Authors' Response

Developing a representative snow monitoring network in a forested mountain watershed
Kelly E. Gleason, Anne W. Nolin, and Travis R. Roth

Dear Editor and Referees,

Thank you very much for your considerate review of our research paper entitled, "Developing a representative snow monitoring network in a forested mountain watershed", for submission in Hydrology and Earth System Sciences. Your comments throughout the first and second iterations of this manuscript have greatly improved the quality of the final manuscript. Please see our responses to each of your comments below, as well as in the final manuscript.

Sincerely,
Kelly

Point-by-Point Response to Reviews

Comments by Anonymous Referee #1

I would like to thank the authors for making substantive revisions to their original manuscript. It is a much more focused paper as a result, which was very necessary after my original appraisal. In particular, omitting the SNOTEL climate change analysis is a sensible refinement, as well as focusing on peak SWE rather than a rule of thumb, but somewhat arbitrary, 1 April SWE value. Additionally using three years of data, rather than just 2009 is a significant improvement. To summarize, I am happy with all the responses made to my original review. However, there are two comments that came out of the response letter which I would like to see included. They are minor, but I think will help future readers of this paper:

1. Could brief information be given on the precipitation partitioning used by Sproles et al. (2013)? While I understand the authors desire for brevity in this section, so they can just get on with using these data, brief knowledge of the changes made to precipitation would provide critical added value to those who only read this paper.

The information in the methods section has been expanded to include the following statement, "The model was modified by Sproles et al., (2013) to account for rain/snow precipitation phase partitioning using a linear function of air temperature from -2° to 2° C (USACE, 1965), and snow *albedo decay in forested landscapes using an empirically-based exponential decay function (Burles and Boon, 2011)."*

2. Two comments made in the response letter were very helpful to my understanding of the scope of this paper: "We don't expect the BRT model to predict actual SWE volume on the landscape, but to predict the spatial distribution of similar SWE characteristics across the landscape, and we believe we have achieved this goal in this revised manuscript." and "We did not expect to advance scientific knowledge, but to provide an objective technique for distributing point based monitoring locations which represent the spatial variability across the watershed." Neither statement made its way as explicitly into the paper as it was made in the response letter. To focus the reader on the scope of this work, I would like to see the main thrust of both of these statements added to the final paragraph of the introduction. That way the limitations to the goals of this study (not predicting SWE volume, but instead spatial characteristics of SWE; the novelty is through application of a method rather than any revolutionary methodological developments) would be clear.

We appreciate the need for clarity related to two major points requested by Referee #1, including, 1) that this method attempts to capture the spatial characteristics of SWE, and 2) that the novelty of this research is in the application of the method. We explain in the last paragraph of the introduction that this method aims to capture the spatial variability of SWE relative to landscape physiography, in the following statements, "To objectively identify optimal site locations to distribute a snow monitoring network which explicitly captures the spatial variability of snow accumulation relative to the physiographic landscape we used a combination of physically-based, statistical, and geospatial models. This paper presents this objective and relatively simple methodology to distribute a snow monitoring network which captures landscape driven spatial variability in snow accumulation and includes four major objectives:"

Also, we explain the novelty of this research in the Conclusions section of the manuscript which includes the following statement, "The novelty of this research stems from the application of the method, where by the coupling of a traditional BRT classification process with a validated physically-based spatially distributed model, we improved snow observational network design in a forested montane watershed." Particularly because of the comments by Referee #3 that, "this study has novel and useful contributions", we believe this explanation is best in the Conclusions section of the manuscript.

Comments by Anonymous Referee #3

SUMMARY

The authors did an excellent job in revising the manuscript to address my concerns from the first review. The reframing of the analysis to focus on three different snow years (rather than climate change projections) alleviated the concerns I raised about the comparability of different years on a fixed date. Likewise, they adequately addressed my concerns about multi-collinearity. Contrary to other reviewers, I find this study has novel and useful contributions. I recommend publication after considering a few additional minor comments (below).

TECHNICAL COMMENTS

- P1 L12: Should read “an average snow year”.

The suggested change has been made in the abstract.

TABLE AND FIGURE COMMENTS

- Figure 1: Either include the Columbia basin located in Canada in the shaded region, or note in the caption that the shaded region only includes the Columbia basin in the USA. Currently it suggests the Canada-USA border is coincident with the basin boundary, when it is not.

The entire Columbia river basin (including the Canadian section) is now included in Figure 1.

- Figures 2-4: Consider arranging the three years more consistently across figures. For example, Figure 3 has 2008, 2009, then 2005 while the others have 2009, 2008, then 2005. This is a minor suggestion.

In Figures 2-4, the study years are now arranged 2009, 2008, then 2005 for consistency.

- Figure 2: The legends are too small and make it hard to read without zooming. Please enlarge.

The legends in Figure 2 and Figure 4 have been enlarged.

- Figure 3: It is not clear in the figure or caption which vertical axis corresponds to the gray dashed line, the elevation fraction (or percent?). Otherwise, this is an outstanding figure.

This has been clarified in the figure caption which includes the following text, “The dashed grey line indicates the % / 100 of the area represented by each 100 m elevation band, and its values are associated with the left y-axis.”

- Figure 5: Consider reducing the size of the star symbols a little bit.

The size of the star symbols has been reduced by 30%.

List of All Relevant Changes

1. *The information in the methods section was expanded to further explain the precipitation phase partitioning used in the modelled data.*
2. *The aim of this research to capture the spatial variability in SWE, and the novelty of this research in the application of the method were clarified in the introduction and conclusions sections of the manuscript.*
3. *The typo in the abstract was corrected.*
4. *The entire Columbia River Basin was included in Figure 1.*
5. *The study years have been arranged consistently in all figures from 2009, 2008, and 2005*
6. *The legends in Figures 2 and 4 were enlarged.*
7. *The caption Figure 3 was corrected to include the association of the dashed grey line with the left y-axis.*
8. *The stars in Figure 5 have been enlarged.*

Developing a representative snow monitoring network in a forested mountain watershed

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Abstract. A challenge in establishing new ground-based stations for monitoring snowpack accumulation and ablation is to locate the sites in areas that represent the key processes affecting snow accumulation and ablation. This is especially challenging in forested montane watersheds where the combined effects of terrain, climate, and land cover affect seasonal snowpack. We present a coupled modelling approach used to objectively identify representative snow monitoring locations in a forested watershed in the western Oregon Cascades mountain range. We used a binary regression tree (BRT) non-parametric statistical model to classify peak snow water equivalent (SWE) based on physiographic landscape characteristics in an average snow year, an above average snow year, and a below average snow year. Training data for the BRT classification were derived using spatially distributed estimates of SWE from a validated physically-based model of snow evolution. The optimal BRT model showed that elevation and land cover type were the most significant drivers of spatial variability in peak SWE across the watershed (R^2 = 0.93, p-value < 0.01). Geospatial elevation and land cover data were used to map the BRT-derived snow classes across the watershed. Specific snow monitoring sites were selected randomly within the dominant BRT-derived snow classes to capture the range of spatial variability in snowpack conditions in the McKenzie River Basin. The Forest Elevational Snow Transect (ForEST) is a result of this coupled modelling approach and represents combinations of forested and open land cover types at low, mid, and high elevations. After five years of snowpack monitoring, the ForEST network provides a valuable and detailed dataset of snow accumulation, snow ablation, and snowpack energy balance in forested and open sites from the rain-snow transition zone to the upper seasonal snow zone in the western Oregon Cascades.

1 Introduction

Mountain snowpack is declining as a result of the warming climate (Kunkel et al., 2016; Knowles, 2015; Pederson et al., 2013; Rupp et al., 2013; Pederson et al., 2011; Mote, 2006), subsequently shifting timing (Fritze et al., 2011; Clow, 2010) and volume of streamflow (Woodhouse et al., 2016; Berghuijs et al., 2014; Luce and Holden, 2009) across the western United States. Luce et al., (2013) argue that the declining snowpack is also the result of weakening westerlies leading to a decline in mountain precipitation in the interior West. The volume and seasonality of water produced from these snow-dominated watersheds varies spatially and temporally as a function of precipitation and temperature (Tennant et al., 2015; Barnett et al., 2005; Regonda et al., 2005), as well as local physiographic effects of topography, geology, and vegetation dynamics (Molotch and Meromy, 2014; Clark et al., 2011; Jefferson et al., 2008; Ffolliott et al., 1989).

Montane snow-dominated river basins are topographically complex. Elevation, slope, aspect, and exposure influence snowpack dynamics across a watershed through alterations of precipitation amount and phase (rain vs. snow), wind speed, temperature, and humidity. The degrees to which these physiographic variables control snow persistence vary as functions of snow accumulation and snow ablation, from the plot to regional spatial scales (López-Moreno et al., 2015; Biederman et al., 2014; López-Moreno et al., 2013; Deems et al., 2006; Molotch and Bales, 2005), and from daily to seasonal scales (Fassnacht et al., 2012; Jepsen et al., 2012). In the Pacific Northwest, montane basins are a successional patchwork of variable forest cover driven by forest harvest and replanting, pest infestations, and fire disturbance. In forested regions, snow accumulation and ablation processes are strongly influenced by vegetation structure (Veatch et al., 2009; Musselman et al., 2008; Jost et al., 2007; Trujillo et al., 2007; Sicart et al., 2004; Murray and Buttle, 2003; Pomeroy et al., 2002; Link and Marks, 1999). Both vegetation and topography influence the distribution of solar radiation (Musselman et al., 2015; Musselman et al., 2012; Davis et al., 1997; Dozier, 1980;), snow-surface albedo (Gleason and Nolin, 2016; Gleason et al., 2013; Molotch et al., 2004; Melloh et al., 2002), net longwave radiation (Lundquist et al., 2013; Sicart et al., 2004) , wind speed (Winstral and Marks, 2002) and turbulent fluxes (Burns et al., 2014; Garvelmann et al., 2014; Marks et al., 2008).

Snow water equivalent (SWE) is a critical hydrologic resource in the montane western US that has been actively monitored for decades by the Natural Resources Conservation Service (NRCS). The NRCS currently manages approximately 858 Snowpack Telemetry (SNOTEL) stations across the western US (http://www.wcc.nrcs.usda.gov/snotel/SNOTEL_brochure.pdf). These stations provide near real-time measurements of SWE, temperature, and precipitation; essential data for operational streamflow forecasts used by water managers who balance a wide range of needs including irrigation, aquatic habitat, hydropower, recreation, and municipal water use. While most SNOTEL sites have been operating since the early 1980s, the data are meant to be used as indices to forecast discharge. These records are valuable but the stations were not designed to be nor are they representative of the total snow volume across a basin (Meromy et al., 2013; Molotch and Bales, 2006a). The SNOTEL monitoring stations in the Oregon Cascades are located within a narrow elevation range (1140–1510 m) that may not capture the inherent variability in the spatial distribution of snow under present day or warmer climate conditions (Nolin, 2012; Brown, 2009).

Modelling has been shown to be an effective means of augmenting remote sensing, and a valuable tool for predicting spatially distributed snow conditions in the rugged, forested, and frequently cloud-covered montane watersheds of the Pacific Northwest (Sproles et al., 2013; Tague and Grant, 2009; Veatch et al., 2009; Luce et al., 1999; Cline et al., 1998). Landscape characteristics have been used to predict snowpack conditions at hillslope scales using non-parametric binary regression tree (BRT) statistical classification models (Molotch et al., 2005; Anderton et al., 2004; Erxleben et al., 2002; Winstral et al., 2002; Balk and Elder, 2000; Elder et al., 1998). Larger scale BRT approaches have also been conducted using remotely sensed snow-covered area and interpolation methods (Molotch and Meromy, 2014; Molotch and Bales, 2006b). However, no study to date has used landscape characteristics in conjunction with modelled and validated physically-based and spatially distributed SWE data to understand physiographic drivers of snow accumulation at broad scales (watersheds > 1000 km^2) or to identify optimal locations for snowpack monitoring. Additionally, most of the research on the physiographic relationships to snow processes has been done in cold-dry continental snowpacks where mid-winter melt events are infrequent and wind redistribution is substantial (Molotch et al., 2005; Erxleben et al., 2002; Winstral et al., 2002; Balk and Elder, 2000). Much less is known about how physiographic conditions influence the temperature sensitive snowpacks in the forested maritime basins of the Pacific Northwest.

To objectively identify optimal site locations to distribute a snow monitoring network which explicitly captures the spatial variability of snow accumulation relative to the physiographic landscape we used a combination of physically-based, statistical, and geospatial models. This paper presents this objective and relatively simple methodology to distribute a snow monitoring network which captures landscape driven spatial variability in snow accumulation and includes four major objectives:

1. Determine the key physiographic drivers of spatial variability in snow accumulation;

2. Classify snow classes in the watershed based on key physiographic drivers using a non-parametric statistical model;

3. Spatially distribute these snow classes across the watershed using a geospatial model;

4. Select site locations for a snow monitoring network which spans the spatial variability in snow water equivalent in the McKenzie River Basin.

2 Methods

2.1 Study Site

The McKenzie River, located in the western Oregon Cascades, is a major tributary of the Willamette River (Figure 1). The McKenzie River Basin (MRB) drains an area of 3,041 km^2, and covers about 12% of the land area in the greater Willamette River Basin. The MRB is a densely forested mountainous watershed, ranging in elevation from 150 m to 3150 m, which is a managed for timber production throughout much of the seasonal snow zone. Brooks et al., (2012), determined that 60-80 % of summer flow in the Willamette River originated from elevations above 1200 m in the Oregon Cascades. The porous basalts in this geologically young landscape allow much of the snowmelt to percolate into groundwater systems (Tague and Grant, 2009; Jefferson et al., 2008; Tague and Grant, 2004). The groundwater-fed McKenzie River provides 25 % of the late season volumetric base flow to the Willamette River at its confluence with the Columbia River (Hulse et al., 2002).

2.2 Data Sources

Gridded data were obtained for physiographic variables shown in the literature to influence snow accumulation and ablation, including elevation, slope, aspect, incoming solar radiation, wind, and three vegetation variables from the following sources for the extent of the MRB. A Digital Elevation Model (DEM) was obtained from the National Elevation Dataset at a 10-m resolution. Slope, aspect, and incoming solar radiation were calculated from the DEM using the Spatial Analyst and Solar Radiation toolboxes in ArcGIS 10.1 (ESRI, Redlands, CA). Upwind contributing area data, which captures the variability in snow deposition as a result of wind redistribution for each cell throughout the watershed (Winstral et al., 2002), was calculated following Molotch et al., (2005). The 2006 National Land Cover Data (NLCD) was used to classify land cover across the watershed (Fry et al., 2011). Land cover data were reclassified into a binary product of forest and open land cover classes. The US Geological Survey (USGS) LANDFIRE Data Distribution Site provided the Existing

Vegetation – Percent Canopy Cover (EVC) data at 30-m spatial resolution. Normalized Difference Vegetation Index (NDVI) data were obtained from the Moderate Resolution Imaging SpectroRadiometer (MODIS) MOD13Q1 – Vegetation Indices, 16-day Land Product for the earliest date possible in April 2009, at a 250-m spatial resolution. Watershed boundaries were defined using the USGS National Hydrography Dataset. Public land ownership data were provided by the Oregon Department of Forestry, and obtained from the website, http://www.oregon.gov/odf/pages/gis/gisdata.aspx. All spatial data were masked to the McKenzie River Basin and converted to the same projection and spatial resolution: NAD83, UTM Zone 10, and a 100-m grid cell size. Spatial data were processed using ArcGIS 10.1 using bilinear interpolation for continuous data and nearest neighbour interpolation for discrete data.

Modelled and gridded SWE data across the MRB (Figure 2) were provided by Sproles et al., (2013). These data were developed using a physically-based spatially distributed snow mass and energy balance model, SnowModel (Liston and Elder, 2006). SnowModel uses micrometeorological and topographic data to distribute snow across the landscape accounting for climatic, topographic, and vegetation variability. ~~The model was modified by Sproles et al., (2013) to account for rain/snow precipitation phase partitioning, and snow albedo decay in forested landscapes.~~ The model was modified by Sproles et al., (2013) to account for rain/snow precipitation phase partitioning using a linear function of air temperature from -2° to 2° C (USACE, 1965), and snow albedo decay in forested landscapes using an empirically-based exponential decay function (Burles and Boon, 2011). This model was calibrated and validated using data from the four SNOTEL sites, meteorological data from the HJ Andrews Long Term Ecological Research site and National Weather Service stations, and Landsat fractional snow covered area data over the sampling period 1989-2009 (Sproles et al., 2013). The model was run at 100-m spatial resolution on a daily time step. We used modelled peak SWE data as the predicted variable in the BRT model. Sproles et al., (2013) showed that 2009 was considered an average snow year (normal snow year) so we used peak SWE from 2009 (five days centred on 04 April 2009) as our reference year. Additionally, we used peak SWE from 2008 (five days centred on 24 April 2008) as an above average snow year (high snow year), and peak SWE from 2005 (five days centred on 20 April 2005) as a below average snow year (low snow year).

2.3 Analysis

A BRT model was developed to characterize the spatial variability of snow accumulation across the MRB based on independent physiographic variables using the Classified and Regression Trees (CART) software

(Salford Systems, San Diego, CA). The BRT model is a hierarchical non-parametric statistical model that characterizes the mean and variance of a dependent variable using a suite of independent explanatory variables. Modelled SWE and physiographic variable data were used as input data for each cell where snow was present during peak SWE in 2009 (5 day average centred on 04 April 2009). An optimal tree was produced to minimize the standard error of the model, which was pruned to the simplest tree possible within one standard error of the optimal tree and so each terminal node represented at least 1% of the variability in peak SWE. The resultant tree identified 21 terminal nodes that characterized the spatial variability in snow accumulation through combinations of independent drivers into 21 BRT-derived snow classes (Table 1). The BRT model identified elevation, land cover, NDVI, insolation, percent canopy cover, slope, and wind as significant explanatory drivers of the spatial variability of peak SWE (all selected variables had p-values < 0.05 and are listed above in order of significance). Although elevation and land cover were the dominant predictive variables, and all other physiographic variables each explained less than 1% of the variability in peak SWE. In order to reduce the multi-collinearity between related variables and reduce the risk of overfitting the model, we simplified the final optimal model to only include elevation and land cover. Within the CART software, the final optimal BRT model was validated using reserved data from an independent set of 20,000 randomly selected grid cells from within the MRB. The final parameters developed in this optimal tree for peak SWE in a normal snow year (2009), were used to develop equivalent BRT models using peak SWE input for a high snow year (2008), as well as to peak SWE during a low snow year (2005).

Using a Geographic Information Systems (GIS) geospatial model and statistically-derived parameters, the 21 BRT-derived snow classes were spatially distributed across the MRB. The geospatial model used physiographic data to distribute the areal extent of each BRT class across the MRB by assigning cells that met the statistically-derived criteria for each BRT class. Because the BRT-model did not determine a lower elevation limit on snow extent, we excluded areas with an elevation less than 600 m to prevent over-prediction of snow-covered area below elevations where it was observed in the modelled data. Total volumetric SWE (SWE depth × area) was calculated for each BRT class across the watershed, using the mean and variance of SWE, and the spatial extent of each BRT class. To validate the spatial distribution of the BRT derived snow classes, we calculated the overall accuracy of the high snow year (2008) and low snow year (2005) relative to the reference year (2009) snow classes using an error matrix of omission vs. commission statistics (Campbell and Wynne, 2011).

To create a set of feasible locations for the *in situ* snow monitoring network we evaluated the accessibility of locations within the MRB. Using a GIS-based binary selection model, we masked out all private lands and public lands where the presence of endangered Northern Spotted Owl prevented permitted access. To prevent contamination from the road network, but still define accessible site locations, we also identified areas within 100-500 m of a snowmobile-accessible road. From these accessible areas, the final sites were then randomly selected from each of the dominant BRT-derived snow classes within the seasonal snow zone.

3 Results

Modelled peak SWE for all years had a positively skewed distribution across the range of elevations throughout the MRB (2009; kurtosis=1.8, skewness=1.62; 2008, kurtosis=2.1, skewness=1.7; 2005, kurtosis=1.5, skewness=1.7) with the greatest volume of snow located in the mostly forested area between 1300 and 1500 m in elevation (Figure 3). The final optimal BRT model from the normal snow year (2009) identified elevation and land cover as the dominant drivers of the spatial variability of SWE, and characterized SWE across the MRB into 21 distinct snow classes (2009 BRT model; R^2 = 0.93, p-value < 0.01, RMSE = 0.16 m). The final BRT model applied to the high snow year (2008) characterized SWE across the MRB into 21 snow classes with similar spatial extent as during the normal snow year (2008 BRT model; R^2 = 0.95, p-value < 0.01, RMSE = 0.18 m) (Figure 4; Table S1). The final BRT model applied to the low snow year (2005) characterized SWE across the MRB into 21 snow classes with similar spatial variability relative to land cover but differing extents relative to elevation than during the normal snow year (2005 BRT model; R^2 = 0.895, p-value < 0.01, RMSE = 0.09 m) (Figure 4; Table S2).

Elevation explained the most variance in modelled SWE across the basin, and was the primary driver of all snow classes (2009 BRT model with only elevation; R^2 = 0.91, p-value < 0.01). In the middle elevations, land cover was also statistically important in distinguishing snow classes between forested and open land cover types (Figure 4, 5). During the normal snow year (2009), snow classes were distinguished by forest vs. open land cover types across the elevation range from 951-1442 m. This elevation range where the forest vs. open distinction was statistically important was lower during the high snow year (2008) from 949-1299 m, but much higher during the low snow year (2005) from 1193-1747 m. In the high-elevations, above treeline, only elevation was statistically important in classifying the spatial variability in snow accumulation. Snowpack accumulation increased with increasing elevation, resulting in a greater mean SWE per unit area at the highest elevations. Although deep snowpack at the highest elevations only covers a small aerial extent of the MRB, which resulted in decreasing contribution of total basin-wide SWE above approximately 1700 m during the normal and high snow years. In contrast, during the low snow year, the highest elevation classes contributed the most to total basin-wide SWE (Figure 5).

The BRT-derived volumetric SWE estimates had a similar positively skewed distribution across the elevational gradient as the SnowModel-derived SWE data in the MRB (Figure 5). The BRT-derived estimate of 1.49 km^3 total SWE stored in the snowpack on 04 April 2009 within the MRB was less than 1% greater than the SnowModel-derived estimate of 1.48 km^3. The BRT-derived estimate of 1.94 km^3 total SWE stored in the snowpack on 24 April 2008 within the MRB was less than 1% greater than the SnowModel-derived estimate of 1.93 km^3. The BRT-derived estimate of 0.38 km^3 total SWE stored in the snowpack on 20 April 2005 within the MRB was 2.6% less than the SnowModel-derived estimate of 0.39 km^3. The final optimal BRT model from the normal snow year (2009) applied to the high snow year (2008) demonstrated an overall accuracy of 63%, whereas the BRT model applied to the low snow year (2005) demonstrated an overall accuracy of 26% (Table S1, S2). The BRT model performed well across the low and high elevations, where errors of omission and commission were generally lowest (Table S1, S2). Although across the mid-elevations which consist of a patchwork of forest harvest and fire disturbance, were the areas with the greatest error between the BRT models. The high elevations above tree line, were the most consistently classified areas with low error between BRT models. The high error across the mid-elevations was due at least in part to the renumbering of classes when the model is rerun for each year, and therefore these statistics may underrepresent the accuracy of the BRT-model in predicting overall spatial patterns of physiographically derived snow classes between years. The BRT-modelled snow classes captured the spatial variability in peak SWE across the MRB relative to elevation and land cover during an average, above average, and below average snow year and were used to objectively inform the site selection of a snow monitoring network.

The geospatial selection model identified 16 of the 21 classes as being accessible during winter (on public land without permit restrictions and within 100-500m of a snowmobile accessible road). The highest elevations in the MRB are far from winter-accessible roads and difficult to monitor due to steep and avalanche prone slopes. Within the area covered by these 16 classes, random site locations were selected within the six most abundant classes across the MRB to capture low, medium, and high elevations, with forested and open land cover classes. The resultant Forest Elevation Snow Transect (ForEST) monitoring network site locations were thus objectively selected to sample across the range of spatial variability in SWE (Figure 4). The ForEST network, composed of six meteorological stations and snow survey transects, was deployed in November 2011, and continues to provide high quality snow and climate data to evaluate snow-forest-climate interactions in the MRB (Figure 6).

4 Discussion

With warming winter temperatures, mountain snowpack in the western US will likely continue to decline with potential impacts to forest health (Albright and Peterson, 2013) and streamflow (Jung and Chang, 2011; Cayan et al., 2010), as well as snow-related recreation and tourism (Gilaberte-Búrdalo et al., 2014; Nolin and Daly, 2006). There remains uncertainty around the magnitude of these impacts (Warren et al., 2011; Maurer, 2007; Xu et al., 2005) thus, it is important that monitoring networks not only capture normal snowpack conditions, but capture the range of variability in peak SWE across the landscape and through time.

Pacific Northwest forests play a key role in affecting snow accumulation and ablation across multiple scales however, most research has been conducted at the stand scale (Storck et al., 2002) or in areas with cold-dry continental snowpacks (Ellis et al., 2013; Pomeroy et al., 2012). By distinguishing snow classes based on forest vs. open land cover across a range of elevations, this study emphasizes the watershed-scale control that vegetation and particularly land cover change relative to timber harvest (and potentially fire disturbance) has on snowpack accumulation in the maritime western Oregon Cascades. During low snow years, the significant influence of forest cover on the spatial variability in snow accumulation moved up in elevation from a normal snow year, suggesting that forest effects may have a more profound influence at higher elevations under future warming climate conditions. Understanding the forest structure effects on snow accumulation and ablation across elevation gradients is increasingly important to help guide decision making by local and regional water and forest managers in response to a changing climate.

We developed a snow monitoring network representative of the spatial variability of peak SWE relative to physiographic landscape characteristics across the MRB for an average, above average, and below average snow year, by coupling a spatially distributed physically-based SnowModel, a BRT statistical classification model, and a geospatial selection model. This objective method is a useful tool in classifying snow characteristics across the landscape to determine representative locations for intelligent snowpack monitoring particularly in physiographically complex landscapes. Although it is an improvement over more commonly used heuristic approaches to site selection, the method incorporates uncertainty as a result of compounding physically-, statistically-, and spatially-based models which justifies caution in implementing these estimates in management decisions. However, the method meets assumptions of non-parametric data analysis, is performed with relative ease, and if data are available for the research basin of interest, it can be well validated. As even physically-based models incorporate inherent empirically-based historically-derived assumptions, there is also uncertainty in using this approach to represent future spatial variability in snow accumulation.

The ForEST network contributes to the existing SNOTEL network to explicitly investigate snow-vegetation-climate interactions across the range of elevations and forest types in the watershed. The ForEST network is unique in that the monitoring site locations were selected based on statistical classification and geospatial analysis, rather than subjective methods that may incorporate bias. The paired forest-open land cover site selection process has already led to important understanding of key sub-canopy snow processes (Storck et al., 2002; Golding and Swanson, 1986). But here, the assumptions driving paired site selection process have been validated using coupled physically-based spatially-distributed snow model input data and non-parametric BRT statistical modelling across a forested montane watershed. After five consecutive years of snow monitoring, we have created a valuable and detailed dataset of snow accumulation, snow ablation, and snowpack energy balance that spans the spatial variability in forest and open land cover types across an elevational gradient (Figure 6).

5 Conclusions

The BRT model characterized peak SWE conditions in an average year, an above average year, and below average year to provide spatially-distributed SWE volume estimates based on physiographic landscape characteristics. This integrated approach informed the distribution of an objective and representative monitoring network that spans the spatial variability in the seasonal snowpack across the MRB (Figure 4). Throughout the maritime Pacific Northwest, it is critical we monitor snow-vegetation interactions across the elevation gradient, particularly at higher elevations where snow-vegetation interactions may be more relevant in low snow years and under a warming climate.

By quantifying the spatial variability in the key drivers of natural resource distribution, researchers can focus on sensitive areas which may not be identified through traditional site selection means. The use of validated model outputs as a predictor of the spatial variability in snow-vegetation interactions is not new (Randin et al., 2014). The novelty of this research stems from the application of the method, where by the coupling of a traditional BRT classification process with a validated physically-based spatially distributed model, we improved snow observational network design in a forested montane watershed.

As the scientific community turns to more complex models to predict ecosystem responses to change, there is still a place for simple modelling approaches to inform scientific research priorities as well as natural resource monitoring and management. Particularly in rugged and densely forested mountain regions, such as the western Oregon Cascades, where there are few alternatives to modelling spatially distributed SWE, this coupled modelling approach provides a validated hypothesis to guide representative and objective snow monitoring efforts.

6 Acknowledgements

This research was made possible through funding from the National Science Foundation (EAR-1039192). Thanks are expressed to Eric Sproles who provided the modelled SWE data for the MRB, to Glen Liston who provided the SnowModel code, and to the Willamette National Forest who provided permits for the ForEST network. Additional thanks are expressed to the many interns who helped install and maintain the ForEST network. Finally, we would like to thank three anonymous reviewers whose comments greatly improved the final manuscript.

7 References

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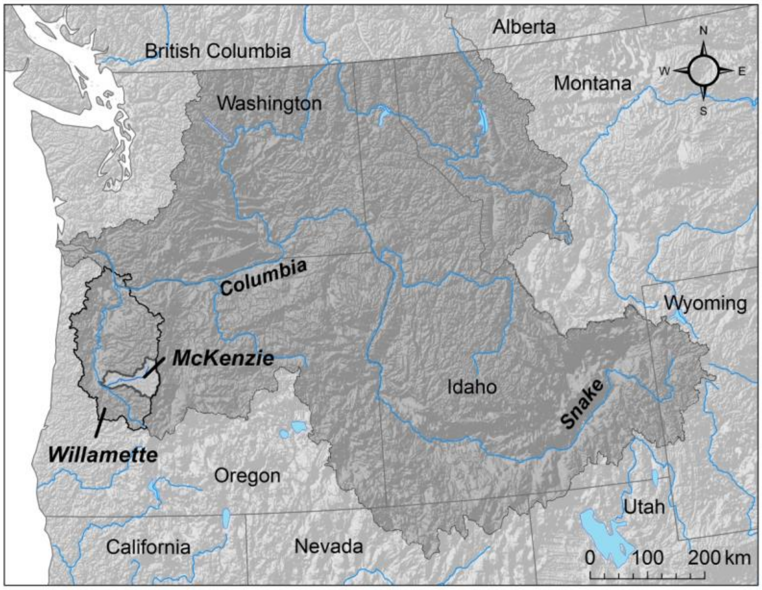
8 Tables

Table 1. The binary regression tree (BRT) model characterized SWE within the McKenzie River Basin into 21 snow classes defined using the physiographic parameters elevation (m) and land cover grouped by all land covers (A), forested land cover (F), and open/clear-cut land cover (O) types. The bold lines represent the BRT snow classes used for the ForEST network of snow monitoring stations which have been continuously monitoring snow processes in paired forest and open sites at low, medium and high elevations since November 2011.

BRT Snow class	**Normal Snow Year (2009)**			**High Snow Year (2008)**			**Low Snow Year (2005)**		
	Elevation	Land	Mean SWE / St. Dev.	Elevation	Land	Mean SWE / St. Dev.	Elevation	Land	Mean SWE / St. Dev.
1	≤ 834	A	0.002 / 0.2	≤865	A	0.002 / 0.03	**≤1193**	**A**	**0.001 / 0.01**
2	834-951	A	0.04 / 0.12	865-949	A	0.06 / 0.16	1193-1299	F	0.02 / 0.07
3	951-1067	F	0.11 / 0.21	949-1067	F	0.14 / 0.26	1193-1299	O	0.08 / 0.15
4	951-1067	O	0.24 / 0.28	949-1067	O	0.31 / 0.36	**1299-1422**	**F**	**0.04 / 0.12**
5	**1067-1142**	**F**	**0.26 / 0.28**	**1067-1115**	**F**	**0.31 / 0.34**	1422-1470	F	0.09 / 0.16
6	**1067-1142**	**O**	**0.45 / 0.35**	**1115-1142**	F	0.45 / 0.36	**1299-1390**	**O**	**0.16 / 0.22**
7	1142-1174	F	0.41 / 0.3	1067-1142	**O**	**0.59 / 0.43**	1390-1470	O	0.29 / 0.28
8	1174-1212	F	0.51 / 0.3	1142-1200	F	0.64 / 0.36	**1470-1496**	**F**	**0.16 / 0.18**
9	1142-1212	O	0.68 / 0.34	1142-1200	O	0.91 / 0.4	1496-1517	F	0.23 / 0.19
10	1212-1265	F	0.64 / 0.29	1200-1235	F	0.83 / 0.33	1517-1536	F	0.28 / 0.19
11	1265-1310	F	0.79 / 0.27	1235-1299	F	1.0 / 0.3	1536-1563	F	0.34 / 0.2
12	1212-1310	O	0.95 / 0.31	1200-1299	O	1.21 / 0.34	**1470-1563**	**O**	**0.54 / 0.29**
13	**1310-1364**	**A**	**0.96 / 0.24**	**1299-1338**	**A**	**1.23 / 0.27**	1563-1620	F	0.44 / 0.19
14	1364-1442	F	1.07 / 0.58	1338-1385	A	1.37 / 0.21	1620-1663	F	0.59 / 0.18
15	1364-1442	O	1.18 / 0.17	1385-1445	A	1.49 / 0.14	1663-1713	F	0.63 / 0.19
16	**1442-1486**	**A**	**1.28 / 0.13**	**1445-1563**	**A**	**1.62 / 0.1**	1713-1747	F	0.75 / 0.19
17	1486-1563	A	1.24 / 0.12	1563-1779	A	1.73 / 0.09	1563-1747	O	0.84 / 0.19
18	1563-1779	A	1.31 / 0.09	1779-1931	A	1.89 / 0.1	1747-1787	A	0.91 / 0.19
19	1779-1910	A	1.43 / 0.09	1931-2016	A	2.17 / 0.15	1787-1866	A	1.04 / 0.12
20	1910-2101	A	1.64 / 0.1	2016-2226	A	2.38 / 0.74	1866-2152	A	1.14 / 0.05
21	>2101	A	1.89 / 0.09	>2226	A	2.66 / 0.12	>2152	A	1.29 / 0.05

9 Figures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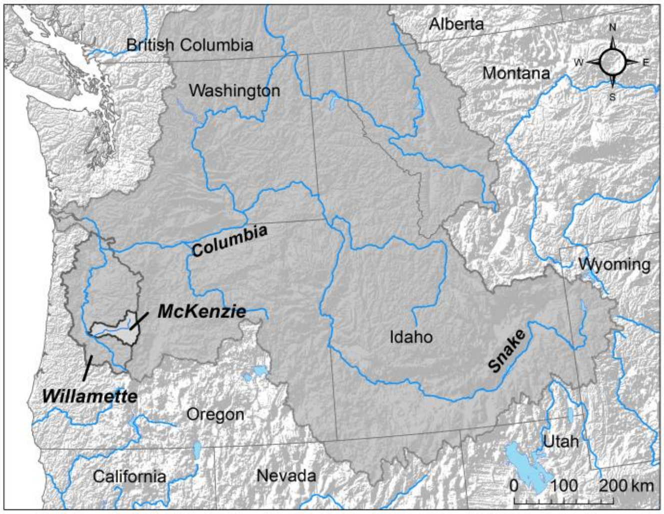
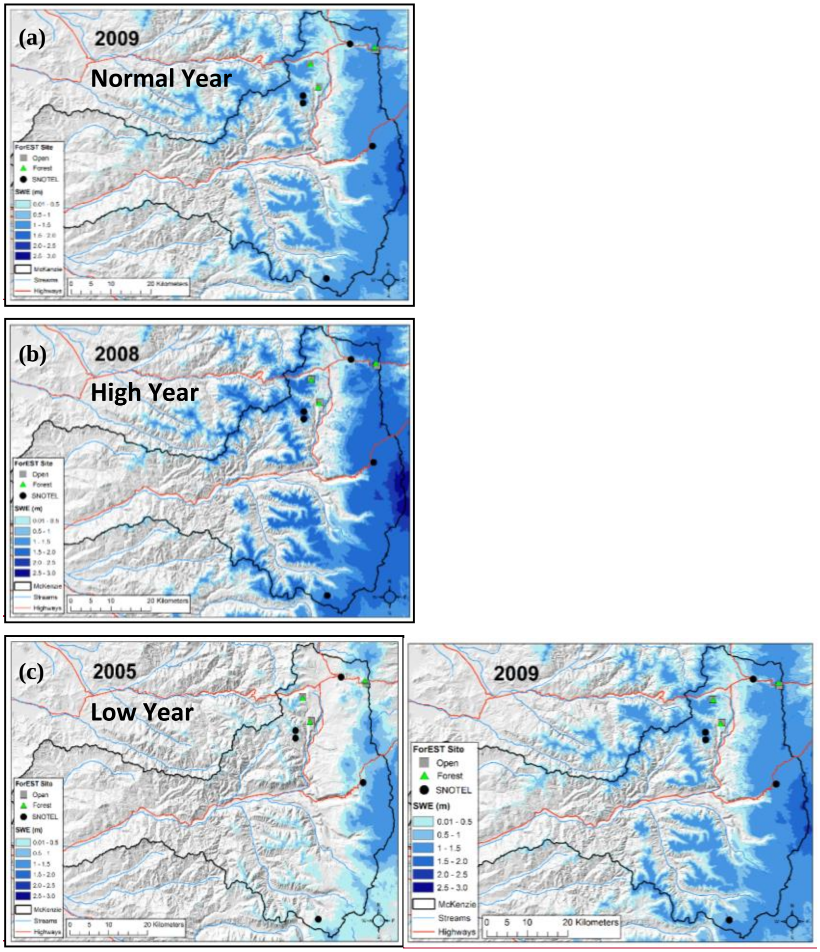


Figure 1. The M~~M~~cKenzie River Basin is nested in the Willamette River Basin within the greater Columbia River Basin.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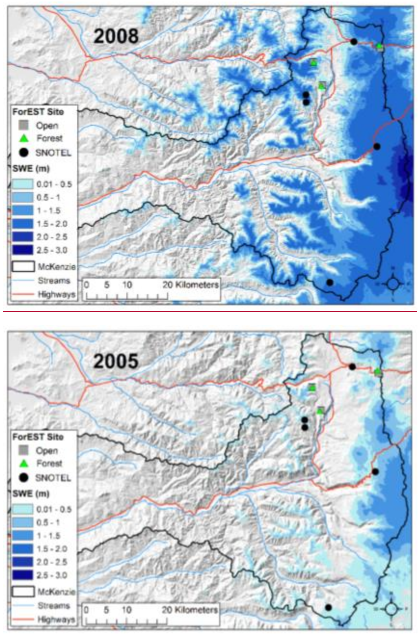

Figure 2. SnowModel-derived snow water equivalent (SWE) (m) is shown in blue for the date of peak SWE from Sproles *et al.*, (2013) for, a) a normal snow year (2009), b) a high snow year (2008), and c) a low snow year (2005), for the modelling domain around the McKenzie River Basin. The locations of the current SNOTEL sites are shown in black circles. The locations of the ForEST sites are shown in grey squares for open sites and green triangles for forested sites.

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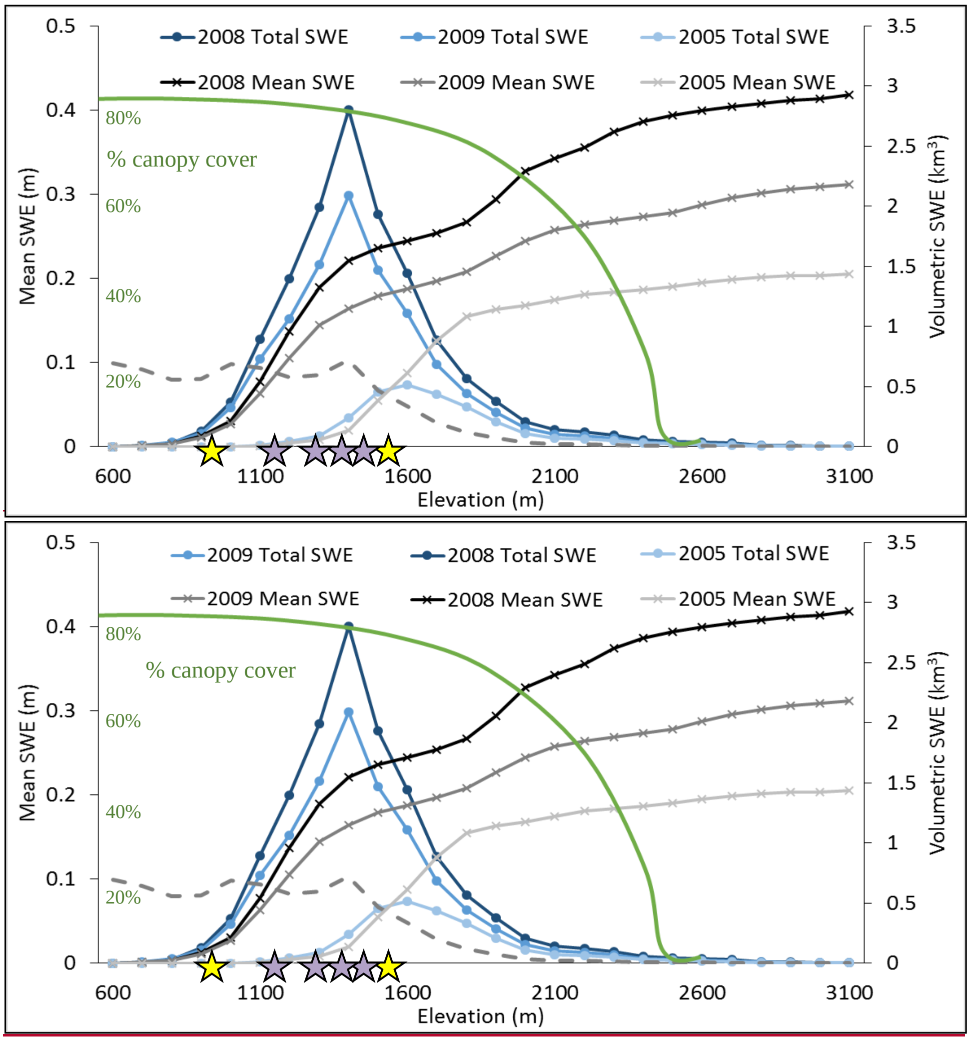

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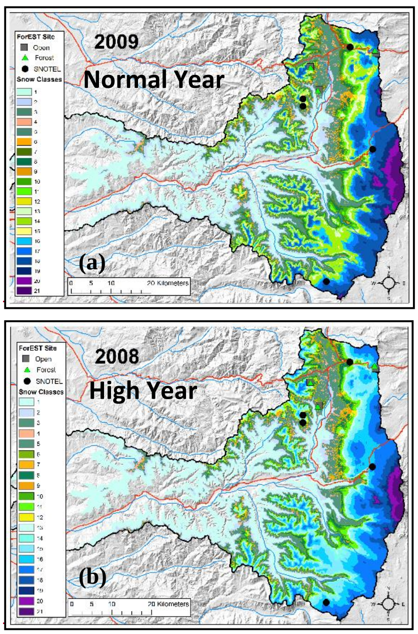
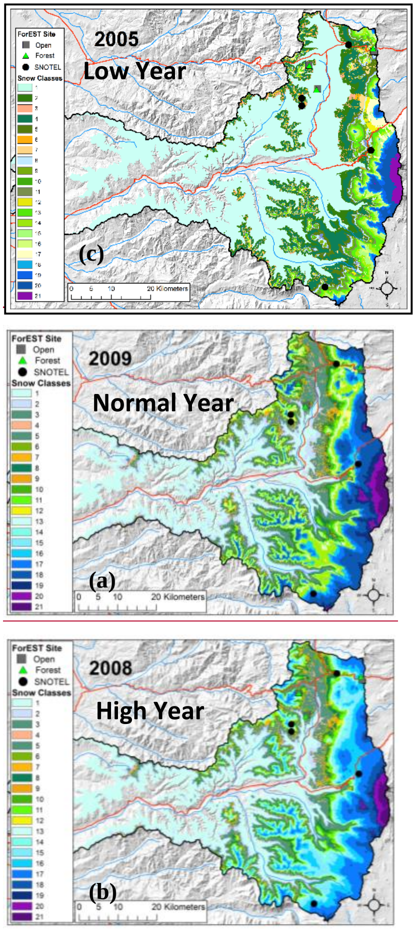
Figure 3. Elevation distribution (using 100 m elevation bands) of SnowModel-derived snow water equivalent (SWE) in the McKenzie River Basin for peak SWE during an average snow year (04 April 2009), an above

average snow year (24 April 2008), and a below average snow year (20 April 2005). Mean SWE for each elevation band is shown in greyscale, and total basin wide volumetric SWE is shown in blue scale for 2009, 2008, and 2005. The green line indicates the elevation distribution of the percent canopy cover. The dashed grey line indicates the % / 100 of the area represented by each 100 m elevation band, and its values are associated with the left y-axis. The area of the greatest volumetric SWE persists in a narrow elevation range which is monitored by four historical and two newly installed (as of 2012) SNOTEL stations (elevations of historical stations shown in purple stars and new stations in yellow stars).




ForEST Site
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Snow Classes
2009
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ForEST Site
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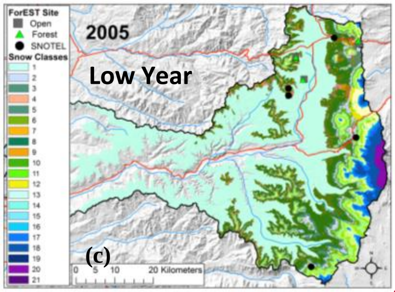

Figure 4. Spatially distributed snow classes derived from the binary regression tree model and geospatial model for, a) a normal snow year (2009), b) a high snow year (2008), and c) a low snow year (2005). Blue/purple colours represent snow classes distributed by elevation for all land covers, green colours represent snow classes distributed by elevation and forest land covers, and orange/yellow colours represent snow classes distributed by elevation and open land covers. The selected locations for the snow monitoring sites were not evenly distributed in space, but were selected to span the range of spatial variability in snow-vegetation-climate interactions.

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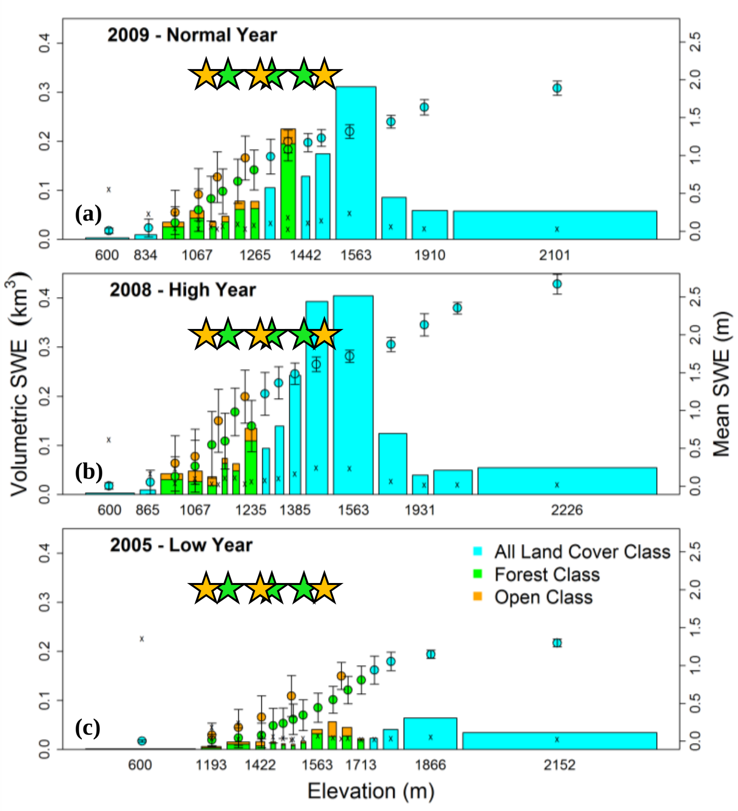

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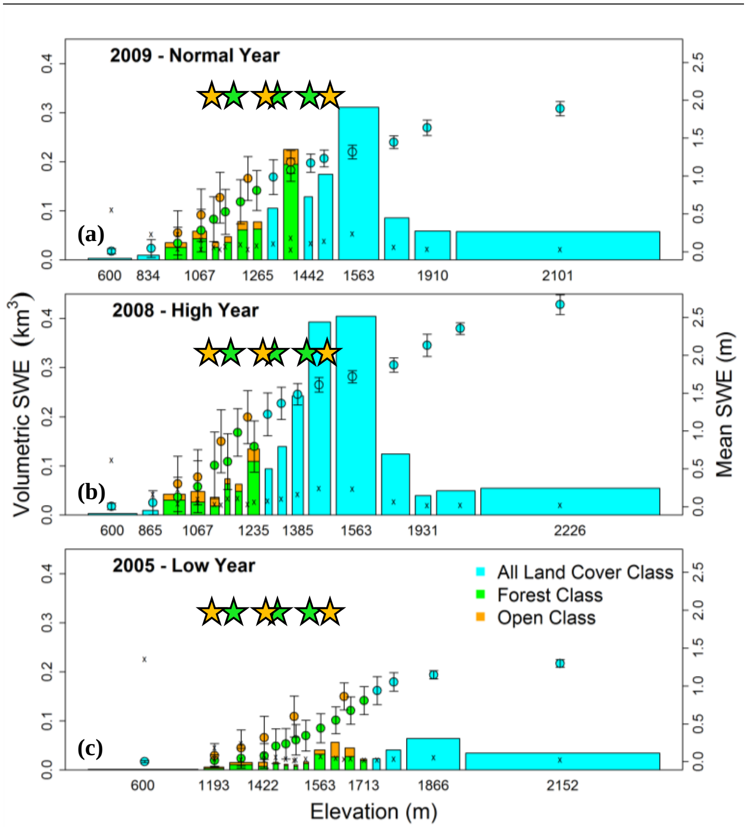

Figure 5. Volumetric SWE (km^3) (shown as bar height), across the elevation range where the classes are located (shown as bar width), of the 21 binary regression tree (BRT) derived snow classes for, a) a normal snow year (2009), b) a high snow year (2008), and c) a low snow year (2005) -with the minimum elevation for each class labelled on x-axis. Mean SWE (m) (shown in coloured circles), standard deviation (shown as error bars), and area (shown as black x) within each BRT-derived snow class across the elevation range where the classes are located. The elevations of ForEST station locations are shown in orange stars for open sites and green stars for forested sites.

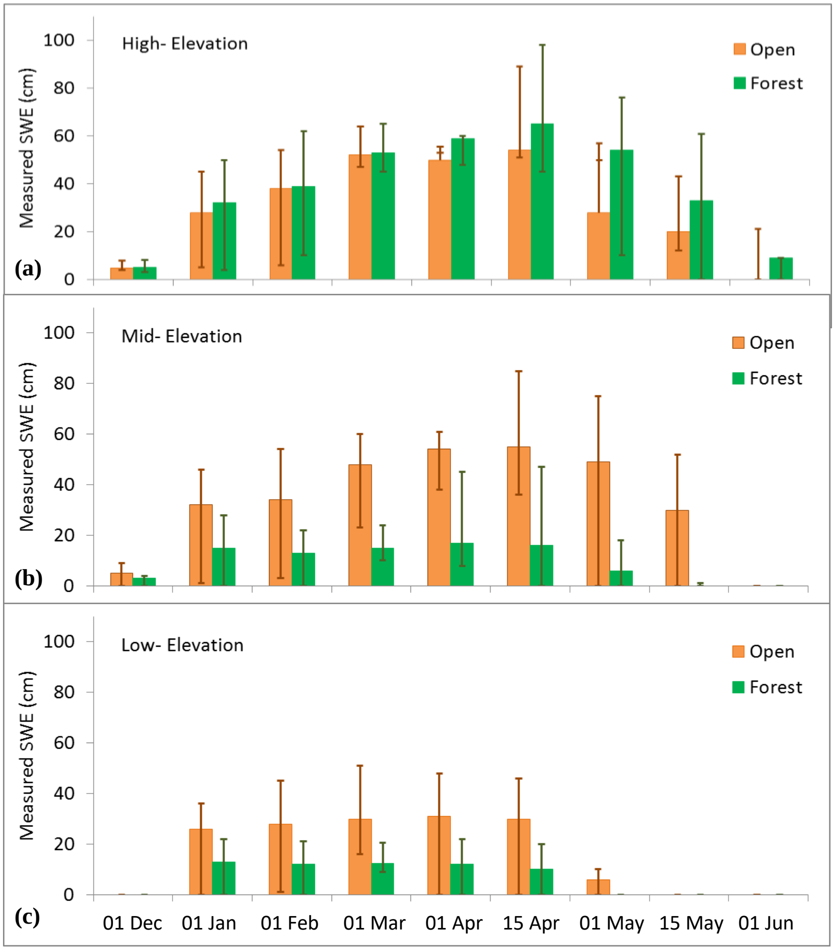

Figure 6. Mean SWE (cm) from snow course measurements collected at the paired open and forested snow monitoring sites in the ForEST network at, (a) high- (1483 and 1467 m), (b) mid- (1335 and 1332 m), and (c) low- (1113 and 1139 m) elevations during the winters of 2012, 2013, and 2014. Orange bars represent mean SWE (cm) in open sites. Green bars represent mean SWE (cm) in forested sites. Error bars indicate the maximum and minimum measured SWE (cm) from 2012, 2013, and 2014.