THIS PAPER HAS BEEN JUDGED

"BEST STUDENT PAPER"

AT THE WESTERN SNOW CONFERENCE

CHARACTERIZATION OF WIND INDUCED SNOW REDISTRIBUTION WITH GIS DERIVED PARAMETERS

by

Adam Winstral[1], Kelly Elder[2], Robert Davis[3]

ABSTRACT

In order to develop a physically based model of spatial snow distribution, parameters that characterize the natural controls affecting distribution patterns are necessary. Stratification of the study area, Blackcap Basin, CA, based on timberline indicates that elevation, radiation, and slope exhibit a strong linear relationship to snow depth below timberline, but above timberline the strength of these relationships is greatly attenuated. Based upon field observations of the increased importance of wind redistribution in the exposed alpine region, we apply two terrain parameters which affect wind patterns on the ground to account for this process in our modeling efforts. Surface curvature, a direct output in most Geographic Information System software, and a wind exposure index derived specifically for this study, are tested for their efficacy in explaining the observed alpine snow distribution. The wind exposure index is shown to be a better predictor of snow accumulation in the alpine region than any of the aforementioned predictors. Curvature measured over a large area effectively discriminates convex regions as areas containing anomalously high and low snow depths. An adequate analysis of localized curvature is hindered by both the spatial resolution of the digital elevation model and registration of the data points.

INTRODUCTION

Forecasts of seasonal runoff volumes have traditionally been made based upon point measurements of snow-water equivalence (SWE) from established snow courses. Correlation of these points to basin runoff form the basis of a linear regression model that is then used to make current predictions [U.S. Army Corps of Engineers, 1956] . This method for forecasting runoff was developed in the 1950's and although these regression equations are now based on datasets with up to 60 years of data, problems are still encountered. Basically, this procedure works well for years in which climatic conditions do not greatly vary from the historical mean conditions upon which the model was developed but has difficulty forecasting years which are dissimilar [Day, 1989]. For example, the 1995 winter season in the Sierra Nevada brought above average temperatures and above average precipitation. In the Kings River Basin, when late season snow course measurements were measuring small amounts of snow water equivalence, a high volume of snow remained at the higher elevations, seemingly undetected. This resulted in a forecast that under-predicted runoff.

The current system can be improved through the development of a physically based model which takes advantage of modern technology. Geographic Information System (GIS) software enables modelers to quickly derive terrain-based data layers (e.g. elevation, net radiation, and slope), which can be further combined with existing coverages (e.g. canopy density and ground cover) to establish a linked set of factors that affect snow accumulation. Statistical modeling techniques currently available facilitate the understanding and development of the complex relationships that exist between the independent variables and snow distribution. The linkage of controls and effects forms the basis of

[1]Master's Candidate, Department of Earth Resources, Colorado State University, Fort Collins, CO 80523, Tel: 970-416-6582, Email: awinst@cnr.colostate.edu

[2]Department of Earth Resources, Colorado State University, Fort Collins, CO 80523, Tel: 970-491-5454, Email: kelder@cnr.colostate.edu

[3]Cold Regions Research and Engineering Laboratory, 72 Lyme Rd., Hanover, NH 03755, Tel: 603-646-4219, Email: bert@crrel41.crrel.usace.army.mil

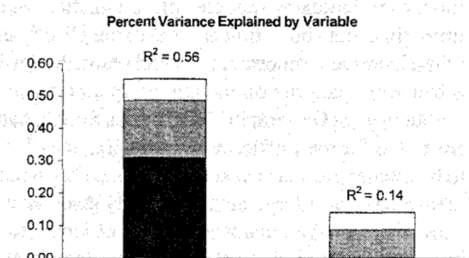
Presented at the Western Snow Conference, Snowbird, Utah, 1998

a physical model. Integration of an increasingly accurate physical model with similar advances in remotely sensed snow-covered area (SCA) is affording forecasters the potential for significant improvements in the accuracy and expeditiousness of their predictions. Improved accuracy ultimately results in increases in agricultural and energy production, decreases in potential flood damages, and improvement in the overall efficiency of the management of our water resources.

GIS software also allows modelers to develop algorithms that can extract application-specific information from an existing raster grid. Functions inherent to many GIS software packages were developed in this manner. This study is a "first approximation" of the applicability of two raster derived terrain parameters, wind exposure and curvature, to physically based spatial snow modeling. The index of wind exposure is derived specifically for this study whereas curvature is a function available in most GIS packages.

Background

The snow depth and density data used in this study were gathered from 5 to 7 May 1993. Concurrent with fieldwork, aerial photographs and a Landsat TM image of the study area were obtained to analyze SCA. Elder et al. [1997] presented this initial analysis of SWE and SCA, in which SWE was modeled over the entire basin as a function of elevation, radiation, and slope. Winstral et al. [1997] then stratified the data based on crown closure (i.e. timberline) and found striking differences in the relationships between these same predictor variables and snow depth in the stratified datasets (Figure 1). Whereas elevation, radiation and slope combined to linearly explain over half of the observed variance in snow depth below timberline, the strength of these relationships greatly diminished above timberline. The primary difference above treeline is the lack of cover which leads to increased surface winds and therefore, redistribution. This study takes a closer look at the alpine dataset in an effort to improve modeling efforts in areas such as these.



	Forested	Alpine
Slope	0.07	0.05
Radiation	0.18	0.09
Elevation	0.31	0.00

Figure 1. Contribution of the elevation, radiation, and slope parameters in linear models of snow depth (based on Type III sums of squared errors).

It is the stochastic nature of redistribution that has hindered snow distribution models, and wind and avalanches greatly increase redistribution above treeline. In order to accurately characterize the spatial distribution of snow in regions where the processes of scouring, sublimation, and redeposition due to wind are present, modeling efforts must include allowances for these effects. The redistribution of snow precipitation by wind is a complex process controlled by the interaction of wind flow, snow properties, land surface roughness, and topography. The process is sufficiently complex that the development of a physical model of snow redistribution is virtually impossible at this time [Kind, 1991]. At present though data is being collected in an attempt to develop just such a model for an alpine setting [G. Liston, personal communication, 1997].

In the absence of such a redistribution model, geomorphometric variables established through digital terrain modeling have been employed to characterize snow redistribution. Lapen and Martz [1993] used cardinal direction fetch analysis and directional relief as indices of topographic sheltering and exposure to wind in a low-relief, agricultural landscape in a Saskatchewan prairie. Cline [1993] employed gross topography and local topographic discontinuities to characterize convergent and divergent wind flow patterns in modeling the redistribution pattern of an early season snow event at a high elevation site in the Colorado Front Range.

We have enhanced the fetch algorithm developed by Lapen and Martz [1993] to include omni-directional fetch calculations in an application to an alpine setting. An average fetch, here referred to as wind exposure, can then be calculated through a 90 degree window to the prevailing wind direction from fetches calculated at five degree increments. It is felt that these "windows" provide a more accurate depiction of exposure compared to the directional constraints of the previous work.

Curvature, the second derivative of a surface fitted to elevation, is a measure of the concavity or convexity of the terrain at a particular point or pixel. Concavities and convexities are synonymous with surface depressions and protrusions, respectively. Curvature and its offshoots, profile curvature (curvature measured in the direction of slope) and planform curvature (curvature measured transverse to the slope direction) have primarily been used to model flow patterns of water. Curvature has been used to model soil water content [e.g. Zaslavsky and Sinai, 1981], profile curvature as a means of determining flow acceleration and deceleration to determine erosion and deposition processes at the hillslope scale [e.g. Moore and Burch, 1986], and planform curvature to model flow convergence and divergence [e.g. Thorne and Zevenbergen, 1986]. Here curvature is used to identify hollows or valleys protected from the wind, and hills or mountains that are susceptible to the wind-induced scour, redeposition, and coincident sublimation of snow.

STUDY SITE

The study area is Blackcap Basin, a headwater catchment of the North Fork of the Kings River, California (Figure 2). This site was chosen as a representative upper basin catchment for the Kings River basin through comparisons of elevation histograms. The study watershed covers 9280 ha, ranging in elevation from 2476 m to 3927 m. Alpine cirques and dense forest cover substantial portions of the basin. At the time of the survey, snowpack temperatures measured at elevations between 3300 and 3500 m indicated that the snowpack was not yet isothermal in the upper basin. Snowpack temperatures in conjunction with regional snotel data [http://cdec.water.ca.gov/snow] indicated that meltout had already begun at the lower elevations.

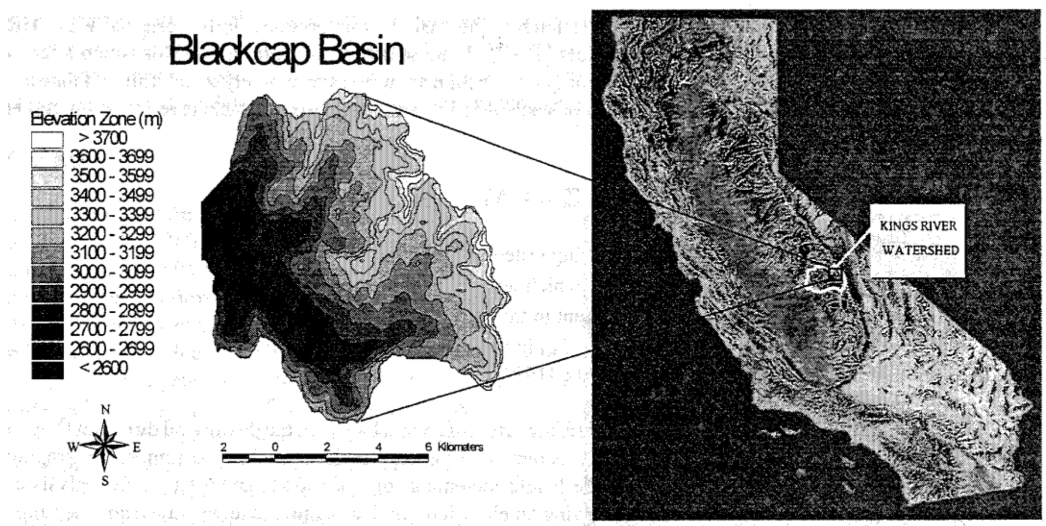


Figure 2. The study area

METHODOLOGY

Field data was collected by two teams from 5 to 7 May, 1993, one team working above timberline and the other below timberline. Snow depths were measured with aluminum probes along transects; snow density with the Federal (Mt. Rose) Sampler and snow pit profiles. Five measures of density were obtained in each of the regions. Since a significant relationship could not be established between any of the predictor variables and density, depth is used as the dependent variable in all modeling. This choice of dependent variable allows the modeling of a known quantity rather than one which introduces additional variance into the model.

Below timberline 304 depth measurements were made along six transects at 10 m intervals. In the alpine zone 405 depth measurements were taken along transects at 10 and 20 m resolutions. In the lower basin, UTM coordinates for the data points were determined with a Geographic Positioning System (GPS). In the upper basin, above timberline, the location of data points was established via compass sightings to terrain features which were distinguishable on a

1:24000 USGS topographic map. Each depth measurement was registered to a 30 m USGS Digital Elevation Model (DEM) from which the independent variables were generated. The selection of the transect locations was subjective and does introduce some bias into the results of this study, but such decisions must be made when surveying large basins with limited time and personnel [Elder et al., 1997]. In addition, the resolution of the depth measurements contributes to spatial autocorrelation amongst all of the variables, thereby limiting the scope of this study.

Elevation, slope, and aspect were derived for each point using the ARC/INFO GIS which uses bi-linear interpolation for the extraction of point data from a raster coverage. An index of potential net radiation was calculated using the algorithm of Dozier [1980] as developed in IPW software [Frew and Dozier, 1986] and using atmospheric parameters derived from LOWTRAN7 [Kneizys et al., 1988]. Potential clear-sky net radiation was calculated for the 15th of each month from December through April, summed and implemented as an index of seasonal radiation input. The radiation coverage thus generated was imported into ARC/INFO where values for each of the data sites were similarly extracted. Elevation, slope, aspect, and radiation index are all modeled with a 30 m pixel resolution.

Wind Exposure/Average Fetch

The definition of fetch used here is the distance in a specified direction from a point in the landscape to a topographic obstacle [Lapen and Martz, 1993]. This definition differs slightly from that used by Tabler [1994] in analyzing the snow carrying capacity of wind in a high plains environment. At a given point, fetch represents the degree of exposure to wind in a given direction when measured in the prevailing upwind direction.

For this study, a C program was written to calculate fetch. The basis of this program is the original FETCHR FORTRAN-77 program developed by Lapen and Martz [1993]. In these programs, from the cell for which fetch is being determined, the cells encountered in a specific compass direction are tested successively to determine if they are topographic obstacles. If a cell is determined to be an obstacle then the distance to that obstacle is returned. A cell is considered a topographic obstacle if:

$$Z_{test} \geq Z_{core} + NI$$

where

Z_{test} = elevation of the cell being tested as a topographic parameter
Z_{core} = elevation of the cell at which fetch is being determined
I = obstacle height increment in the same units as elevation
N = distance from Z_{core} to Z_{test} in the same units as elevation
(Lapen and Martz, [1993])

The obstacle height increment (I) accounts for the decreasing effect of a wind barrier in the downwind direction [Lapen and Martz, 1993]. The smaller the obstacle height increment the more sensitive fetch is to minor topographic irregularities. Lapen and Martz [1993] tested obstacle height increments of 0.025, 0.05, and 0.1 in their analysis of snow cover patterns in a 2 km^2 agricultural prairie having an elevation range of 22 m and an average snow depth of 14 cm. They found that fetch patterns calculated with the largest obstacle increment (I = 0.1) reflected only the well-defined valleys of the major drainage courses and concluded that the smallest obstacle increment (I = 0.025) was the most useful in discriminating snow patterns. For this study conducted at a much larger spatial scale over rugged terrain with far greater snow accumulations, we were concerned with large scale variations in snow accumulation patterns. Therefore, we decided to test fetch patterns calculated with obstacle increments of 0.1 and 0.2.

In order to perform a multi-directional fetch analysis, not limited to the cardinal directions, the FETCHR algorithm is combined with a derivation of Breshenham's algorithm for drawing lines in a planform grid of pixels [Barkakati, 1990; developed by D.J. Dean, personal communication, 1998]. This implementation of Breshenham's algorithm takes as input the start and end points of a line segment. The program then proceeds from the starting point selecting each successive pixel which best represents this line segment based on the slope of the line (Figure 3).

The starting points input to the program are the nearest pixel coordinates of each depth sample while the endpoints are determined by the direction and maximum distance of each individual fetch analysis. As each new pixel along the line is selected, its elevation is tested to see if it is an obstacle and if so the distance to that pixel is returned. If the border of the grid or the end point of the line is reached before an obstacle is encountered, the distance at that point is returned and flagged. In this basin, data points are a sufficient distance away from the boundaries of the DEM and the geography of the basin is such that any flagged fetches were considered to be infinite and assigned the maximum search distance.

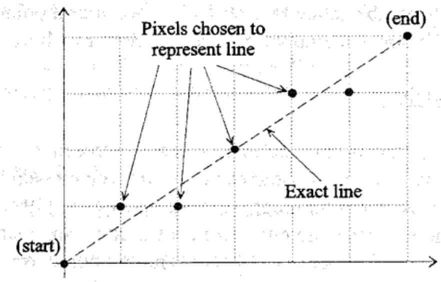


Figure 3. Drawing a line out of pixels. (adapted from Barkakati, 1990)

Fetches were calculated for each data point in 5 degree increments for a 90 degree window centered on the predominant wind direction for the accumulation season. The predominant wind direction applied in this study is southwest (225°). This direction was chosen for several reasons: the predominance of Southern Pacific winter storms which approach from this direction upon the southern Sierra Nevada , the general northwest/southeast trend of this mountain range, and the predominance of glacial cirques with northeast aspects in this region. Fetch calculations were conducted with two, five, and seven kilometer maximums. The larger the maximum distance, the greater the impact of small terrain openings (e.g. a narrow valley in alignment with the upwind quadrant) on the average fetch. At each distance maximum a set of values with increment factors of 0.1 and 0.2 were generated. Each of the six sets of nineteen fetch values were then averaged to obtain respective indices of wind exposure. These six derived wind exposure indices were individually regressed on depth to determine the one that is most appropriate for modeling alpine snow distribution in this basin.

Curvature

Values of curvature were derived from the DEM using an ARC/INFO defined function. As implemented in ARC/INFO, this function is based on the algorithm developed by Zevenbergen and Thorne [1987] which is a modification of that previously introduced by Evans [1980] for topographic analysis. In this application, a fourth-order polynomial surface is fit to a 3 x 3 submatrix of pixels such that the surface passes exactly through the nine pixel elevations. Differentiating to obtain the second derivative and subsequent solution of the resulting equation for the central point of the submatrix yields the curvature value for that particular pixel [Zevenbergen and Thorne, 1987]. The units of the output as presented here are in 1/100 m. Negative values reflect surface concavities, positive values surface convexities, and zeros either flat areas or areas where convex and concave curvatures cancel each other out, such as saddlepoints (Figure 4) [Blaszczynski, 1997].

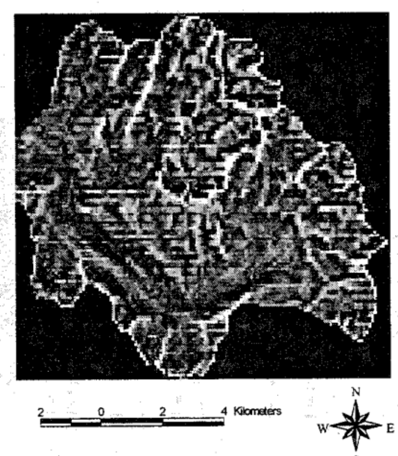


Figure 4. Curvature grid where pixels have been resampled to 90 m. Bright areas are indicative of convex terrain and dark areas of concave.

In this application of curvature, terrain analysis is limited to the aforementioned 3 x 3 submatrix of pixels. Therefore, in order to analyze curvature at different spatial scales the DEM was resampled to increasingly larger pixels using a cubic convolution scheme. Cubic convolution places an average of elevations from the original smaller cells within the enlarged, resampled cell thereby providing a more accurate depiction of elevation within the enlarged cell as compared to the use of a nearest neighbor scheme. A corresponding curvature grid for each of the resampled DEMs was created and values extracted for each data point. Each spatial scale of curvature was independently analyzed for its statistical relationship to the dependent variable, depth. It must be noted that the fitted surface in itself does not fully replicate the actual land surface between grid points [Zevenbergen and Thorne, 1987]. This problem is accentuated at the larger spatial scales created here through resampling.

Modeling

A general linear model and a regression tree model were used to evaluate the performance of and the potential for these newly developed parameters in full-scale modeling of snow distribution (see Breiman et al. [1984] for a thorough discussion of regression trees and Elder et al. [1995] as applied to snow distribution). In these models, parameters of wind exposure and curvature were used in conjunction with the traditional predictors: elevation, radiation, and slope. The use of a linear model here is not proposed as a means of modeling alpine snow distribution but rather solely as a means of evaluating the independent variables via model selection techniques. The node decisions of the regression tree, selected based upon the decision which has the greatest reduction in overall model deviance, similarly provide insight into the relative significance of the parameters in the overall model. Due to the constraints imposed by the nature of this dataset (e.g. spatial autocorrelation and errors associated with the registration of data points) we do not evaluate the overall fit of these models. Our objective is simply to evaluate the validity of these terrain parameters and determine a course for future development.

RESULTS AND DISCUSSION

The exposure indices, based upon fetch in the upwind quadrant, and their statistical relationship to depth is presented in Figure 5. As the cap on calculated fetch distance decreased to two km the strength of the relationship to the observed distribution of sampled depths increases. At each set maximum, the fetch values calculated with an increment factor of 0.2 exhibit a closer relationship to depth than those calculated with a 0.1 factor. One additional exposure factor based on a weighted average of fetch derived with the two km maximum and an increment factor of 0.2 was also tested. This latter derivation doubles the importance of fetch calculated in the directions between 205 and 245 degrees inclusive. This directionally weighted index of exposure however, did not improve results.

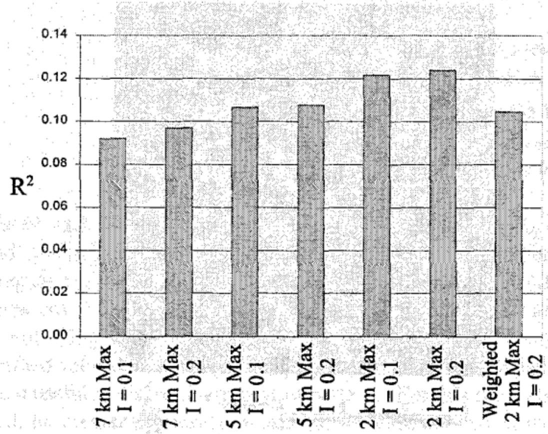


Figure 5. Relationship of wind exposure indices with different distance maximums and obstacle increments to the observed snow depth.

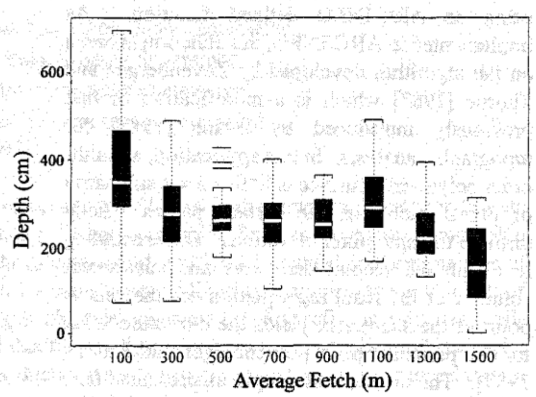


Figure 6. Box-and-whisker plot of average fetch in the upwind quadrant calculated with a 2 km maximum and an obstacle increment factor of 0.2. The x-axis labels are the midpoints of each 200 m bin of fetch; y-axis is the observed snow depth.

These observations indicate that for these data, an equally weighted, average fetch calculated with an increment factor of 0.2 through a 90 degree upwind window provides the best exposure index as related to snow depth. The box-and-whisker plot (Figure 6) indicates the value of minimums and maximums of exposure as indicators of regions containing anomalously high and low depths respectively.

The results of the curvature analysis were not as straightforward. Although all of the scaled curvature predictors are significant ($p < .05$) in the full data set, R^2 values are still generally low (Table 1). All of the correlation coefficients are negative coinciding with the expected trend of decreasing snow depth in conjunction with terrain grading from concave to convex. At the larger scales at which curvature was derived, a confounding trend developed (Figure 7). Due to the large area analyzed in these calculations, the convex regions delineate ridges encompassing both the windward and leeward sides of the convexity. Thus, in areas of large spatial convexity, high and low extremes of depths are found which decreases the statistical significance of the large-scale curvature parameters.

Table 1.
Relationship of Curvature Measured at Varying Scales to Depth

Curvature Scale	R^2		
Pixel size in 3 x 3 submatrix (area of submatrix)	Full Dataset	NE aspects removed	NE and SW aspects removed
30 m (0.8 ha)	.020	.009	.007
60 m (3.2 ha)	.018	.007	.004
90 m (7.3 ha)	.012	.017	.001
120 m (13. ha)	.024	.031	.028
150 m (20. ha)	.014	.035	.033
240 m (52. ha)	.023	.057	.029
300 m (81 ha)	.019	.062	.040
400 m (144 ha)	.044	.082	.054
500 m (225 ha)	.012	.103	.069

In order to better appraise the validity of the curvature values in assessing snow distribution, data points having lee aspects (i.e. NNE) and windward aspects (i.e. SSW) were successively removed from the dataset and R^2 values for each of the curvature scales recalculated (Table 1). In each of these subsets, R^2 values increased for the larger scales of curvature and decreased for the smaller scales. The insignificance of the small-scale curvatures in this dataset is not surprising given the errors associated with the field registration of the data points and the inherent inaccuracies contained in this 30 m USGS DEM. Errors associated with the quality of the DEM are plainly visible in the streaked patterns of the 90 m pixel curvature grid (Figure 4).

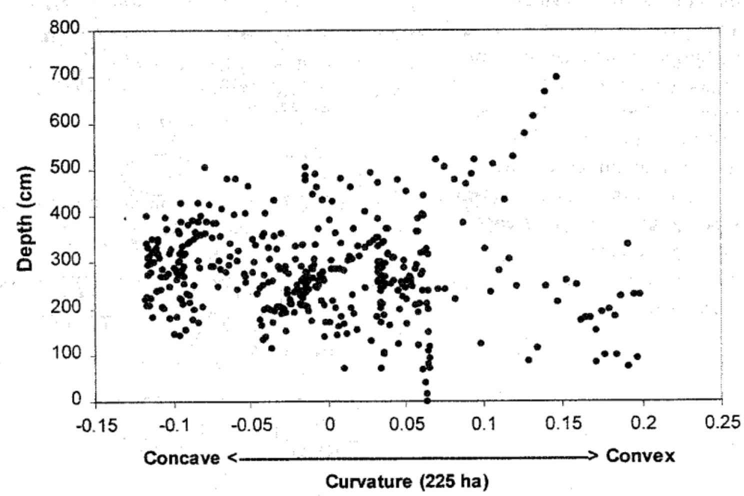


Figure 7. Curvature values calculated with a pixel size of 500 m (225 ha region) plotted against snow depths.

The exposure index with the highest statistical significance and all of the significant curvature parameters ($p < .05$) for the full dataset were combined with the elevation, radiation, and slope parameters to form a set of independent variables in the construction of a linear model. Variable selection was based on the combination of variables having the highest R^2 value for each subset size. Models where all of the chosen predictors are significant ($p < .05$), do not exhibit colinearity, and where the addition of an extra variable increased the coefficient of determination are shown in Table 2. All of the models have residual distributions that are heavy tailed suggesting a slight deviance from normality. Given the slight robustness of linear models to non-normality of the residuals and the nature of this investigation, this does not affect our qualitative assessment of the variables.

Table 2. Results of Linear Model Variable Selection

# of Variables	Variables Chosen	R^2
1	Wind Exposure	0.124
2	Radiation, Curvature (400 m pixel / 144 ha region)	0.193
3	Wind Exposure, Radiation, Curvature (400 m pixel / 144 ha region)	0.248

As can be seen from the chosen models, curvature measured with 400 m pixels, and average wind exposure were chosen before the elevation, and slope parameters. A comparison of the three variable model with fetch, radiation, and curvature (R^2=0.25) to the three variable model with elevation, radiation and slope (R^2=0.14) shows an improvement with the inclusion of these new parameters.

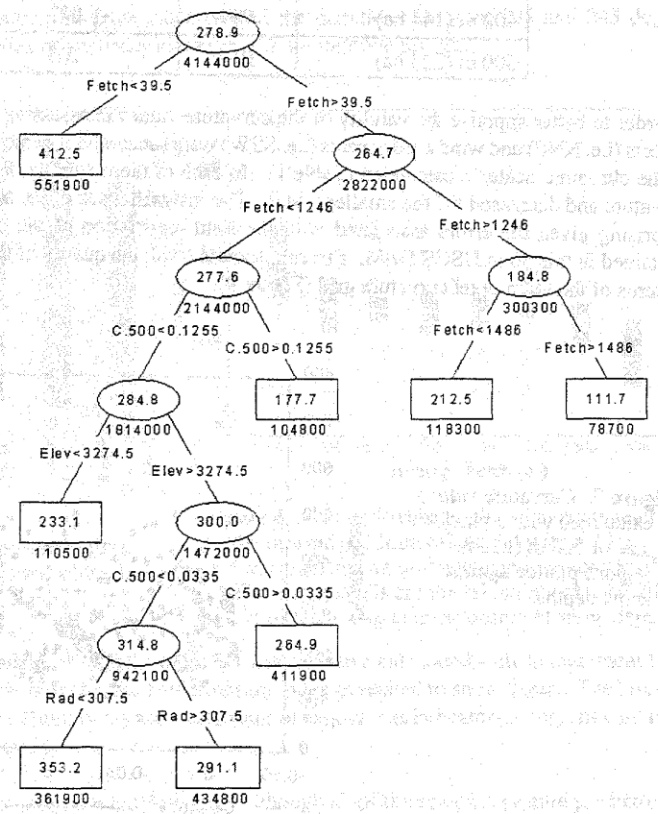


Figure 8. Upper node splits of the pruned regression tree grown on the wind exposure index ("Fetch"), 500 m pixel curvature ("C.500"), elevation, radiation (mJ), and slope. Values within the ellipsoids and rectangles are the averages of all data points contained in that node. Values beneath the boxes and ovals are the residual deviance within each node. Since this is a pruned tree there is not a functional difference between nodes pictured as ellipsoids and those as rectangles.

A regression tree was grown using the exposure index with the highest correlation to depth, curvature measured with 500 m pixels, elevation, radiation, and slope as the independent variables. The 500 m pixel curvature parameter was used due to the significance of its relationship to depth in the data subsets, a condition which regression trees are formulated to recognize. The upper splits of the regression tree (Figure 8) indicate that the initial binary decisions which bring about the greatest reductions in deviance are based upon these newly derived parameters. It can be seen that increasing upwind exposure and increasing convexity (once the leeward slopes are separated out by the first node spit) lead to lower average snow depths. The tree recognizes the patterns in the data brought out in the earlier plots (Figures 6 and 7). Elevation and radiation input come into play once areas having high degrees of sheltering, wind exposure, and convexity have been accounted for.

CONCLUSIONS

Two raster derived geomorphometric variables have been applied to the modeling of alpine snow distribution. Wind exposure as related to average fetch distance in the upwind directional quadrant has been shown to clearly discern areas of snow scour and accumulation as related to wind redistribution. Inclusion of a wind exposure parameter in modeling efforts enabled the large-scale differences in observed depths to be easily distinguished. Surface curvature as it relates to the concavity and convexity of surface features has also been shown to have a significant relationship to the observed snow distribution in this basin. In this study, curvature analysis based on a scale that brought out the large scale features of the basin (e.g. ridges and valleys) had the best overall statistical results.

The effects of wind redistribution and the significant contribution of these eolian forces in affecting snow distribution patterns in alpine terrain is plainly seen by the field observer and in the shortcomings of previous modeling efforts. In side-by-side models containing wind exposure, large-scale curvature, elevation, radiation, and slope parameters the predictors used to characterize the redistribution effects of wind improved model fit and accounted for more of the observed variance in the response variable than the traditional parameters. The significance of the wind exposure index and surface curvature in modeling the effects of wind redistribution and thus the spatial distribution of snow in alpine terrain has been shown.

This study suggests that the large-scale variations in alpine snow accumulation patterns could be discerned using these techniques. Difficulties were, however, still encountered in attempting to account for the smaller scale variability. We are encouraged by these results and now look to improve upon the resolution of our parameters, in particular the derivation of the curvature parameter. Rather than confining curvature analysis to a 3 x 3 cell matrix whereby resolution is lost in resampling of the DEM to obtain larger scale analysis, we are working with and developing algorithms that will examine each cell in the original DEM so that large scale curvature values are obtained by enlarging the matrix window rather than enlarging the cells [Blaszczynski, 1997]. We are also looking into the possibility of merging the exposure and curvature parameters by directionally weighting the curvature parameter. Further exploration will also encompass terrain analyses that have been developed in the related fields of water hydrology and energy balance modeling. We are currently working on a dataset where the data points have been differentially corrected and registered using GPS units in order to minimize the registration errors. We are optimistic that these improvements will increase the significance of the localized curvatures and lead to further improvements in our snow distribution models.

Acknowledgments. Support for this project was provided by the USACE Cold Regions Research and Engineering Laboratory contract DACA89-96-K-0008. Denis J. Dean provided source codes for the revised Breshenham's algorithm and for accessing data from raster maps. Field work was greatly facilitated by the expertise of Sue Burak, Rod Newcomb, and Scott Wheeler. The USFS Region 5 contributed the GIS vegetation coverage.

REFERENCES

Barkakati, N., *The Waite Group's Microsoft Macro Assembler Bible*, 1st ed., 754 pp., Howard W. Sams & Company, Carmel, IN, 1990.

Blaszczynski, J.S., Landform characterization with geographic information systems, *Photogramm. Eng. and Remote Sens.*, 63 (2), 183-191, 1997.

Breiman, L., J. Friedman, R. Olshen and C. Stone, *Classification and Regression Trees*, Wadsworth & Brooks, Pacific Grove, California, 1984.

Cline, D.W., Modeling the redistribution of snow in alpine areas using geographic information processing techniques, *Proc. Eastern Snow Conference*, 13-24, 1993.

Day, G. N., A methodology for updating a conceptual snow model with snow measurements, Ph.D. dissertation, The Johns Hopkins University, Baltimore, MD, 1989.

Elder, K., J. Michaelsen, and J. Dozier, Small basin modeling of snow water equivalence using binary regression tree methods, in *Biogeochemistry of Seasonally Snow-Covered Catchments* , IAHS-AIHS and IUGG XXI General Assembly, Boulder, CO, July, 1995, IAHS, Wallingford, UK, 129-139, 1995.

Elder, K., W. Rosenthal, and B. Davis, Estimating the spatial distribution of snow water equivalence in a montane watershed, *Proc. Western Snow Conference*, 65, 29-41, 1997.

Evans, I.S., An integrated system of terrain analysis and slope mapping, *Z. Geomorph., N.F.*, 36, 274-295, 1980.

Frew, J. and J. Dozier, The Image Processing Workbench - portable software for remote sensing instruction and research, in *Proceedings IGARSS '86*, ESA SP-254, 271-276, European Space Agency, Paris, 1986.

Kneizys, F., E. Shettle, L Abreu, J. Chetwynd, G. Anderson, W. Gallery, J. Selby, and S. Clough, Users Guide to LOWTRAN 7, *Report AFGL-TR-88-0177*, Air Force Geophysics Laboratory, Bedford, MA, 1988.

Kind, R.J., Mechanics of aeolian transport of snow and sand, *Jour. Wind Engineering and Industrial Aerodynamics*, 36 (2), 855-866, 1991.

Lapen, D.R. and L.W. Martz, The measurement of two simple topographic indices of wind sheltering-exposure from raster digital elevation models, *Computers & Geosciences*, 19 (6). 769-779, 1993.

Moore, I.D., and G.J. Burch, Modelling erosion and deposition: topographic effects, *Trans. Am. Soc. Agr. Engrs.*, 29, 1624-1630, 1640, 1986.

Tabler, R.D., Design guidelines for the control of blowing and drifting snow, *Rep. SHRP-H-381*, 364 pp., Strategic Highway Research Program, National Research Council, Washington, D.C., 1994.

Thorne, C.R. and L.W. Zevenbergen, Ephemeral gullies as sources of sediment, *Proc. of the Fourth Federal Interagency Sed. Conf.*, U.S. Govt. Printing Office, 3.152-3.161, 1986.

U.S. Army Corps of Engineers, *Snow Hydrology: Summary report of the snow investigations;*; North Pacific Division, Portland , OR, 437 pp., 1956.

Winstral, A., K. Elder, and B.Davis, Alpine basin stratification by gross vegetation in statistical modeling of spatial snow distribution (abstract), *Eos Trans. AGU*, 78 (46), F209, 1997.

Zaslavsky, D. and G. Sinai, Surface hydrology: I - explanation of phenomena, *J. Hydraul. Div., Proc., Am. Soc. Civil Engrs.*, 107, 1-16, 1987.

Zevenbergen, L.W. and C.R. Thorne, Quantitative analysis of land surface topography, *Earth Surface Process and Landforms*, 12, 47-56, 1987.