Topographic control of snowpack distribution in a small catchment in the central Spanish Pyrenees: intra- and inter-annual persistence

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Abstract:

In this study we analyzed the relations between terrain characteristics and snow depth distribution in a small alpine catchment located in the central Spanish Pyrenees. Twelve field campaigns were conducted during 2012 and 2013, which were years characterized by very different climatic conditions. Snow depth was measured using a long range terrestrial laser scanner and analyses were performed at a spatial resolution of 5 m. Pearson's r correlation, multiple linear regressions and binary regression trees were used to analyze the influence of topography on the snow depth distribution. The analyses were used to identify the topographic variables that best explain the snow distribution in this catchment, and to assess whether their contributions were variable over intra- and inter-annual time scales. The topographic position index (index that compares the relative elevation of each cell in a digital elevation model to the mean elevation of a specified neighborhood around that cell with a specific shape and searching distance), which has rarely been used in these types of studies, most accurately explained the distribution of snow accumulation. Other variables affecting the snow depth distribution included the maximum upwind slope, elevation, and northing. The models developed to predict snow distribution in the basin for each of the 12 survey days were similar in terms of the explanatory variables. However, the variance explained by the overall model and by each topographic variable, especially those making a lesser contribution, differed markedly between a year in which snow was abundant (2013) and a year when snow was scarce (2012), and also differed between surveys in which snow accumulation or melting conditions dominated in the preceding days. The total variance explained by the models clearly decreased for those days on which the snow pack was thinner and more patchily. Despite the differences in climatic conditions in the 2012 and 2013 snow seasons, similarities in snow distributions patterns were observed which are directly related with terrain topographic characteristics.

Keywords: snow depth distribution, snowpack evolution, topography, mountains, cold region

1. Introduction

Assessing the snow distribution in mountain areas is important because of the number of processes in which snow plays a major role, including erosion rates (Pomeroy and Gray, 1995), plant survival (Keller et al., 2000; Wipf et al., 2009), soil temperature and moisture (Groffman et al., 2001), and the hydrological response of mountain rivers (Bales and Harrington, 1995; Barnett et al., 2005; Liston, 1999; Pomeroy et al., 2004). As mountain areas are highly sensitivity to global change (Beniston, 2003), snow accumulation and melting processes are likely to be subject to marked changes in coming decades, affecting all processes influenced by the presence of snow (Caballero et al., 2007; López-Moreno et al., 2011, 2012b; Steger et al., 2012). For these reasons, much effort has been devoted to understanding the main factors that control the spatial and temporal dynamics of snow (Egli et al., 2012; López-Moreno et al., 2010;; Mott et al., 2010; Schirmer et al., 2011).

One of the main difficulties in snow studies is obtaining reliable information of the variables that describe snow distribution, including snow depth (SD), snow water equivalent (SWE) and snow covered area (SCA). Manual measurements have traditionally been used to provide information on the distribution of snowpack, with different sampling strategies having been applied at various spatial scales (Jost et al., 2007; López-Moreno et al., 2012a; Watson et al., 2006). However, manual sampling is not feasible for large areas because of the time involved, especially when SWE measurements are also acquired. In the last decade the use of airborne laser scanners (ALS) (Deems et al., 2006) and terrestrial laser scanners (TLS) (Prokop, 2008), both of which are based on LiDAR (light detection and ranging) technology, have provided for major advances in obtaining data on the SD distribution at unprecedented spatial resolutions. These developments have enabled studies of several factors that in the past have been only marginally considered, including scaling issues (Fassnacht and Deems, 2006; Mott et al., 2011; Schirmer and Lehning, 2011; Trujillo et al., 2007), the detailed dynamics of snow accumulation and ablation (Grünewald et al., 2010; Schirmer et al., 2011; Scipión et al., 2013), and snow transport processes (Mott et al., 2010). In addition, the high density measurements provided by LiDAR technologies are a valuable resource for detailed investigation of the linkage between snow distribution and topography. In the past, this linkage has mostly been studied using manual measurements, and hence with generally limited spatial and temporal resolution (López-Moreno et al., 2010).

Previous studies have highlighted the marked control of topography on snow distribution in mountain areas (Anderton et al., 2004; Erickson et al., 2005 Lehning et al., 2011; Mott et al., 2013), and the importance of vegetation and wind exposure (Erxleben et al., 2002; Trujillo et al., 2007). The most commonly used approach has been to develop digital elevation models (DEM) that describe the spatial distribution of elevation, from which other terrain variables are derived such as slope, terrain aspect, curvature, wind exposure or sheltering, and potential solar radiation. This enables to analyze the linear or non-linear relation of these variables to punctual SD or SWE values to be established (Grünewald et al., 2010; Schirmer et al., 2011). Various statistical methods have been applied for this purpose, including linear regression models (Fassnacht et al., 2003; Hosang and Dettwiler, 1991), generalized additive models (GAM) (López-Moreno and Nogués-Bravo, 2005), and binary regression trees (BRT) (Breiman, 1984) which have been widely applied in a diversity of regions (Elder et al., 1991; Erxleben et al., 2002; McCreight et al., 2012;)

The extent to which topographic variables explain snow distribution can change during the snow season; the variability of terrain characteristics can drive processes related to the spatial variability of snow accumulation (snow blowing, terrain curvature) (Lehning et al., 2008), or affect the energetic exchange between terrain and the snowpack (temperature, incoming solar radiation), so the importance of topographic variables is modified during the season (Molotch et al., 2005). In addition, during a snow season the terrain changes markedly (is smoothed) by snow accumulation (Schirmer et al., 2011). However, few studies have systematically analyzed the intra- and inter-annual persistence of the relation between snow distribution and topography. Recent studies have assessed whether the influence of topography is constant among different years; e.g. the similarities observed at the end of the accumulation season (Schirmer and Lehning, 2011; Schirmer et al., 2011), or the consistent fractal dimensions in two analyzed years (Deems et al., 2008); in both cases there was a relation with the dominant wind direction, which highlights the predictive ability of topographic variables.

The main focus of this study was to assess the influence of topography on the spatial distribution of snowpack and its evolution over time. The high temporal and spatial density of the dataset collected during the study enabled analysis of the main topographic factors controlling snow distribution, and assessment of whether topographic control of the snowpack varied during the snow season and between years having very contrasting climatic conditions. For this purpose, we conducted 12 surveys over 2012 (6) and 2013 (6) in a small mountain catchment representing a typical subalpine environment in the central Spanish Pyrenees, and obtained high resolution SD measurements using LIDAR technology using a TLS.

2. Study area and snow and climatic conditions

The Izas experimental catchment (42°44′N, 0°25′W) is located in the central Spanish Pyrenees (Fig. 1). The catchment is on the southern side of the Pyrenees, close to the main divide (Spain–France border), in the headwaters of the Gallego River valley, and ranges in elevation from 2000 to 2300 m above sea level. The catchment is predominantly east-facing, with some areas facing north or south, and has a mean slope of 16°. There are no trees in the study area, and the basin is mostly covered by subalpine grasslands dominated by Festuca eskia and Nardus stricta, with rocky outcrops in the steeper areas; flat, concave and convex areas occur in the basin.

The climatic conditions are influenced by the proximity of the Atlantic Ocean, with the winters being humid compared with zones of the Pyrenees more influenced by mediterranean conditions. The mean annual precipitation is 2000mm, of which snow accounts for approximately 50% (Anderton et al., 2004). The mean annual air temperature is 3°C, and the mean daily temperature is < 0°C for an average of 130 days each year (del Barrio et al., 1997). Snow covers a high percentage of the catchment from November to the end of May

The two years analyzed in the study represent climatic extremes during recent decades. Severe drought occurred during 2012, leading to snow accumulation well below the long-term average. The thickness of the snowpack, measured at the automatic weather station (AWS, Fig. 1), during winter in this year was less than the 25th percentile of the available historical data series of this AWS (1996–2011) (Fig. 2). Only at the end of spring did late snowfall events increase the amount of snow, but this rapidly melted. The opposite occurred in 2013, which was a year in which the deepest snowpack and the longest snow season of recent decades were recorded. Winter and spring in 2013 were extremely humid, with temperatures mostly between the 25th and 75th percentiles of the AWS historical series. Snow depth accumulation was very high between February and June (exceeding the 75th percentile); in some areas of the basin it lasted until late July, which is one month longer than in most of the preceding years for which records are available.

3. Data and methods

3.1. Snow depth measurements

During the study period high resolution SD maps were generated using a long range TLS (Riegl LPM-321), which enables safe acquisition of SD information with short acquisition times from remote areas, compared with measurements obtained manually. This technique has been extensively tested (Prokop et al., 2008; Revuelto et al., 2014; Schaffhauser et al., 2008), and systematically applied to the study of snow distribution in mountain terrain (Egli et al., 2012; Grünewald et al., 2010; Mott et al., 2013; Schirmer et al., 2011). In a previous study the mean absolute error in the most distant areas of the catchment was less than 10cm

(Revuelto et al., 2014), which is consistent with errors reported in previous studies (Grünewald et al., 2010; Prokop, 2008; Prockop et al., 2008; Schaffauser et al., 2008).

TLS provides high resolution three dimensional information on the terrain Nevertheless, error sources need to be considered because they can have large effects on the measurements. To reduce the influences of TLS instability (originated by small displacements of the tripod because TLS vibrations while it is operating), which leads to misalignment with reference points; and atmospheric change, a well-defined protocol must be applied. The protocol applied in this study for generating high resolution SD maps with a 1m cell size was described by Revuelto et al., (2014). This protocol has these main points: data collection; which includes experimental setup design and information acquisition by the scanning procedure; and data processing, where data is filtered, quality checked and the SD maps generated. Mainly, the methodology was based on differences between DEMs obtained with snow coverage in the study area and a DEM taken at 18 July 2012, when the catchment had no snow cover. Twelve snow depth maps at a spatial resolution of 5m were generated for the 2012 and 2013 snow seasons (Fig. 3). In each year three surveys were undertaken from February to April (2012: 22 February, 2 April, 17 April; 2013: 17 February, 3 April, 25 April), and three were undertaken from May to June when dominated intense melting conditions (2012: 2, 14 and 24 May; 2013: 6, 12 and 20 June). The average SD and SCA, and the maximum SD are shown in Table 1. It shows that much lower SD and SCA were observed in 2012 compared to 2013.

3.2. Digital elevation model and topographic variables

From the two scan stations located in the study area (Fig. 1), 86% of the total area of the catchment was surveyed using TLS. DEMs of 1m grid size were initially obtained from point clouds of varying density in different areas, but always with a minimum of 1point/m^2 (Revuelto et al., 2014). Some of the predictor variables cannot be calculated where data gaps occur in the DEM (e.g. the topographic position index), and others require a DEM with a greater surface than the area scanned during the study (e.g. to calculate the potential solar radiation, including the shadow effect from surrounding topography, or to calculate the maximum upwind slope parameter, it is included topographic information for distances up to 1200m from the exterior limit of the DEM obtained with the TLS). Thus, a DEM having a 5 m grid-size, available from the Geographical National Institute of Spain (Instituto Geográfico Nacional, www.ign.es), was combined with the snow-free DEM obtained using the TLS resampled from 1 m to 5 m resolution (the empty raster of the Geographical National Institute was used for the resampling, averaging all values within each cell). The 1 m grid-size SD maps were also resampled to 5 m to enable matching of the two different data sources.

To characterize the terrain characteristics, eight variables were derived from the final DEM, including: (i) elevation (*Elevation*), (ii) slope (*Slope*), (iii) curvature (*Curvature*), (iv) potential incoming solar radiation under clear sky conditions (*Radiation*), (v) easting exposure (*Easting*), (vi) northing exposure (*Northing*), (vii) the topographic position index (*TPI*) and (viii) maximum upwind slope (*Sx*).

Elevation was obtained directly from the DEM, while the other variables were calculated using ArcGIS10.1 software. This calculates *Slope* as the maximum rate of change in value from a specific cell to that of its neighbors (10 m window size), and C*urvature* is determined from the second derivative of the fitted surface to the DEM in the direction of maximum slope of the terrain for the neighbors cells (10 m window size too). *Radiation* was obtained using the algorithm of Fu and Rich (2002) and reported in Wh/m^2 meter based on the average conditions for the 15-day period prior to each snow survey. This algorithm calculates the potential clear sky radiation, which logically may strongly differ from the real radiation as a consequence of cloud cover. This measure provided the relative difference in the extraterrestrial incoming solar radiation among areas of the catchment for a given period under given topographical conditions (Fassnacht et al., 2013). *Easting* and *Northing* exposure were calculated directly as the sine and cosine, respectively, of the angle between direction north and terrain orientation or aspect. It provided information on the east (positive)/west (negative) exposure and the north (positive)/south (negative) exposure.

The *TPI* provides information on the relative position of a cell in relation to the surrounding terrain at a specific spatial scale. Thus, this index compares the elevation of each cell with the average cell elevation at specific radial distances as follows (De Reu et al., 2013; Weiss, 2001):

$$TPI = z_o - \bar{z} \tag{1}$$

$$\bar{z} = \frac{1}{n_R} \sum_{i \in R} z_i \tag{2}$$

Where z_o is the elevation of the cell in which *TPI* is calculated and $\bar{z}$ is the average elevation of surrounding cells obtained from (2) for a radial distance *R*. For each pixel the *TPI* was calculated for 5, 10, 15, 25, 50, 75, 100, 125, 150 and 200 meters radial distances (scale factors).

For specific wind directions, the maximum upwind slope parameter, averaged for 45º upwind windows (*Sx dash*; Winstral et al., 2002) provided information on the exposure or sheltering of individual cells at various distances, resulting from the topography. Rather than considering the contribution for the dominant wind directions (Molotch et al., 2005), *Sx dash* (*Sx* further on) values for eight directions were selected and directly related to the SD. The directions were: 0° for north (N), 45° for northeast (NE), 90° for east (E), 135° for southeast (SE), 180° for south (S), 225° for southwest (SW), 270° for west (W), and 315° for northwest (NW). For *Sx* the searching distances (Winstral et al., 2002) considered were 100, 200, 300 and 500m. These distances were selected to enable assessment of the range at which *Sx* exhibited greatest control on SD dynamics, as has occurred in previous studies (Schirmer et al., 2011; Winstral et al., 2002).

3.3. Statistical analysis

The 12 SD maps at 5 m spatial resolution were related to each of the topographic variables considered (including the 40 *Sx* combinations, and the 9 distances for *TPI*). The large number of cells for which snow depth data were available enabled robust correlations between topography and snow distribution to be obtained, and provided a very large dataset for training and validation of the SD distribution models.

Pearson's r coefficients were obtained between SD and each topographic variable. Using the whole dataset each variable was correlated, for all available points, against the SD value for the specific survey day. Given the large amount of data for surveys, the degrees of freedom for the correlation analyses were very high and hence it can inform of statistically significant correlations even with very low correlation coefficients. Moreover, the use of a very dense dataset of observations may have associated problems derived from spatial autocorrelation (Elsner and Schmertmann, 1994). For this reason we followed a Monte Carlo procedure, in which 1000 random samples of 100 SD cases were extracted from the entire dataset and correlated with topographic variables for assessing significance. A threshold 95% confidence interval ($\alpha < 0.05$) was used to assess the significance of correlations (r = +/– 0.197, based on 100 cases). The spatial scales of *Sx* and *TPI* for which SD showed a higher correlation; 200m and 25m respectively, were selected for further analysis (not presented in the manuscript).

To assess the explanatory capacity when all topographic variables were considered simultaneously, two statistical models were used: (1) multiple linear regressions (MLRs) and (2) binary regression trees (BRTs). A wide variety of regression analyses for interpretation of much more complex spatial data are available with greater capacity than MLRs and BRTs to deal with spatial autocorrelation issues and the non-linear nature of the relationship between predictors and the response variable (Beale et al., 2010). However, in this study we used MLRs and BRTs because these methods have been and are still widely used in snow studies, and because both enable to isolate accurately the weight of each independent variable within the model, which was the main objective of this research, rather than deriving models with maximum predictive capacity. Prior to run the models a principal component analysis (PCA) was applied to the topographic variables for detecting correlations between independent variables that could originate multicolinearity in MLR and BRT. This analysis (not shown) grouped the topographic variables in three components, from which it is observed that *TPI* and *Curvature* are highly correlated, and also *Northing* and *Radiation* (but in this case inversely) presented almost identical correlations with the three identified components. As *TPI* and *Northing* showed higher correlations with their respective components and also show in general higher Pearson's r coefficients with SD (see result section), the variables *Curvature* and *Radiation* were discarded as predictors in MLR and BRT analyses.

(1) *Multiple linear regression* estimates the linear influence of topographic variables on SD. Despite its simplicity and the rather limited capability under nonlinear conditions (López-Moreno et al., 2010), MLR was used to quantify the relative contribution of each variable to the entire SD distribution model. SD was calculated from the topographic variables at a specific location for a given day. The threshold for a variable to enter in the model was set at $\alpha < 0.05$. Beta coefficients (obtained dividing the standardized units by the coefficients by the mean value of each variable) were used to compare the weight of each variable within the regression models. Again, in order to avoid an excessive number of observations that may lead to spurious identification of statistically significant predictor variables, we first randomly extracted a reduced dataset (1000 cases) for selecting the topographic variables by means of a stepwise procedure. Once variables to be included for each survey were determined, they were used to obtain the final model, but using the entire data set (except 5000 cases for model validation), forcing variables entrance in models.

(2) *Binary regression trees* have been widely used to model snowpack distribution from topographic data (Erxleben et al., 2002; Molotch et al., 2005). These are nonparametric models that recursively split the data sample, based on the predictor variable that

minimizes the square of the residuals obtained (Breiman, 1984). One BRT was created for each sampling date. The BRTs were run until a new split was not able to account for 1% of the explained variance, or when a node had less than 500 cases; a maximum of 15 terminal nodes was set, to reduce tree complexity. As there were no over-fitting problems associated with sample size, 15,000 cases were used to grow the trees and 5,000 cases were used for validation. By scaling the explained variance of each variable introduced into each BRT (based on the % of the total explained variance by the BRT), we were able to compare the relative importance of each topographic variable between the different models.

Coefficients of determination (r^2) and Willmott's D statistic were used to assess the ability of each model to predict snow depth over an independent random sample of 5,000 cases. Willmott´s D was determined using equation (3) (Willmott, 1981):

$$D = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)}{\sum_{i=1}^{N}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \qquad (3)$$

where N is the number of observations, O_i is the observed value, P_i is the predicted value, and $\bar{O}$ is the mean of the observed values. The index ranges from 0 (minimum) to 1 (maximum predictive ability).

4. Results

4.1. Single correlations

Table 2 shows the correlation between SD and *Sx* for the eight wind directions at a distance of 200 m (identified as the best correlated searching distance in previous analysis). Despite differences in magnitude, the correlations for surveys carried out at the beginning of the season (22 February 2012 and 17 February 2013) in each year showed that SD was clearly affected by N and NW wind directions. This was particularly evident in 2013, as the correlation values were higher for both days. The contribution of N and NW wind directions is clearly evident for the surveys on 17 February 2013 (Figure 4, were wind roses with average wind speeds and direction, for the 15 day period before each survey are presented), when greater SD was recorded in the leeward slopes from a northerly direction (Fig. 3, upper areas of the maps). In the two years of the study a correlation with W and SW wind directions was observed to increase progressively during the snow season (Fig. 4 and Table 2 correlations). In 2013 this phenomenon was less marked because of the greater SD accumulation at the beginning of the snow season accompanied with NW direction winds, which resulted in only moderate changes in the *Sx* for the most strongly correlated wind directions. It was also observed that in both study years once the snow had started to melt (the last three surveys in each season) the snow distribution did not change in relation to *Sx* directions. When the best correlated *Sx* directions for each survey are compared with wind roses (Fig. 4) a good agreement is observed. These directions for survey days are: 315º for 22 Feb. 2012, 270º for 02 and 17 April 2012, and 225º for the three surveys in May 2012; in 2013, 315º was the best correlated direction for 17 Feb. and 270º for the other five surveys of the snow season

Correlations between the most correlated *Sx* direction for each day and SD were compared with correlations between SD and the other topographic variables (Table 3). This showed that *Sx* had one of the greatest coefficient of correlation with SD (range 0.22–0.56). The correlations were higher during the accumulation periods, especially in the 2013 snow season, with a reduction in correlations values occurring during the melt period at the end of each snow season.

The *TPI* at 25 m showed the highest correlation with SD for nearly all of the 12 sampled days. During 2012 the mean correlation values ranged from –0.32 to –0.58 for those surveys during which snow accumulation dominated in the days preceding the surveys. The r values were closer to the significance level for the surveys where the preceding days were dominated by melting conditions (14 and 24 May). In 2013, the *TPI* was more highly correlated with SD than in 2012, with Pearson's r coefficients < –0.6 for all survey days. *Curvature* also had a high correlation with SD, and similar to *TPI* with a 25 m searching distance was significantly correlated on all the survey dates, but unlike the *TPI,* the correlation of *Curvature* with SD did not decrease during the snowmelt periods. The significant correlations of *TPI* and *Curvature* with SD highlight the importance of terrain curvature on the SD distribution. The importance of terrain curvature at different scales for SD distribution is clearly evident in Figure 3, which shows that higher SD values were usually found for concave areas, which showed snow presence until the end of each snow season.

The correlation between *Elevation* and SD varied among survey days (Table 3). The correlations were usually positive, but only statistically significant (or approaching significance) for days when melting dominated (the last two surveys in 2012 and 2013). *Slope* was relatively weakly correlated with SD during the 2012 snow season. In 2013 the correlation was greater, and was statistically significant on some days. As with *Elevation*, the correlation between *Slope* and SD was variable between the two study years, and showed a similar temporal pattern to *Easting*, probably because of the presence of steeper areas on the east-facing slopes.

The correlation between *Northing* and SD was rarely statistically significant, was highly variable, and contributed to explaining SD in a very different ways in 2012 and 2013. In 2012 no correlation between SD and *Northing* was found during the accumulation period, but during the melting period a slight positive correlation was observed, as snow remained longer on north-facing slopes. The 2013 snow season started with a large precipitation event dominated by strong winds from a northerly direction, leading to high levels of snow accumulation on the south-facing slopes. This explains the strong and statistically significant negative correlation of SD with *Northing* for 17 February 2013. This event influenced the rest of the season (as evident in Table 2 in 2013), but a progressive decrease in its influence was evident for the following survey days. *Radiation* had an almost opposite influence on SD to that observed for *Northing*. During the melting period in each year the Pearson's r correlation between SD and *Radiation* was negative, indicating a thinner snowpack on the most irradiated slopes; the relation was statistically significant at the end of the 2013 snow season. However, during the accumulation period in 2013 statistically significant positive correlations were observed with *Northing* and *Radiation*, which are connected to the strong snow redistribution by winds from N-NW directions.

4.2. Multiple Linear Regression and Binary Regression Tree models

Figure 5 shows the Willmott's D values and the coefficients of determination (r^2) obtained in the comparison of observed and predicted values using MLRs and BRTs for a dataset reserved for validation (5000 cases). The MLRs produced r^2 values ranging from 0.25 to 0.65 and Willmott's D values ranging from 0.60 to 0.88, while the BRTs produced r^2 values ranging from 0.39 to 0.58 and Willmott´s D values ranging from 0.72 and 0.85. For both methods the relationship between the observed and predicted values was stronger for 2013. Accuracy decreased at the end of the snow season, when the snowpack was mostly patchy across the basin; this was particularly the case for the end of the 2012 season. Overall, the performance of the MLRs was more variable than that of the BRTs, which were more constant amongst the various snow surveys. For those days on which the models were most accurate in predicting SD variability, the MLRs showed slightly better scores than the BRTs. However, for days on which the accuracy between predictions and observations was lower, the BRTs provided better estimates than the MLRs. For 2012, slightly better results were obtained using MLRs, while the opposite occurred in 2013. Nevertheless, only large differences in the accuracy of each model were evident by the end of 2012 snow season, in the two last surveys, which were characterized by thin and patchy snowpack. In general, there was good agreement between the models for each survey day, so results obtained with each model could be compared.

As shown for single correlations*,* the *TPI* variable explained most of the variance in MLR models developed for all analyzed days (Table 4). The contribution of the other variables varied markedly among surveys, particularly when the two years were compared. In most cases, *Elevation* was the second most important variable explaining the SD distribution in 2012, followed by *Sx* and *Slope*. The other variables made a much smaller contribution, or were not included in the models. The contribution of *Elevation* was much less in 2013, and it was not included in three of the six surveys, whereas in 2012 it was included in all surveys. For the entire 2013, *Sx* was the second most important variable, followed by *Easting*, which had an almost negligible influence in 2012. *Northing* was only included in the models for the surveys carried out during periods dominated by snow accumulation, and was not included in the models during the periods dominated by melting.

Figure 6 shows two examples of BRTs, obtained for the days 2 May 2012 (upper panel) and 3 April 2013 (bottom panel), which accounted for the largest amount of snow accumulation in each of the two years. The variable *TPI* determined the first branching point, and this occurred in the majority of the trees obtained (not shown). After the first branching, other variables were significant in the model, including *Sx* and *TPI* for 2 May 2012,and *Sx* and *Northing* for 3 April 2013, demonstrating the importance of these variables in the subsequent branching of the trees.

The relative importance (scaled from 0 to 100) of each topographic variable in each BRT is shown in Table 5. This shows that *TPI* was the first most important variable explaining SD for all survey days. For the 2012 snow season, *TPI* explained more than 67% of the total explained variance in all BRTs, and 75% during the accumulation period (the first three surveys). Thus, for most of the survey days the variance explained by the other variables was <30%. The second most important variable explaining the SD distribution in 2012 differed amongst the survey days. Thus, *Sx* was the second most influential variable during May (except for 24 May 2012), following the largest snowfall in the season (which occurred the 1 May 2012), and *Elevation* was the most important variable in the other surveys during 2012. *Northing* also had an evident influence during the two first surveys of the year, but subsequently had minimal explanatory capacity, as was the case for all the other variables. In 2013 *TPI* was also the main contributor to the total explained variance, exceeding 50% for almost all survey days, and approaching or > 70% during the snowmelt period. The influence of *Sx* was more important in 2013 than in the previous year. At the beginning of 2013 the contribution of *Sx* to the total explained variance was almost 46%, and remained >20% for the rest of the snow season; an exception was the last survey, when melting dominated and its effect declined to 12%. When snow was not mobilized for long periods by wind, the SD distribution was more dependent on variables related to terrain curvature (*TPI* and *Curvature*). During 2013, *Elevation* contributed approximately 5% to the total explained variance during the entire snow season. *Northing* made a significant contribution to the model (14.7%) on only one day (3 April 2013), and a much smaller contribution on the following survey day (25 April 2013). Where included in the BRTs, the other variables (*Easting*, *Radiation*) made no, or only minor, contributions to the total explained variance.

5. Discussion

The distribution of snow in mountain areas is highly variable in space and time, as was shown for the Izas experimental catchment during two consecutive years. Many meteorological and topographic parameters affect the snow distribution and its evolution through time with different weights subjected to several factors. In this context, we demonstrated that topography was a major controlling factor affecting SD in a subalpine catchment, and showed that its effect evolved during the snow accumulation and melting periods over two years having highly contrasting climatic conditions and levels of snow accumulation.

There have been many studies analyzing the spatial distribution of SD in mountain areas (Anderton et al., 2004; Erickson et al., 2005; López-Moreno et al., 2010; Mccreight et al., 2012). Besides some researches have also focused their attention in long-term inter-annual snow distribution analyses (Jepsen et al., 2012; Sturm and Wagner, 2010, Winstral and Marks, 2014) but there are very few datasets that have enabled investigation of the intra- and inter-annual variability of the topographic control on the snowpack distribution, being important to investigate both time scales. The results of previous research have highlighted the difficulties in fully explaining the distribution of snow in complex mountainous terrain. In addition, the results have differed among studies, and suggest that different variables govern the distribution of snowpack among areas as consequence of their differing characteristics and geographical settings, including surface area and altitudinal gradients, the importance of wind redistribution, the presence or absence of vegetation, and the topographic complexity (Grünewald et al., 2013).

Most of the topographic variables investigated in this study have been included in previous studies, including *Elevation, Slope, Radiation, Curvature* and *Sx*. Other variables, in particular *TPI*, have received little attention in previous research (López-Moreno et al., 2010). We showed that *TPI* at a scale of 25 m had the greatest capacity to explain the SD distribution in the study catchment. *Curvature* (which refers to a small spatial scale of terrain curvature) was also highly correlated with the SD distribution, but not as highly as *TPI*, reinforcing the importance of considering terrain curvature at various scales in explaining the SD distribution in mountain environments. The correlation between snowpack and the *TPI* decreased during melting periods, whereas the correlation with *Curvature* remained constant. This suggests that snow accumulates more in small, deep concavities, but is shallower at the end of the season in wider concave areas that were identified by the 25 m *TPI* scale. This effect was evident at the end of the snow season, when snow was present only in deep concavities, as shown in Figure 3. To explain the snow distribution, Anderton et al. (2004) compared the relative elevation of a cell with the terrain over a 40 m radius, and observed that this had a major role on SD distribution, what reinforces curvature importance at different scales.

The maximum upwind slope (*Sx*; Winstral et al., 2002) has also been identified as a key variable explaining snow distribution, improving the results obtained when it is introduced into models. Our results are comparable with those of other studies that have shown that the optimum searching distance for correlating *Sx* with the SD distribution is 300 m (Schirmer et al., 2011), so it is not a large difference for the considered distances in this work which reaches 500m. As it is observed from the reported wind information, Izas experimental catchment has W-NW dominant wind direction what is consistent with the best correlated *Sx* directions. For this reason, the *Sx* preferred direction for each date was selected, and showed that there were intra-annual shifts in the most highly correlated direction. The change in the most important *Sx* direction was similar between the 2012 and 2013 snow seasons; it started with a northerly component and evolved to a dominant westerly direction. We also found a decrease in the correlation between *Sx* and the snow distribution at the end of each snow season, when melting conditions dominated; this is consistent with the findings of previous studies (Winstral and Marks, 2002).

Sx parameter takes into account sheltering effects with topographic origin in relation to wind directions. As it has been observed in this study, higher SD amounts are observed in leeward slopes, which for this study site are in E-SE slopes, being perceived this effect in the SD distribution maps. *TPI* is not able to explain snow drifts, because this index considers the topographic characteristics in all directions. Nevertheless, terrain characteristics at the study site in relation to SD distribution have shown a higher importance of *TPI* when compared to *Sx*. The most likely explanation of this result is that the basin has a rather reduced size, shows the same general aspect (SE facing) and topography is relatively gentle. Under such conditions, during wind blowing events snow is accumulated in all the wide concavities of the basin (represented by *TPI*) independently of its specific location. Nonetheless, wind redistribution will be affected by a combination of local topography in relation to the main wind directions; what makes necessary to consider the *Sx* parameter, and this effect lasts in time until the melting season is advanced. Nonetheless, under such conditions more snow is accumulated according to main wind directions; what makes necessary to consider *Sx* parameter, and this effect lasts in time until the melting season is advanced.

Only for two days (22 February 2012 and 2 April 2012) was there no (or a minor) contribution of *Sx* to SD, according to the BRTs and MLRs. On these days *Northing* was introduced into the models, and was found to explain some of the variance of *Sx* from northerly direction (the best correlated direction for these days (Table 2).

Although *Elevation* has been found to largely explain the snow distribution in areas having marked altitudinal differences (Elder et al., 1998; Erxleben et al., 2002; Molotch and Bales, 2005) in our study no strong association was found between SD and *Elevation*, with significant correlations occurring only during the snowmelt period. This is because of the low elevation range of the study area (300 m). During the accumulation period the entire catchment is generally above the freezing height. However, during spring the 0°C isotherm shifts to higher elevations, which may lead to different melting rates within the basin. Despite the relatively weak correlation between Elevation and SD, this variable was introduced as a predictor in the MLRs and BRTs for most of the days analyzed. Similarly, López-Moreno et al. (2010) reported that elevation was of increasing importance as the grid size increased. Anderton et al. (2004) also informed about the importance of elevation to explain snowpack distribution in the same study area. The results of the present study suggest the increase in importance of Elevation at the end of the snow season, and particularly when it is considered in combination with other topographic variables in MLR and BRT models.

Slope was only a weak explanatory factor for snow distribution, probably because the slope in most of the catchment is not sufficient to trigger gravitational movements including avalanches and slushes during the snowmelt period, which could thin the snowpack on the steepest slopes (Elder et al., 1998). Maybe some of *Slope* explanatory capacity is included on *Radiation* explanatory capacity, because it affects solar light incident angle, and also, the steeper areas of the catchment are in south facing zones, nevertheless quantifying such kind of effects is highly difficult due to the high complexity of SD dynamic in mountain terrain.

Radiation, *Northing* and *Easting* showed no close correlation with the snowpack distribution; their relationships with SD were variable over time, with statistically significant correlations occurring on some days and only weak correlations on other days. The results suggested that *Radiation* and *Northing* (which showed almost opposite patterns) may be related to SD for two different reasons. During the accumulation period in 2013 heavy snowfalls associated with northerly winds led to the accumulation of deep snow on south-facing (more irradiated) surfaces, whereas during the snowmelt period the greater exposure of the southern slopes to solar energy led to a positive (negative) correlation with *Northing* (*Radiation*). This phenomenon was also observed by López-Moreno et al. (2013), using a physically-based snow energy balance model in the same study area. Moreover, the high and opposite correlation between *Northing* and *Radiation* obtained in PCA results (not shown in the manuscript), prevented us of potential problems of multicollinearity. Thus, only *Northing* was considered for MLRs and BRTs (the same occurred with *TPI* and *Curvature*, being only considered in statistical models the *TPI*). Although *Northing* did not show a significant correlation with SD during accumulation periods, when the surveys were closer to the snowmelt period the negative correlation of this variable with SD was much more evident, possibly due to the increase of the difference in the energetic exchange between the sun exposed and shaded areas. The importance of *Northing* in MLR models, combined with the contribution of *Easting* during the accumulation period may be related to the high snow redistribution originated by wind directions from N- NW directions. In such a way terrain aspect (considered with *Northing* and *Easting*) during winter is more related to the accumulation patterns resulting from wind redistribution, whereas in spring they were associated with the unequal distribution of solar radiation, which leads to higher melting rates on the most irradiated slopes, what has shown better explanatory capacity than *Radiation* at Izas Experimental catchment.

The MLRs and BRTs provided reasonably high accuracy scores when observed and predicted SD data were compared. The scores were comparable, and in some cases better, to values reported in previous researches using similar methods. Molotch et al., (2005) reported r^2 values between 0.31 and 0.39 with BRT; and Winstral et al., (2002), considering different number of terminal nodes of BRT with similar topographic variables, obtained an optimal tree size of 16 nodes (which is quite similar to the tree size selected in this study, in spite of differences in the study area, the nature of the dataset, etc) with an r^2 value close to 0.4. Moreover results presented here were obtained from a separate dataset, and data used to create the models are not considered for testing, thanks to the large available data set. One reason for the improvement may be the use of the *TPI* as a SD predictor, as this variable has not been considered in previous studies. Nevertheless, it should be noted that the study sites considered in other studies, could differ in terms on complexity of terrain, and also in SD accumulation amounts. For the 12 survey days the *TPI* had the greatest explanatory capacity in both approaches. However, based on comparison of the different dates and surveys, the other variables made more varying contributions, as a result of the different roles they play during the snow accumulation and melting periods, and the wind conditions during the main snowfall events. The models had less capacity to explain spatial variability of the snowpack when the snow was thinner and patchy. The BRT and MLR approaches were consistent with respect to error estimates. The results obtained using each approach were comparable, so the trends in the variable ranking for both models for each survey day were very similar. Only during conditions of snow scarcity did the BRT approach demonstrate better capability to relate SD to topography. This is probably a consequence of the greater capacity of BRTs to take account of the nonlinear response of the snowpack to topography, and the occurrence of sharp thresholds typical of days when the snowpack is patchy (López-Moreno et al., 2010; Molotch et al., 2005).

In spite of model results differ between survey days and years, some variables are always present in the models and their contribution to the total explained variances are rather similar. Moreover for 2012 and 2013 a consistent inter-annual distribution of the snow pack in the catchment is observed; the areas of maximum SD and the location of snow free zones were consistent between both years of the study, and more importantly there is a strong consistency of the effect of topography on SD is clear. This spatial consistency of snowpack has implications for soil dynamics and plant cycles, because some parts of the basin will tend to remain free of snow cover during longer periods favoring the presence of temporary frozen soils, and reducing the isolation effect of snowpack to the plants (Keller et al., 2000; Pomeroy and Gray, 1995). Moreover, it suggests that the information acquired from TLS during several years could be useful to design long-term monitoring strategies of SD in the basin based on few manual measurements in representative points according their terrain characteristics.

6. Conclusions

Topographic variables related to terrain curvature were shown to contribute more to explaining snow distribution than other variables. In particular, the *TPI* at a 25 m searching distance was the major variable explaining SD in the Izas experimental catchment. This suggests the importance of including this index in future snow studies, and the need to establish the best searching distance for relating this variable to SD distribution at other study sites. The maximum upwind slope at a searching distance of 200 m was also an important variable explaining the SD distribution. However, its influence varied markedly between years and surveys, depending of the specific wind conditions during the main snowfall events. The influence of the other topographical variables on the spatial distribution of SD was less, and showed greater intra- and inter-annual variability. The results from BRTs and MLRs models were consistent, and the explanatory capacities of the main variables were very similar for all surveys. This suggests that the effect of topography on snow distribution has relatively high intra- and inter-annual consistency in the study catchment. Terrain characteristics have shown a major role on snow distribution, as *TPI* explanatory capacity. When snow distribution could be affected by wind action (mainly during the accumulation period), its distribution is modified tightly related with main wind directions and sheltering effects, well described with *Sx* parameter. Several interesting temporal evolutions during the two snow seasons were found in the relation of some topographic variables to SD.

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9. Tables

	Snow season 2012						Snow season 2013					
	22/02	**02/04**	**17/04**	**02/05**	**14/05**	**24/05**	**17/02**	**03/04**	**25/04**	**06/06**	**12/06**	**20/06**
Mean SD (m)	0.72	0.58	0.60	0.97	0.71	0.70	2.98	3.22	2.53	2.28	2.09	1.61
Max SD (m)	5.5	3.8	5.3	6.1	4.4	4.3	10.9	11.2	10.1	9.6	8.9	7.9
SCA (%)	67.2	33.5	94.1	98.8	30.9	18.9	98.8	100.0	96.3	86.4	77.1	67.0

Table 1: Summary statistics of the snowpack distribution and the snow covered area of the basin. Note that snow covered area is expressed as a % of the total area surveyed by the TLS, and the mean SD is the average of all SDs not including zero values.

	Snow season 2012						Snow season 2013					
	22/02	**02/04**	**17/04**	**02/05**	**14/05**	**24/05**	**17/02**	**03/04**	**25/04**	**06/06**	**12/06**	**20/06**
Sx 0º	0,19	0,13	0,09	-0,11	0,06	-0,01	0,51*	0,40*	0,31*	0,23*	0,22*	0,20*
Sx 45º	0,15	-0,02	0,00	-0,16	-0,08	-0,09	0,36*	0,25*	0,17	0,12	0,12	0,12
Sx 90º	0,12	-0,14	-0,07	0,11	-0,11	-0,03	-0,15	-0,15	-0,10	-0,09	-0,09	-0,10
Sx 135º	0,02	-0,05	0,05	0,26*	0,01	0,11	-0,27*	-0,19	-0,10	-0,06	-0,06	-0,06
Sx 180º	0,02	0,14	0,15	0,38*	0,17	0,21*	-0,19	-0,08	0,02	0,08	0,08	0,12
Sx 225º	0,12	0,29*	0,26*	**0,44***	**0,32***	**0,23***	0,06	0,18	0,26*	0,29*	0,29*	0,31*
Sx 270º	0,20*	**0,33***	**0,34***	0,26*	0,27*	0,21*	0,48*	**0,52***	**0,49***	**0,45***	**0,42***	**0,43***
Sx 315º	**0,22***	0,26*	0,27*	0,01	0,22*	0,12	**0,56***	0,50*	0,41*	0,34*	0,32*	0,33*

Table 2: Pearson's r coefficients between SD and *Sx*, calculated for the eight studied wind directions over the survey days. * marks those correlations that were statistically significant ($\alpha<0.05$) in at least the half of the samples (500 out of 1000 samples) from the Monte Carlo approach, and bold r coefficients represent the best correlated *Sx* direction for a specific survey day.

	Snow season 2012						Snow season 2013					
	22/02	**02/04**	**17/04**	**02/05**	**14/05**	**24/05**	**17/02**	**03/04**	**25/04**	**06/06**	**12/06**	**20/06**
Elev.	0,09	0,26*	0,16	0,10	0,29*	0,19	0,09	0,18	0,13	0,18	0,21*	0,26*
Slope	0,06	0,18	0,02	-0,03	0,20*	0,03	0,25*	0,27*	0,20*	0,20*	0,21*	0,26*
Curv	-0,44*	-0,45*	-0,47*	-0,49*	-0,41*	-0,37*	-0,39*	-0,40*	-0,40*	-0,39*	-0,38*	-0,38*
North	-0,06	0,00	0,04	0,19	0,07	0,11	-0,38*	-0,27*	-0,19	-0,09	-0,06	-0,11
East.	0,09	0,21*	0,13	0,13	0,13	0,11	0,25*	0,26*	0,27*	0,22*	0,18	0,14
Rad	0,05	0,04	-0,06	-0,22*	-0,12	-0,11	0,36*	0,21*	0,10	-0,09	-0,12	-0,23*
TPI 25	**-0,56***	**-0,46***	**-0,54***	**-0,58***	**-0,40***	**-0,32***	**-0,66***	**-0,68***	**-0,68***	**-0,66***	**-0,63***	**-0,61***
Sx	0,22*	0,33*	0,34*	0,44*	0,32*	0,23*	0,56*	0,52*	0,49*	0,45*	0,42*	0,43*

Table 3: Pearson's r coefficients between SD and the topographic variables. * marks those correlations that were statistically significant ($\alpha<0.05$) in at least the half of the samples (500 out of 1000 samples) from the Monte Carlo approach, and bold r coefficients represent the best correlated topographic variable for a specific survey day.

	Snow season 2012						Snow season 2013					
	22/02	**02/04**	**17/04**	**02/05**	**14/05**	**24/05**	**17/02**	**03/04**	**25/04**	**06/06**	**12/06**	**20/06**
TPI	-0,69	-0,53	-0,60	-0,59	-0,48	-0,40	-0,78	-0,72	-0,73	-0,80	-0,74	-0,72
Sx		0,11	0,28	0,26	0,20	0,16	0,36	0,31	0,43	0,37	0,38	0,31
Elev.	0,09	0,22	0,34	0,27	0,27	0,35		0,14		0,08		0,13
Slope		-0,25	-0,29	-0,24	-0,21	-0,21		-0,10	-0,14	-0,16	-0,09	-0,15
North	-0,22	0,13	-0,16				-0,12	-0,11	-0,11			
East.	0,10						0,29	0,25	0,25	0,31	0,23	0,20
r2	0,45	0,31	0,40	0,47	0,33	0,25	0,65	0,63	0,60	0,60	0,57	0,51

Table 4: Multiple linear regression beta coefficients for each independent variable and sampled day.

	Snow season 2012						Snow season 2013					
	22/02	**02/04**	**17/04**	**02/05**	**14/05**	**24/05**	**17/02**	**03/04**	**25/04**	**06/06**	**12/06**	**20/06**
TPI	83.2	78.8	75.0	71.7	74.0	66.9	49.1	56.4	64.4	71.2	69.9	77.5
Sx			4.6	12.7	13.4	10.8	45.9	23.1	23.0	21.8	20.1	12.5
Elev.	5.7	6.8	13.2	9.1	8.2	15.2	5.0	5.7	5.0	3.3	5.9	5.4
Slope	1.7	5.4	5.7	6.5	3.2	7.0			2.1			
North	9.3	8.1	1.5		1.3			14.7	4.3	2.4	2.9	3.6
East.									1.2	1.3	1.1	1.0
r2	0.56	0.42	0.52	0.54	0.46	0.39	0.58	0.56	0.55	0.54	0.53	0.51

Table 5: Contribution of the various topographic variables to the explained variance of SD distribution in the binary regression models for 2012 and 2013. Values have been rescaled from 0 to 100.

10. Figures

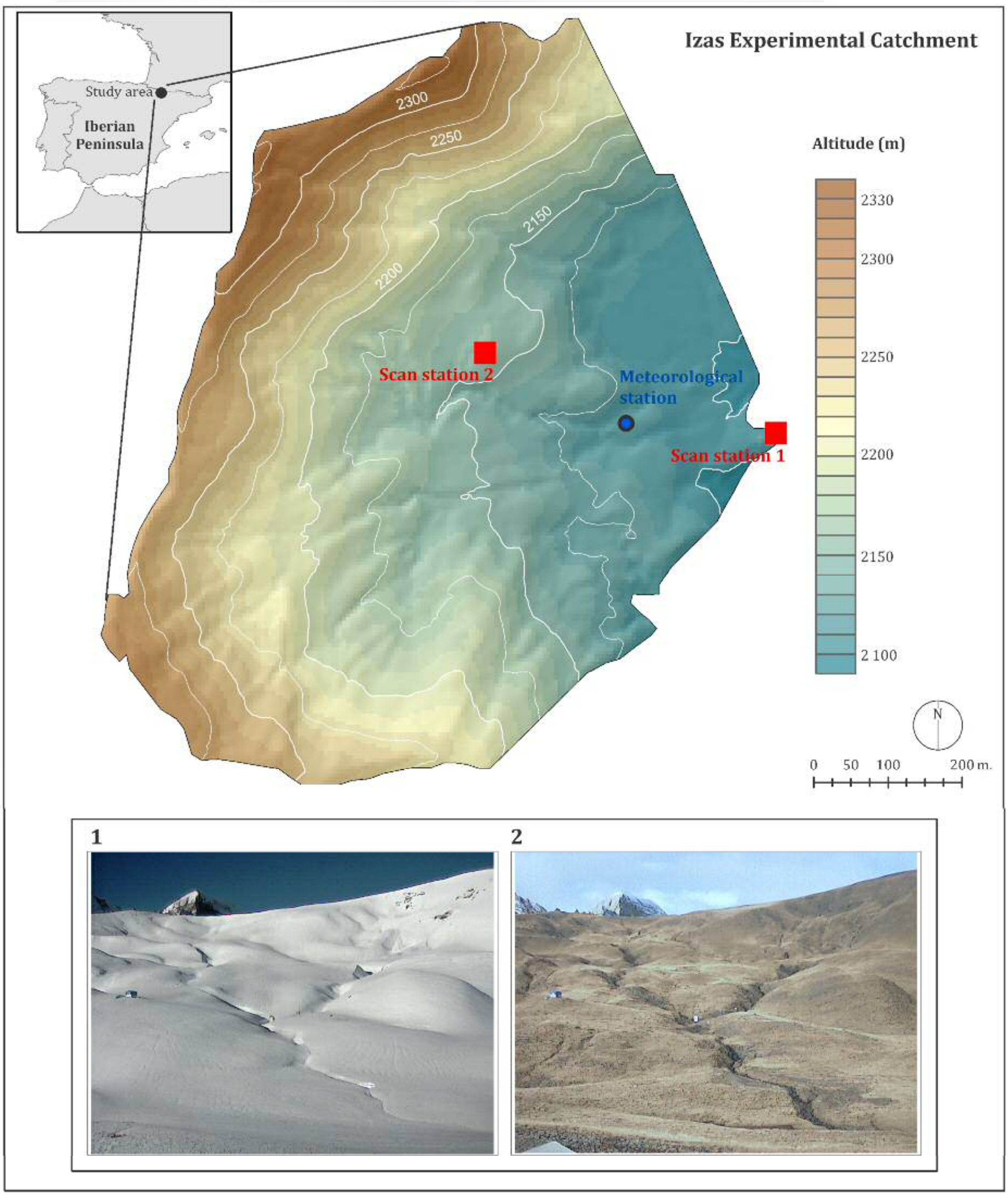


Figure 1: Location of the Izas experimental catchment, and the digital elevation model showing the positions of the scan stations and the automatic meteorological station. The two images in the bottom part of the figure, from Scan Station 1, show the terrain characteristics with (1) and without snow cover (2).

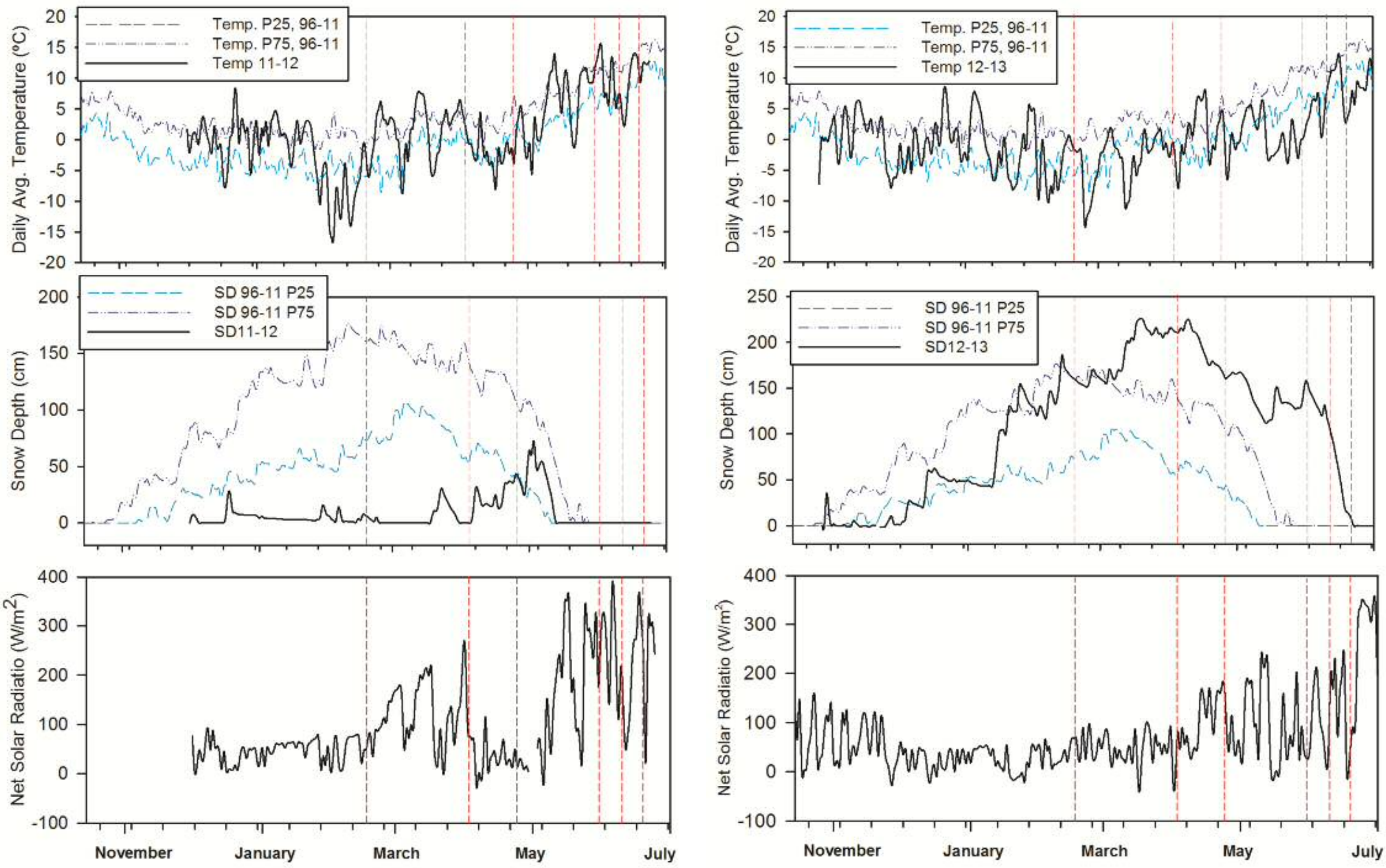
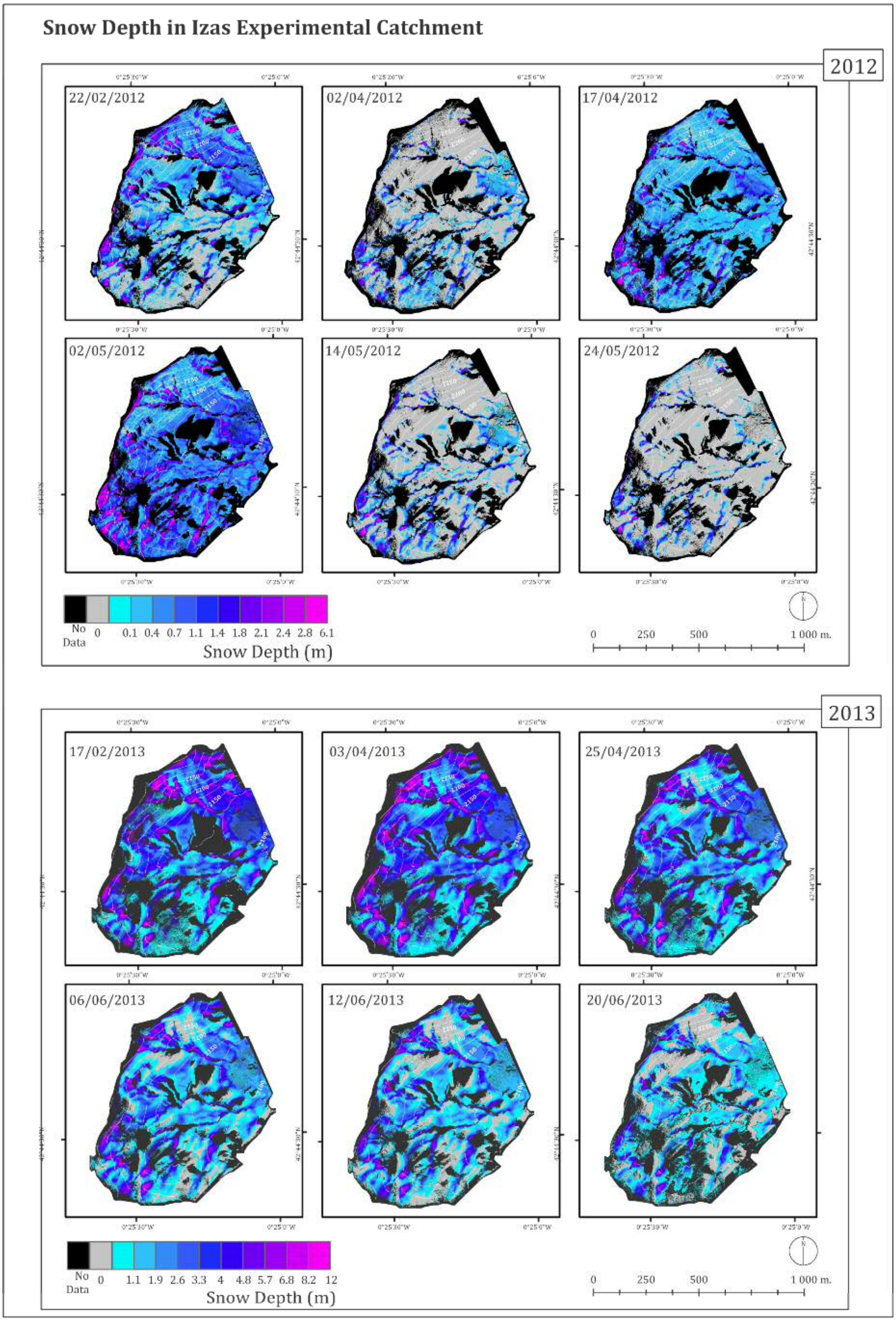
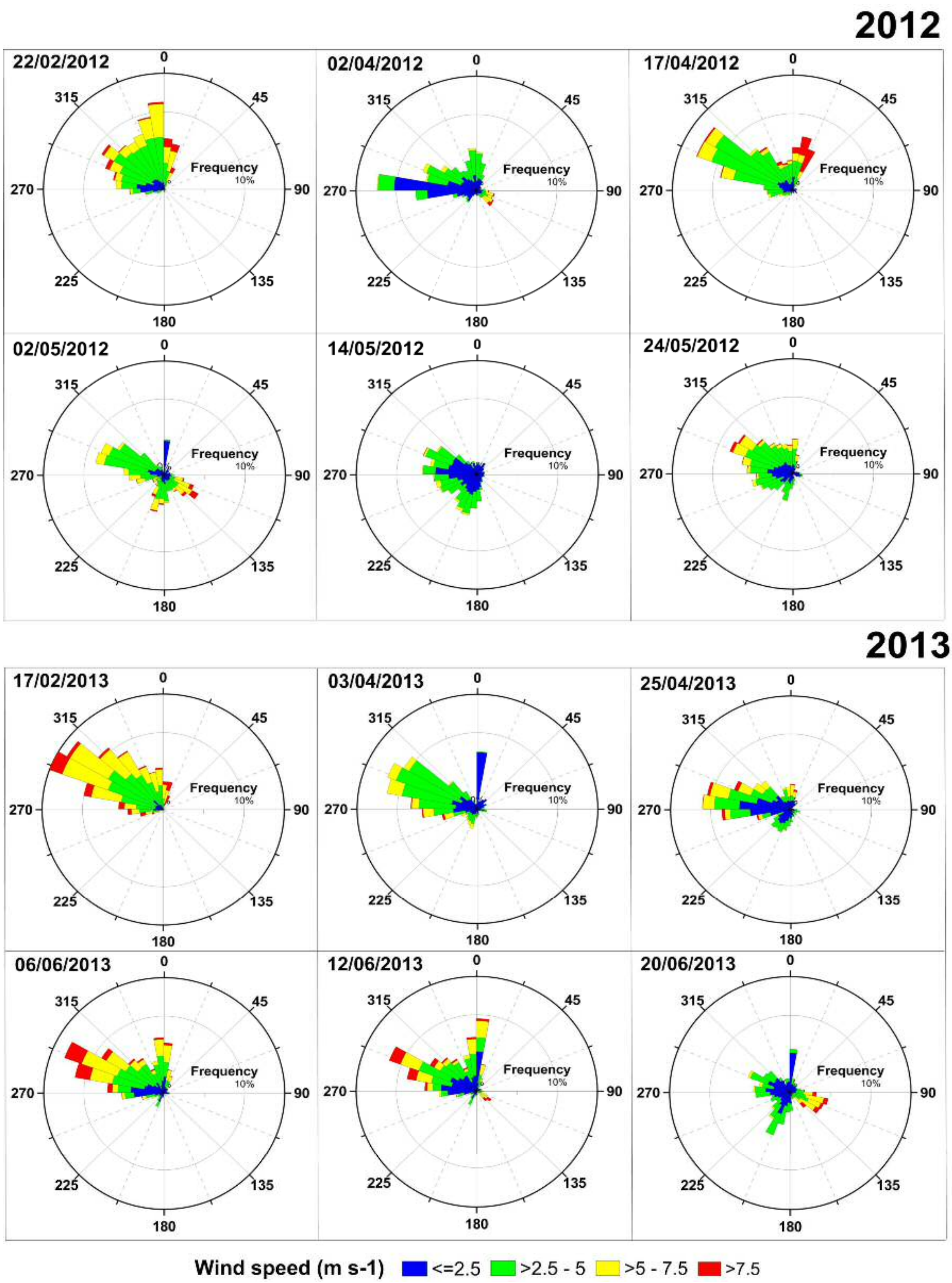


Figure 2: Daily average temperature, snow depth and net solar radiation at the automatic weather station (AWS) for the 2012 (left) and 2013 (right) snow seasons. The continuous lines represent the daily values for 2012 and 2013, and the dashed lines show the 25th and 75th percentiles of historical daily series (1996–2011). The vertical dashed lines show the TLS survey days. Note that during some surveys no snow was present at the AWS, but some areas of the Izas experimental catchment were covered by snow.


Snow Depth in Izas Experimental Catchment
2012
22/02/2012
02/04/2012
17/04/2012
02/05/2012
14/05/2012
24/05/2012
No Data
0
0.1 0.4 0.7 1.1 1.4 1.8 2.1 2.4 2.8 6.1
Snow Depth (m)
0 250 500 1 000 m.
2013
17/02/2013
03/04/2013
25/04/2013
06/06/2013
12/06/2013
20/06/2013
No Data
0
1.1 1.9 2.6 3.3 4 4.8 5.7 6.8 8.2 12
Snow Depth (m)
0 250 500 1 000 m.

855 **Figure 3:** Spatial distribution of snow depth in the Izas experimental catchment in the surveys undertaken in 2012 and 2013.



857

858 **Figure 4:** Wind roses from the automatic weather station placed at the catchment obtained for a 15 day period.

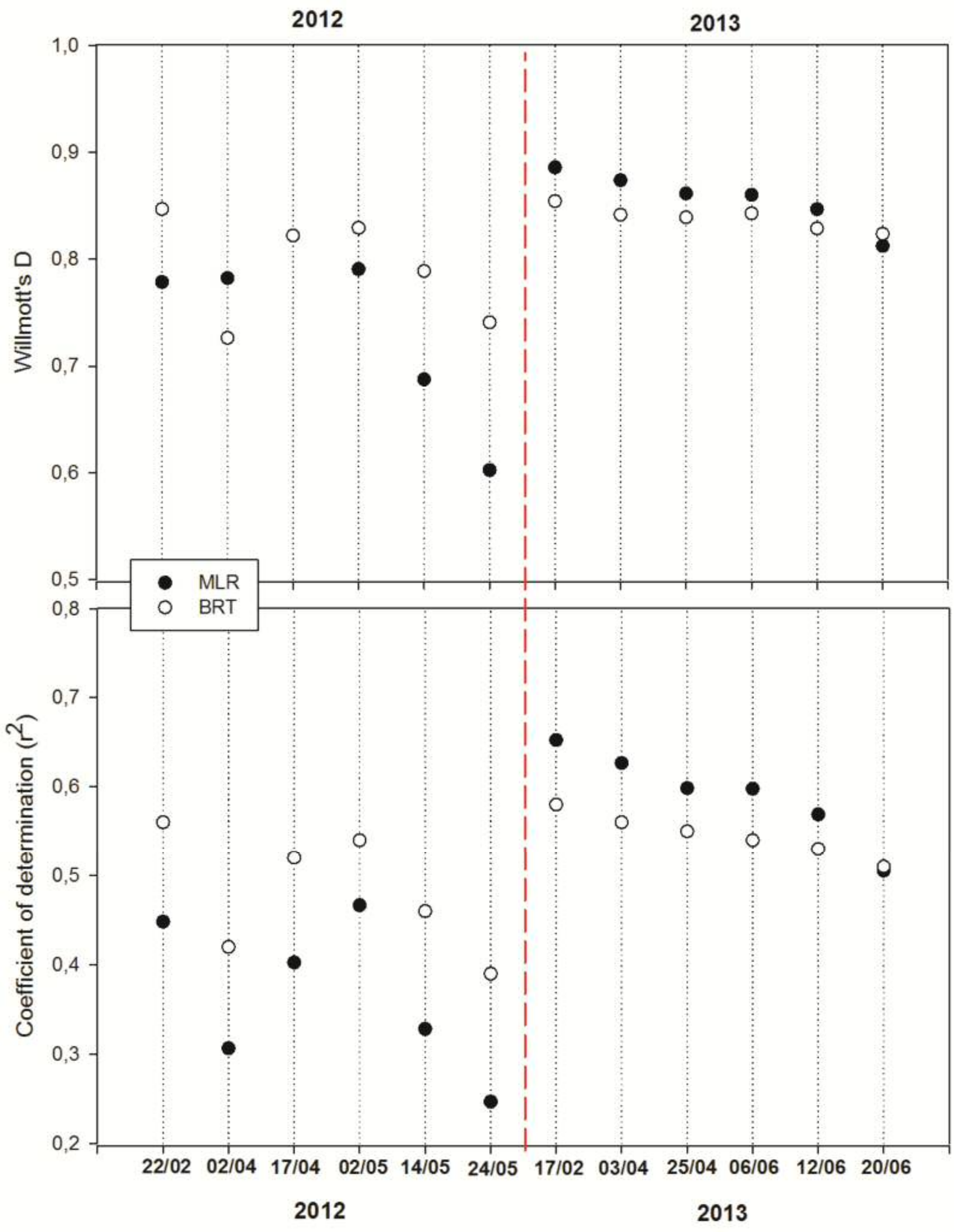


Figure 5: Willmott's D and r^2 values between the observed and predicted SD, based on the multiple linear and binary regression models for all survey days.

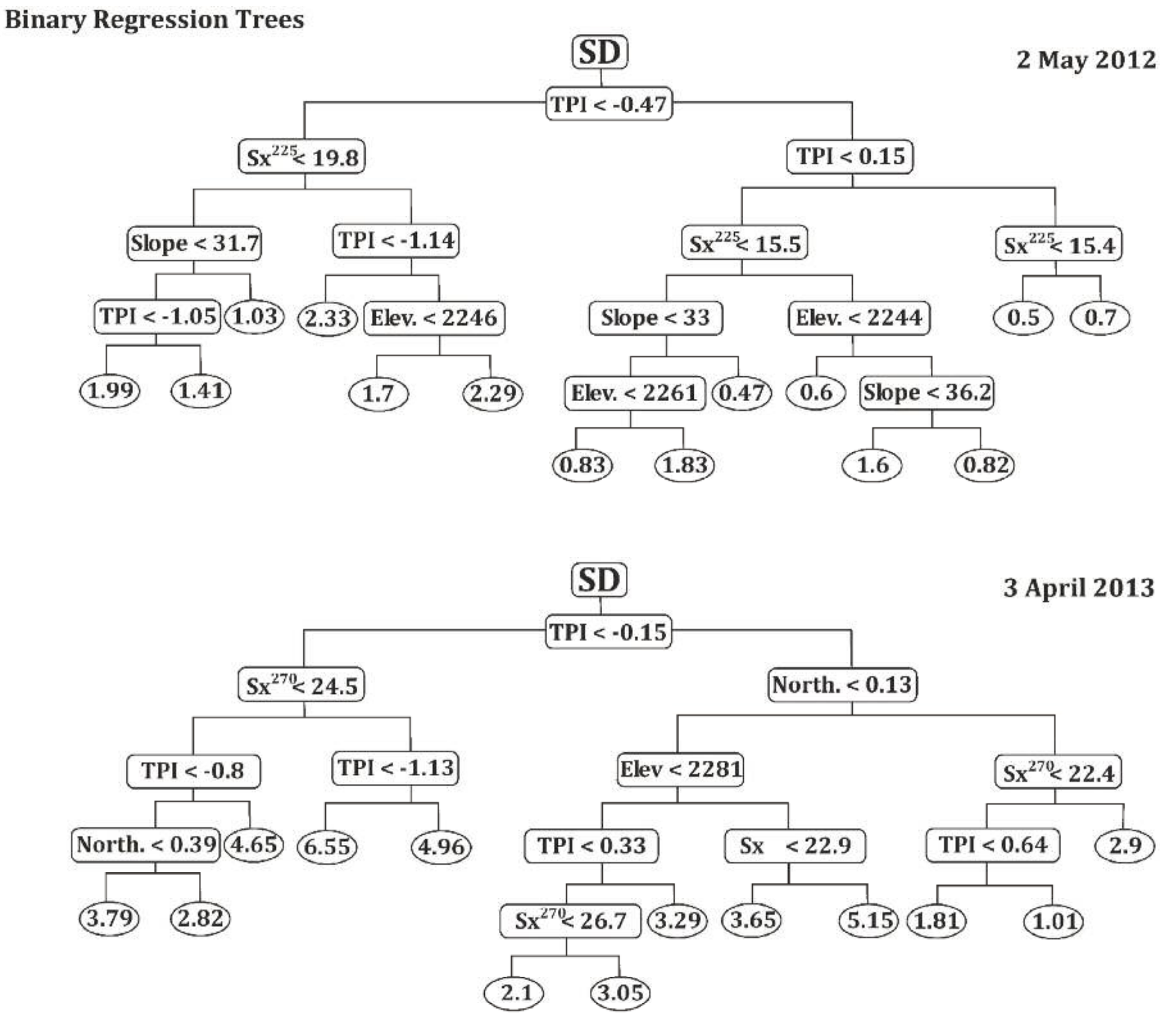


Figure 6: Binary regression tree obtained for 2 May 2012(top) and 3 April 2013 (bottom). The final nodes (with ellipses) show the predicted SD in the zone having the specified terrain characteristics. At each branch point, one topographic variable is considered; if the value is less than the specified value, the left branch is selected, but if it is equal to or greater than the specified value, the right branch is selected.