessary because LIDAR data was available from the whole area. Nevertheless, to increase project efficiency on large areas it was required to get LIDAR data only from a small part of the study area, that is, a LIDAR strip (fig 2). Then, extrapolation was necessary to obtain snow depth data from whole research area.

Geographical Information Systems (GIS) and geostatistics were employed to model snow depth. ArcGIS 9.3® GIS software was used to calculate topographical variables that determine the distribution of snow depth (Marchand 2005, López-Moreno, 2006; among others): slope, aspect, altitude, curvature, distance to main range and solar radiation. Despite DEM resolution was 1m working resolution was established at 5m cell size in order to optimize computer resources.

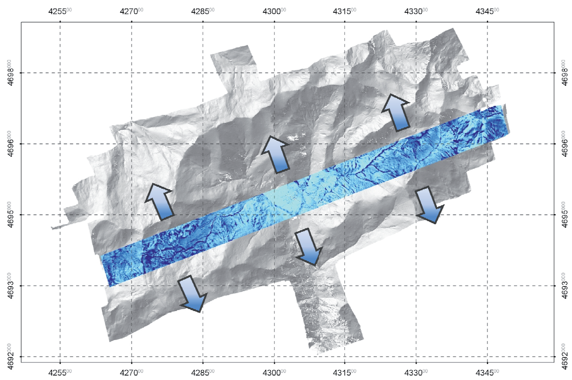

Figure 2. Snow depth data extrapolation from one strip LIDAR data.

In addition to these independent variables other important factors must be taken into account when modelling snow depth. As pointed by Molotch (2005) wind is one of these important factors. Therefore *upwind index*, Winstral (2002), was added to independent variables. *Upwind index* measures exposure of cell in a DEM depending on prevailing wind direction.

This index was calculated with the expression shown(1).

$$Sx_{A,dmax}(x_i, \quad y_i) = \max\left[\tan\left(\frac{ELEV\ (x_v, y_v) - ELEV\ (x_i, y_i)}{[(x_v - x_i)^2 \ + \ (y_v - y_i)^2\ ]^{0.5}}\right)\right] \quad (1)$$

Upwind index expression calculation. Where *ELEV* is the altitude of interest cell, *A* the azimuth of the search direction, (x_i, y_i) coordinates of the cell of interest and (x_v, y_v) the coordinates of the cells found in the same direction of prevailing wind.

Method utilized for extrapolation was *stepwise regression tree* (SRT) proposed and implemented by Loh (2002) in algorithm GUIDE as an evolution of the classical *regression tree* (Breiman, 1984).

Through GUIDE algorithm (it can be accessed on the internet: http://www.stat.wisc.edu/~loh/guide.html) a tree classification was made. In the model, independent variables were used to explain the dependent variable, snow depth. At each final tree node, a stepwise regression was calculated. The regression at each final node ensures a small and homogeneous sample size which implies a better accuracy on prediction and cartography (Huang, 2003).

Regression tree modelling has the advantage to take into consideration no-linearity of dependent variable (De'ath 2000 & Huang 2003).

GUIDE algorithm with regression at each final node jointly with LIDAR technology and the methodology here presented made it possible to overcome some of the problems pointed out by López-Moreno (2006) about regression trees. The result was a cartography representing the snow depth distribution accurately over the research area (see fig. 6).

3 RESULTS AND DISCUSSION

3.1 LIDAR snow depth model.

Validation of original snow depth model result of subtraction of DEMs was necessary due to errors produced by different factors as slope or vegetation (Deems, 2006; Hopkinson, 2001). Validation methods applied were:

1. Creation of control areas where snow depth is equal to 0 identified by field photography (fig 3).
2. Identification of snow accumulation areas on the map and its characterization with snow profiles.

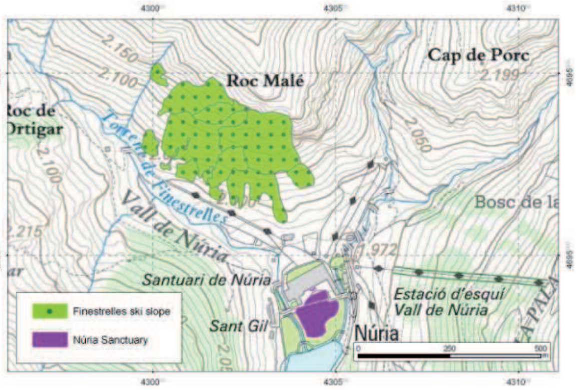

Figure 3. Location of control areas digitalized with known snow depth.

As result of validation process *Root Mean square Error* (RMSE) for the entire control areas was calculated: 0.33m. If difference is made between different control areas (table 1) it is confirmed that slope and vegetation cover have an important role as error sources.

Control areas	RMSE (m)
Finestrelles ski slope	0.351
Núria Sanctuary	0.103

Table 1. RMSE calculated for different control areas.

As shown in map (fig. 3) the surface near Finestrelles ski slope is a rocky area partially covered by shrubs with an average slope of 38°. On the other hand, the area situated near Núria Sanctuary is nearly flat (average slope: 2.5º) and covered by meadows. Consequently, RMSE in Finestrelles ski slope is higher, 0.351m, than in Núria Sanctuary, 0.103m. It is demonstrated how slope and soil cover play an important role in quality of LIDAR data, as demonstrated by Hopkinson (2001) and Deems (2006).

Validation also included the analysis of topographical profiles in areas of extreme high snow accumulation. In total, twelve profiles were obtained from original DEMs (one of them shown in fig 4.). These profiles show evidence that snow depth accumulation up to 11 meters is valid in very specific topographical conditions (deep streams and wind sheltered areas). So in validation process all values higher than 11m were considered erroneous and subsequently eliminated.

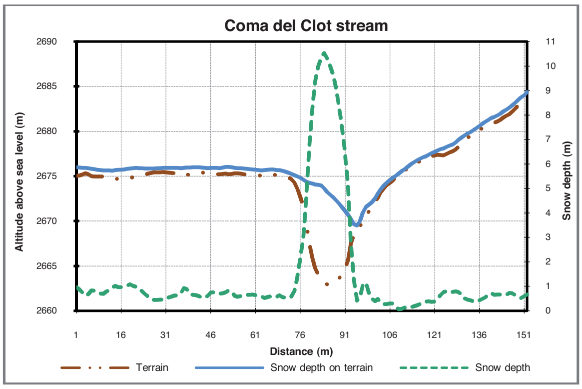

Figure 4. Profile with bare-earth and snow covered DEMs (left) that shows an 11m snow accumulation in a stream (right).

3.2 Snow depth modelling.

Snow depth was modeled with topographical variables mentioned above: slope, aspect, altitude, curvature, distance to main range, solar radiation and upwind index.

Aspect's circularity (Burrough, 2000) was treated dividing aspect in two components, north-south component and east-west component (Marchand, 2005).

Correlation between topographical variables and snow depth is presented in fig. 5. Higher correlation coefficient was found with elevation, 0.251, and curvature, -0.290. Lower temperatures with increment of altitude explain positive correlation between snow depth and elevation. Curvature's high correlation is explained by wind redistribution. The location of Núria valley makes it very exposed to north winds, consequently snow redistribution caused by wind is very important.

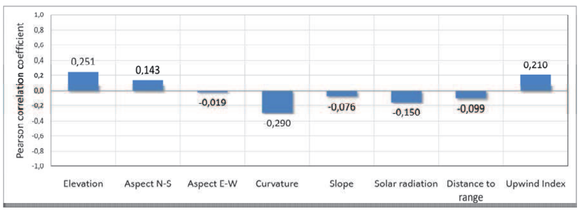

Figure 5. Pearson correlation coefficient between snow depth and considered topographical variables.

As a result of low correlation coefficients in some variables (east-west aspect, slope and distance to range) they were excluded from tree modelling.

The final model presented here is the result of applying LIDAR technology to calculate snow depth data, subsequent validation process and modelling with GUIDE algorithm. As shown before, extrapolation was necessary, for project efficiency on large areas, so data used for the final model corresponds only to one LIDAR flight strip (15% of total research area, see fig. 2). Snow depth data was obtained from this strip and to calculate the independent variables (covering de whole area) bare-earth DEM was used which made it possible to model snow depth for the entire study area. Fig. 6 shows the snow depth map resulting of this process.

Cartography shows different snow depths well represented. Homogeneity is not emphasized by the model (contrary to others models not being presented here). So the map reflects spatial variability of snow depth which is one of its most known characteristics (Elder, 1995).

Other aspects to consider in the map analysis: a) great accumulations in streams are only visible over 1900m so influence of curvature is restricted to high altitudes, b) the map shows slopes facing south and situated at lower heights without snow, matching with field observations, and finally c) areas well oriented, facing north and topographically sheltered from wind, show great snow accumulations and are also well represented at the final model.

Tree model obtained has 33 final nodes and prediction accuracy of the extrapolated model is relatively high, explaining up to 53% of snow depth variability.

The final aim of the project is to evaluate water supplies stored as snow. In this sense more important than snow depth accuracy of the extrapolated model is the difference in total snow volume from validated LIDAR model. So, if snow volume calculated from validated LIDAR model (29.3 hm^3 of snow) is compared to snow volume calculated from extrapolated final model (28.9 hm^3) difference is -1.42%.

Summarizing, snow volume difference between LIDAR model and extrapolated model is only -1.42%. That result seems to validate the methodology and technique used in this research.

4 CONCLUSIONS

As a result of joining together LIDAR technology and the stepwise regression tree modelling technique, a precise cartography can be obtained. Accuracy, which is not achieved with classical interpolation methods from sparse point data.

LIDAR potential to calculate snow depth and subsequent water resources has been demonstrated within this paper. Despite these initial satisfactory results in further studies LIDAR accuracy to determine snow depth is going to be validated with more field data.

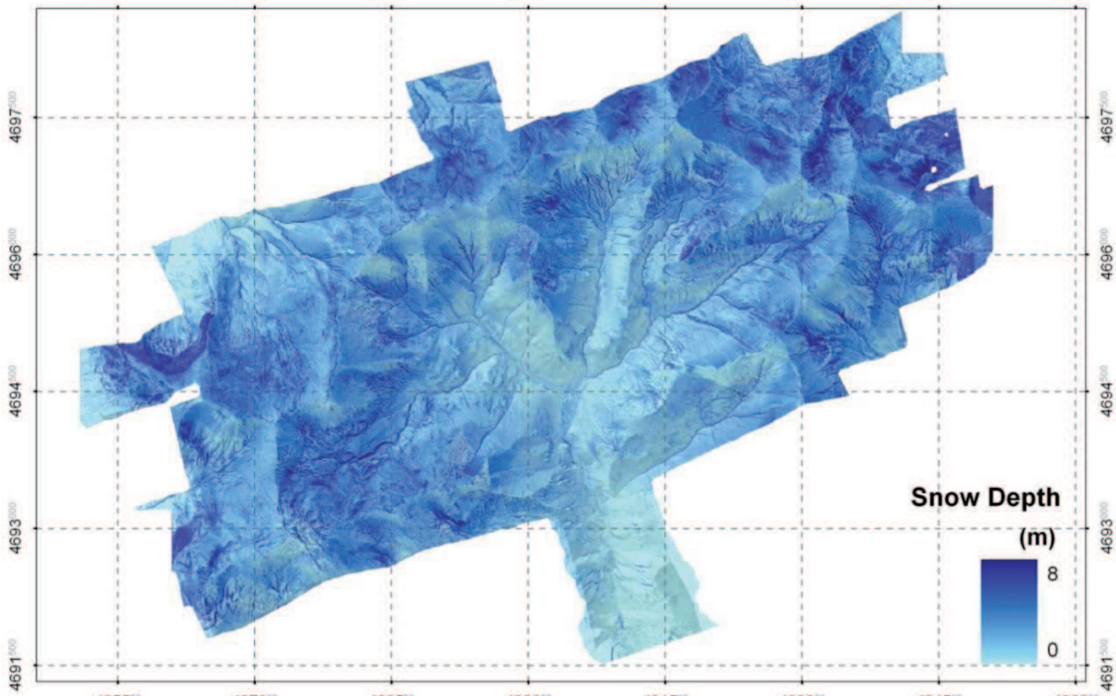

Figure 6. Snow depth map obtained from extrapolated LIDAR data.

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